WATER QUALITY MANAGEMENT OF GOMTI RIVER (INDIA)

By

AMIT KRISHAN

DEPARTMENT OF ENVIRONMENTAL ENGINEERING

Submitted

In fulfillment of the requirements of the degree

of

DOCTOR OF PHILOSOPHY

to

DEPARTMENT OF ENVIRONMENTAL ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

SHAHBAD DAULATPUR, BAWANA ROAD, DELHI - 110042 (INDIA)

September, 2023

WATER QUALITY MANAGEMENT OF GOMTI RIVER (INDIA)

A Thesis

Submitted in fulfillment of the requirements for the award of the degree

of

DOCTOR OF PHILOSOPHY

In

ENVIRONMENTAL ENGINEERING

By

AMIT KRISHAN

(Reg. No. 2K15/PHD/ENE/04)

DEPARTMENT OF ENVIRONMENTAL ENGINEERING

Under the supervision of

Dr. Rajeev Kumar Mishra
Assistant Professor, Department of Environmental Engineering
Delhi Technological University, Delhi

Dr. Anwar Khursheed
Professor, Department of Civil Engineering, Z. H. College of Engineering & Technology, Aligarh Muslim University, Aligarh

DEPARTMENT OF ENVIRONMENTAL ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
SHAHBAD DAULATPUR, BAWANA ROAD, DELHI - 110042 (INDIA)

September, 2023

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering, Since 1941)

Shahbad Daulatpur, Bawana Road, Delhi- 110042

DECLARATION

I hereby declare that the research work presented in this thesis entitled **"Water Quality Management of Gomti River (India),"** is original and carried out by me under the supervision of Dr. Rajeev Kumar Mishra, Assistant Professor, Department of Environmental Engineering, Delhi Technological University, Delhi, and Dr. Anwar Khursheed, Professor, Department of Civil Engineering, Z. H. College of Engineering & Technology, Aligarh Muslim University, Aligarh, and is being submitted for the award of Ph. D. degree to Delhi Technological University, Delhi, India. The content of this thesis has not been submitted, either in part or whole, to any other university or institute for the award of any degree or diploma.

Date: / /2023 (Amit Krishan)

Place: DTU, Delhi. Reg. No. 2K15/PHD/ENE/04

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering, Since 1941)
Shahbad Daulatpur, Bawana Road, Delhi- 110042

Date: - / /2023

CERTIFICATE

This is to certify that the Ph.D. thesis entitled **"Water Quality Management of Gomti River (India),"** being submitted by **Mr. Amit Krishan** for the fulfillment of the requirements for the award of the degree of Doctor of Philosophy in Environmental Engineering, to the Department of Environmental Engineering, Delhi Technological University, Delhi, India, is a bonafide record of original research work carried out by him under our guidance and supervision. The results embodied in this thesis have not been submitted to any other university or institution for the award of any degree or diploma.

Dr. Rajeev Kumar Mishra
Assistant Professor
Department of Environmental Engineering
Delhi Technological University, Delhi

Dr. Anwar Khursheed
Professor
Department of Civil Engineering
Z. H. College of Engineering & Technology
Aligarh Muslim University, Aligarh

Dedicated to My Parents

Late Mr. Krishan Mohan Prasad

Late Mrs. Mina Sinha

ACKNOWLEDGEMENTS

First and foremost, I would wholeheartedly thank ‘The Almighty - GOD,’ for providing me with health, strength, and patience to work in both supportive and tough times. The completion of this doctoral dissertation was possible with the support of several people, and I would like to express my sincere gratitude to all of them.

It is indeed my proud privilege to express my deep gratitude towards my research supervisor, Dr. Rajeev Kumar Mishra, and co-supervisor, Dr. Anwar Khursheed, for their invaluable guidance, support, and motivation throughout the study. I feel fortunate to have them as my Ph.D. supervisors.

I am highly obliged to express my sincere thanks to Prof. (Dr.) Anil Haritash, DRC Chairman and Head, Department of Environmental Engineering, Delhi Technological University. It has also been my singularly good fortune to have a mentor akin to Prof. (Dr.) Govind Pandey (M.M.M. University of Technology, Gorakhpur), who has been one of my prime inspirations. I sincerely thank the university's faculty members, library staff, and administrative help. I am thankful to the Central Water Commission, Lucknow, and the Uttar Pradesh Pollution Control Board, Lucknow.

I accord my heartful thanks to all my colleagues, Dr. Amrit Kumar, Dr. Shailendra Kumar Yadav, Dr. Abhinav Pandey, Mr. Kanagraj Rajagopal, Mr. Vignesh Mohan, Ms. Monika Sharma, and Mr. Ravi Singh Jadoun (Department of Environmental Engineering, Delhi Technological University), for helping me with their suggestions and comments.

My colleagues at LEA Associates South Asia Private Limited, Bharuch, are also the ones to thank, especially Mr. Santosh Kumar Mandal and Mr. Ravi Kumar Pathak, who supported my research work and the time it needed in any fashion.

I want to express my sincere gratitude to my family, especially to my better half, Mrs. Ankita Srivastava, who supported me in every way possible throughout my Ph.D. This journey would not have been possible without her. She and my son (Master Aarush Srivastava) have shown enormous patience during this process and have cheerfully sacrificed the time that belonged to them. I would also like to thank my sister, Mrs. Ritu Sinha, for her belief in me.

A heartfelt special thanks to my in-laws, especially my mother-in-law (Mrs. Sunita Srivastava), my father-in-law (Mr. Ashok Kumar Srivastava), and my brother-in-law (Mr. Aman Srivastava), who have been offering support and believing during the lengthy periods of research assignments.

I am thankful to everyone who supported me through the work. My sincere apologies to anyone I missed inadvertently. I could not have finished this work without the help of many other people, and I am quite grateful for their assistance.

(Amit Krishan)

LIST OF PUBLICATIONS

PUBLISHED ARTICLES

- **Amit Krishan,** Rajeev Kumar Mishra, Anwar Khursheed (2022). "Evaluation of water quality using water quality index, synthetic pollution index, and GIS technique: A case study of the river Gomti, Lucknow, India." Environmental Science and Pollution Research. *https://doi.org/10.1007/s11356-022-21493-3*
- **AmitKrishan,** Rajeev Kumar Mishra, Anwar Khursheed (2022). "Assessment of water quality using water quality index: A case study of the River Gomti, Lucknow, Uttar Pradesh, India." Urban Water Journal, Vol. 19 (5), pp. 520-530. *https://doi.org/10.1080/1573062X.2022.2032210*

ARTICLES UNDER REVIEW

- **Amit Krishan,** Rajeev Kumar Mishra, Anwar Khursheed. "Assessment and forecasting of water quality variables of the river Gomti, Lucknow, India." Sustainable Water Resources Management (SWRM) (Manuscript Number: SWAM-D-23-00316).
- **Amit Krishan,** Rajeev Kumar Mishra, Anwar Khursheed. "A holistic approach towards integrative assessment of temporal and spatial water quality variations in Gomti river, Lucknow (India)." Water, Air, & Soil Pollution (Manuscript Number: WATE-D-23-01889).
- **Amit Krishan,** Rajeev Kumar Mishra, Anwar Khursheed. "Integrated evaluation of river Gomti's water quality in Lucknow, India: A multidimensional approach." Environmental Science and Pollution Research (ESPR) (Manuscript Number: ESPR-D-23-20181).
- **Amit Krishan,** Rajeev Kumar Mishra, Anwar Khursheed. **"**Assessment and forecasting of water quality in the river Gomti, Lucknow, India: Utilizing water quality indexes and statistical modeling." Sustainable Water Resources Management (SWRM).

CONFERENCES

- **Amit Krishan**, Rajeev Kumar Mishra, Anwar Khursheed (2022). "Water quality assessment of the river Gomti, Lucknow (India) using Water Quality Index (WQI) and Synthetic Pollution Index (SPI)." *Vth International Conference on Research, Analyze, Communicate and Evaluate*, held at Dolphin (PG) College of Science & Agriculture Chunni Kalan, Punjab, India on 2nd July 2022.
- **Amit Krishan**, Rajeev Kumar Mishra, Anwar Khursheed (2022). "Assessment of Water Quality of the River Gomti, India by Water Quality Index." *International Conference on "Innovative Researches in Engineering & Technology (IRET-2022)* in Joint Collaboration with Engineering Council of India, New Delhi and Buddha Institute of Technology, Gorakhpur held at Buddha Institute of Technology, Gorakhpur (U.P.), India, During April 21-22, 2022.

ABSTRACT

Many large and small rivers in Uttar Pradesh (India) pass through many cities and provide for the needs of their residents. However, the growing industrialization and urbanization in UP have resulted in a rapid deterioration of river conditions. River water quality is continuously declining, which has prompted numerous government agencies, NGOs, and researchers to conduct studies to address the issue. Some of the rivers, including Gomti, in UP, are among the most polluted rivers in India. The Gomti River routinely conveys pollutants from point and nonpoint sources throughout the river basin, including agriculture waste, sewage from households and offices, wastewater from industries, and other sources. Over the past few decades, the river Gomti has witnessed a surge in human activities, leading to a reduction in the flow of the river and a significant deterioration in its water quality.

The objective of this study was to formulate a water quality management plan by assessing the existing condition and anticipated future state of water quality of the Gomti River, which flows through Lucknow, UP (India). The research was conducted to manage water quality in relation to assimilative capacity and climate change (effect of rising temperatures) by identifying, quantifying, and characterizing a subset of selected pollutants of river Gomti. This study is based on the physicochemical and biological monthly data from 2013-2017 for seven sampling stations collected from the Uttar Pradesh Pollution Control Board (UPPCB), Lucknow (UP), which monitors the water quality along the Gomti River in Lucknow. The data sets were further investigated using descriptive statistics and multivariate statistical techniques (PCA and CA). One-way ANOVA was used to assess seasonal and spatial variation. The Gomti River's water quality was evaluated using four distinct water quality indices (Arithmetic WQI, CPI, SPI, and CPCB-WQI). The results were integrated with GIS to delineate several zones based on the severity of pollution. Four WQIs (Arithmetic WQI, CPI, SPI, and CPCB-WQI) for the river Gomti were forecasted using statistical modeling to help with future water quality conditions and identification of the most appropriate WQI through model performance indicators or metrics. The assimilative capacity of the river was evaluated using DO and BOD, and statistical modeling was used to predict assimilative capacity for future scenarios.

The assessment of physical, chemical, and biological characteristics of the river water samples revealed significant parameter ranges exceeding the prescribed limits (BIS, 2012/WHO, 2011), including those for DO, BOD, COD, EC, TA, TC, and FC. It is abundantly apparent from these findings that the water is unsafe for human consumption. It was established that the entire river stretch was severely polluted, and pollution levels increased from upstream to downstream (S1 to S7), demonstrating the impact of Lucknow's rapid industrialization and urbanization. One-way ANOVA analysis concluded all parameters increase from S1 to S7 except for pH and DO, which exhibit steady declines from S1 to S7. All parameters show temporal and spatial variation, although only a few parameters, including EC, TDS, Ca, Mg, and Cl, also show annual variation.

The main principal components contributing to the decline in water quality throughout the study were pH, Cl, DO, BOD, COD, TC, and FC, with a total variance of 54.65% in the dataset. These elements reflected sewage contamination and organic pollutants from residential wastewater. To prioritize control efforts concerning different pollution sources, the PCA helped locate the study area's point and nonpoint sources of pollution., Cluster analysis of the river Gomti identified three distinct clusters representing areas with moderate (S1, S2, S3, and S4), high (S5 and S6), and very high (S7) levels of pollution. This categorization can reduce monitoring stations, with one per cluster, cutting river sampling costs in resource-limited countries like India.

To help policymakers and stakeholders understand how various policy initiatives affect the water quality of a water body, WQIs simplify complex data. All of the water samples fell into category E (>100), which is unsuitable for drinking and fish culture except at S1, S2, and S3 during the monsoon season, which falls under category D (75-100), according to the results of the Arithmetic WQIs. At all sampling sites, the SPI value indicated very poor (1-3) status and could only be used for irrigation. The CPI value was found in three categories: qualified (0.41-0.8), basically qualified (0.81-1.0), and polluted (1.01-2.0) at different locations and months. The mean values of CPCB-WQI at S1 and S2 lie under the category medium to good, Class - B (50-63), S3 and S4 under the category bad, Class - C (38-50), S5, S6, and S7 under category bad to very bad, Class - D & E (<38). It was also noticed that the river Gomti water was found in all categories classified by CPCB-WQI for different sampling stations. Station S7 recorded the highest value for all estimated WQIs. Statistical analysis further corroborated that the WQIs increased from S1 to S7. PCA investigation further confirms that anthropogenic activities primarily contribute to the deterioration of this region's water quality. As a result, it can be argued that apart from S1 and S2, WQIs are high at all sampling stations.

Statistical modeling for the period of 10 years (2018-2027) based on calculated data of WQIs (Arithmetic WQI, SPI, CPI and CPCB-WQI) reveals similar results as the baseline period (2013-2017). In the case of all four projected WQIs, the maximum value was observed at station S7, followed by the minimum value at S1, and it rose from S1 to S7. RMSE, MAPE, MAE, MaxAPE, and MaxAE were employed as model performance indicators or metrics to track the model's effectiveness. SPI and CPI were determined to be the most appropriate WQIs out of the four based on model performance indicators or metrics values.

Gomti River has an average daily flow of 1,500 MLD, rising to 55,000 MLD after rains and dropping to 500 MLD during the summer, resulting in a reduction of assimilative capacity. The minimum DO concentration at all sampling stations was below the reference limit (4 mg/l), while the maximum DO concentration was well above it. The sampling station S7 had a lower minimum and maximum DO concentration than the reference limit. According to the CPCB’s best-use criteria (IS 2296: 1992), river water at selected sampling stations was inappropriate for all purposes in respect of BOD. DO concentrations at S5, S6, and S7 are excessively low for the predicted period (2018-2027). At S1, DO concentrations are higher than the reference limit for the predicted period, whereas at S2, S3, and S4, higher in the wet season and lower in the dry season. BOD exceeds the reference level (2 mg/l) at all sample locations over the predicted period.

The water quality profile of BWQI for the four different climate change scenarios, RCP 4.5 (2040-2069), RCP 4.5 (2070-2099), RCP 8.5 (2040-2069), and RCP 8.5 (2070-2099) are 38.79, 37.90, 37.75, and 34.83 respectively. It reveals that the BWQI is not significantly different from the previous scenario (2014-2017) as it lies in the bad (26-50) category in the water quality classification; however, a slight decrease in BWQI is expected in the future under all scenarios.

The selected WQIs have been studied through the GIS method. The maps of WQIs showed that 28 drains highly polluted the study area, discharging approximately 461.33

MLD wastewater. Therefore, the Gomti River water should not be used due to its high physicochemical and biological load. Prior treatment should be considered to meet water quality regulations, public expectations, environmental and public health concerns. Direct discharge of industrial and domestic wastewater into river through drains is the leading cause of the significantly polluted water quality.

As a result, management alternatives are suggested to lessen pollution. A sufficient sewage treatment facility should be set up between S2 and S7. It is imperative to remove solid waste and to maintain adequate discharge at all times, particularly during the dry or non-monsoon seasons, to maintain its self-purification capacity.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
AMSL	Above Mean Sea Level
ANOVA	Analysis of Variance
APCS-MLR	Absolute Principal Component Score Multiple Linear Regression
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Auto-Regressive and Moving Average
AT	Air Temperature
BCM	Billion Cubic Metre
BIC	Bayesian Information Criterion
BIS	Bureau of Indian Standards
BOD	Biochemical Oxygen Demand
BWQI	Bascaron Water Quality Index
CA	Cluster Analysis
CBOD	Carbonaceous Biochemical Oxygen Demand
CCA	Canonical Correlation Analysis
CCME	Canadian Council of Ministers of Environment
CDA	Canonical Discriminant Analysis
CGWB	Central Ground Water Board
COD	Chemical oxygen demand
CPCB	Central Pollution Control Board
CPI	Comprehensive Pollution Index
CWC	Central Water Commission
DA	Discriminate Analysis

DO	Dissolved Oxygen
DPR	Detailed Project Report
EC	Electrical Conductivity
ENVIS	Environmental Information System
FA	Factor Analysis
FC	Faecal Coliform
GAP	Ganga Action Plan
GBM	Ganga Brahmaputra Meghna
GEMS	Global Environmental Monitoring System
GHG	Green House Gases
GIS	Geographic Information System
GRB	Gomti River Basin
HAL	Hindustan Aeronautics Ltd.
HCA	Hierarchical Cluster Analysis
ICMR	Indian Council of Medical Research
IDW	Inverse Distance Weighted
IMWQI	Integrated Multi-Parameter Water Quality Index
IPCC	Intergovernmental Panel on Climate Change
IWA	International Water Association
KMO	Kaiser Mayer Olkin
LCL	Lower Control Limit
LDA	Lucknow Development Authority
MAE	Mean Absolute Error
MANOVA	Multivariate Analysis of Variance
MA-PCA	Matrix Augmentation Principal Components Analysis

MAPE	Mean Absolute Percentage Error
MaxAE	Maximum Absolute Error
MH	Million Hectares
MLD	Million Litres Per Day
MLR	Multiple Linear Regression
MoEF&CC	Ministry of Environment, Forest and Climate Change
MPN	Most Probable Number
MRA	Multiple Regression Analysis
MST	Mutivariate Statistical Technique
NASQAN	National Stream Quality Accounting Network
NGO	Non-Governmental Organisation
NSF WQI	National Sanitation Foundation Water Quality Index
NW	National Waterways
OIP	Overall Index of Pollution
OWQI	Oregon Water Quality Index
PACF	Partial Autocorrelation Function
PCA	Principal Component Analysis
PMF	Probability Mass Function
RA	Regression Analysis
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
SPCB	State Pollution Control Board
SPI	Synthetic Pollution Index
SRDD	Scottish Research Development Department
STP	Sewage Treatment Plant

SWARDA	State Water Resources Development Agencies
TA	Total Alkalinity
TC	Total Coliform
TDS	Total Dissolved Solid
TH	Total Hardness
TKN	Total Kjeldahl Nitrogen
TN	Total Nitrogen
TPD	Tonnes Per Day
UCL	Upper Control Limit
UNICEF	United Nations International Children's Emergency Fund
UP	Uttar Pradesh
UPPCB	Uttar Pradesh Pollution Control Board
USGS	United States Geological Survey
WAWQI	Weighted Arithmetic Water Quality Index
WHO	World Health Organization
WQI	Water Quality Index
WQM	Water Quality Model
WT	Water Temperature

CHAPTER - 1

INTRODUCTION

1.1 General

For the ecosystems to function properly and for socioeconomic development, a safe and sufficient freshwater supply is required (Matta et al., 2018; Iqbal et al., 2019; Khan et al., 2020). Rivers and lakes are significant freshwater resources essential to civilizations because they deliver consistent water for domestic uses and diverse agricultural, transportation, and industrial activities. River water offered industrial, agricultural, and economic wealth; therefore, many civilizations thrived there (Tyagi et al., 2013; Tangri et al., 2018). Freshwater resources are crucial for a nation's growth and development because of their socioeconomic and ecological significance. Water quality is negatively affected by accelerated industrialization, fast urbanization, and the resettlement of towns (Wang et al., 2013; Dutta et al., 2018a; Kumar et al., 2020a). Seasonal variations in precipitation, surface runoff, groundwater flow, water interception, and abstraction all have an impact on the quantity and quality of water (Zhao et al., 2011).

Surface water sources are increasingly becoming a pathway via which a wide variety of biotic species are exposed to hazardous components that originate from anthropogenic activity or geological processes. The monitoring of surface water sources is crucial for the generation of trustworthy information on water quality, which will ultimately have a significant impact on preventing and regulating the pollution of surface water (Singh et al., 2004; Varol et al., 2012; Kumar et al., 2022a). To effectively manage the water quality over the long term in the water bodies, one needs to have a comprehensive grasp of the water's physical, chemical, and biological features.

Earth's surface contains about 1.4 billion km^3 of water. Less than 3% of the total volume (about 35 million km^3), or glaciers and ice caps, contain roughly 24 million km^3 of frozen fresh water, making it inaccessible (Kamboj et al., 2020). This demonstrates that although there is a lot of water on the Earth, fresh water only makes up a small percentage. The remaining water (96.5%), known as “salt water,” is found in oceans and contains salts and minerals. While desalination techniques like thermal or reverse osmosis can remove these salts and minerals from salt water, they are not commercially viable (Greenlee et al., 2009). As a result, the management of water resources affects practically every element of society and the economy, particularly in health, food production, house water supply, sanitation, energy, industry, and urban ecosystems (Kumar et al., 2022b).

Six hundred million Indians face extreme to high water stress, according to the NITI Aayog, a think tank run by the government, and the continued absence of necessary actions might lead to an enduring water disaster (Jadeja et al., 2022). The growing urban population, which has grown by 17% over the past ten years, is largely to blame for the demand and water pollution caused by home and wastewater discharges from the industries (Census, 2011). Groundwater has been overused due to widespread migration from rural to urban areas and an increase in utility services. In addition to the growing population, industrialization is responsible for an annual rise in water demand of around 4%, significantly increasing industrial wastewater volume (World Bank, 1998). The combined water demand for the household, industrial, as well as agricultural sectors is anticipated to increase, reaching 103 BCM in 2025 and 1447 BCM in 2050 (World Bank, 1998). Water management in India is made more difficult by the unequal distribution of natural water resources, the ongoing deterioration of surface and groundwater quality, various geographies, climate change, erratic monsoons, trade, and commerce (Jadeja et al., 2022).

1.2 Global distribution of water resources on Earth

Oceans hold a significant quantity, about 96.5%, of the total amount of water in non-consumable or non-potable form. Saline water, found in lakes or groundwater, makes up an additional 1% of all water on Earth. Only 2.5% of the water on Earth is freshwater, and not all of it is suitable for human use (Kamboj et al., 2020). Approximately 68.7% of all freshwater is found in groundwater reserves, which are deeper aquifers, glaciers, and ice caps. Therefore, it is clear that surface water and other freshwater resources comprise just around 2.5% of the entire amount of fresh water on the Earth. The frigid climate stores 68.7% of this water as ice and snow, which hinders the functioning of several biosphere components and prevents it from being directly available for human consumption (Pekel et al., 2016). Over 20.1% of the world's surface water is found in lakes, with the remainder of water being found in rivers (0.46%), swamps including marshes (2.53%), soil moisture (3.52%), biological water (0.22%), and atmospheric water (0.22%) (Kamboj et al., 2020) (Figure 1.1).

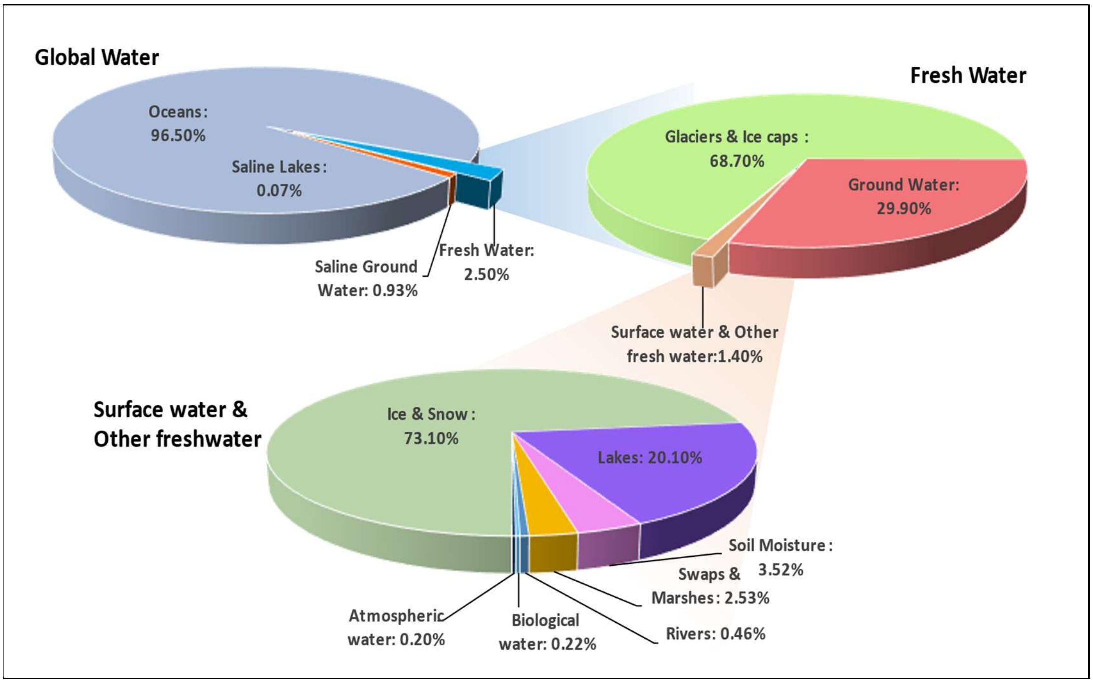


Figure 1.1: Distribution of total water on planet Earth

(Source: Kamboj et al., 2020)

1.3 Water Resources of India

The size of India landmass is 3.29 million km^2, 2.4% of the world's total area. Estimates place the nation's total usable water resources at 1086 km^3 (Kumar et al., 2005). India is lucky to receive a lot of rain, which falls evenly throughout five to six months of the year. The primary source of all water resources is rainfall, and in 2011–12, India got a total of 3669 BCM through rains. The typical annual precipitation in the nation is 1170 mm, but there can be variances of up to 10,000 mm in Cherapunji and 100 mm in Rajasthan's driest parts. The nation's total annual sweet water supply is 4000 BCM. The overall amount of available and usable water is 1953 BCM and 1123 BCM, individually, after more than 1047 BCM of water is gone through evaporation, transpiration, and surface runoff (Rakhecha, 2020). It is alarming to learn that just 18% of rainfall is efficiently used, while 48% enters rivers, most of which end up in the ocean. 728 BCM of the entire useable water comes from surface water, while 395 BCM comes from replenishable ground water. According to estimates from the Indian government, water consumption in India in 2006 was 829 BCM, compared to the aforementioned supply, which is anticipated to increase to 1093 BCM in 2025 and 1447 BCM in 2050. Rivers, canals, reservoirs, tanks, lakes, ponds, brackish water, and abandoned water bodies comprise the nation's water resources (Mall et al., 2007). India has a total water spread area of 7.4 MH, of which 2.9 MH are reservoirs and 2.4 MH are lakes, tanks, and ponds. The country has estimated static fresh groundwater reserves of 10812 BCM (i.e., aquifer zones). Each year, the dynamic component, estimated to be 432 BCM, is replenished. River basins comprise the country's total potential water resources as of 1869 BCM (Mall et al., 2007).

Water for irrigation is just as important as water for drinking, as both are necessary to boost food output and livestock care and provide food security for the growing population. Everyone is alert that an increasing population poses a severe risk to the water supply per person in the future. It was estimated that each person per year in 1951 had access to 5177 m^3 of water when there were only 361 million people in India. When the population reached 1027 million in 2001, the water consumed by each person dropped dramatically to 1820 m^3 per year. The amount of water available per person will decline by 2025, falling to 1341 m^3 and reaching 1140 m^3 by 2050. According to the average amount of water needed for several uses, a scenario is deemed to be under water stress when the annual water availability is between 1000 and 1700 m^3/person, and it is deemed to be under water shortage when it falls below 1000 m^3. Due to the large variations in water availability across the nation caused by rainfall, groundwater reserves, and the vicinity of river basins, by 2020, almost all Indian States will have water stress, and by 2025, there will be water scarcity. As a result of the direct effect of water scarcity on agricultural production, this would further jeopardize global food security (Rakhecha, 2020).

1.4 Rivers: a vital water resource

Rivers are bodies of water that flow in a specific path in a channelized form and affect our civilization and culture. Water was only available from rivers in the early stages of human evolution (Kaushik et al., 2009). Due to this, every ancient civilization developed along the river's bank, such as the Indus Valley Civilization (located near the Indus), Egypt (located near the Nile), Babylon (located near the Tigris), and Mesopotamia (located between the Euphrates and the Tigris) (Singh et al., 2018). Ancient towns also grew up alongside rivers. Many cities such as Haridwar, Rishikesh, Ayodhya, Varanasi, Patna, Delhi, Agra, Lucknow, and others have gained prominence due to the presence of rivers coursing through their urban landscapes. As time passed, people began interacting and holding celebrations, fairs, and other social and religious events along the banks of rivers. Even if the weather is terrible, many ceremonies are not considered to be completed until the participants have taken a dip or bath in a sacred river. Bathing in rivers during festivals like the Kumbh Mela and Makar Sankranti is much more than a celebration. It is also a way for regular people to uphold a tradition and protect the rivers, which are vital to human existence (Tyagi et al., 2013). Over time, humans established a deep and lasting relationship with rivers, converting them into a fundamental part of our daily existence and significant symbols of our society. Consequently, they are revered as our nurturing sources of life. (Singh et al., 2018).

The population, urbanization, industrialization, and farming/agriculture were all in harmony with the environment and waterways during the primary stages of human evolution. Rapid population growth, urbanization, and industry are out of harmony with the river and its surroundings, negatively impacting society and the life-giving river (De Stefano et al., 2017; Kumar et al., 2018). In this manner, once considered a blessing, the river is now a curse on civilization. Indian rivers are distinguished by their narrow waterways enclosed by large valleys (Singh and Awasthi, 2011a). The development of settlement even inside the floodplain and vast river valley results from the pressure that population growth is placing on the land. Man's interference with a river's natural cycle has resulted in water pollution, ecosystem disruption, altered transport capabilities, and increased sediment load, ultimately leading to changes in the river's dynamics. Rivers consequently result in the loss of lives and property due to human meddling with their natural cycle (Singh and Awasthi, 2011b). Despite the terrible state they are in right now, rivers are a naturally replenishable resource.

Since the beginning of time till the present, rivers and streams have been a crucial part of the hydrological cycle that has contributed to the continuous and eternal water flow on Earth (Phiri et al., 2005). Rivers are used for navigation, tourism, and providing freshwater for domestic use, subsistence, and commercial production (agricultural, cattle, and fisheries) (Venkatramanan et al., 2014). The river ecology is crucial for controlling environmental processes, transporting nutrients, assimilating industrial and municipal waste, and controlling floods and droughts. These functions are inextricably linked to elements that indicate the health of rivers, including water quality, ecological condition, and flow (Markandeya et al., 2021; Pandey et al., 2021).

1.5 River water resources in India

There are many rivers and mountains in India. Many small and large rivers, some of which rank among the largest rivers in the world, flow across about 329 MH of land.

Most prehistoric civilizations developed along these rivers' banks (Singh et al., 2018). Millions of people still reside in the cities built along riverbanks and rely on the rivers for their survival today. India is blessed with a vast river system and abundant rainfall. The southwestern monsoon contributes roughly 75% of the country's yearly rainfall (Ghosh and Mistri, 2015).

Our nation is fortunate to have 14 major river basins, which together occupy an area of more than 20,000 km^2, accounting for 82.4% of the country's drainage basin and 85% of its total surface flow. About 80% of the nation's population lives in these river basins. Major river basins in the country include the Brahmaputra, Ganga (including the Yamuna Sub Basin), Indus (including the Satluj and Beas Sub Basins), Godavari, Cauvery, Krishna, Narmada, Mahanadi, Brahmini (including the Baitarni Sub Basin), Tapi, Mahi, Pennar, and Sabarmati (Singh et al., 2018). Based on the size of the catchment area, India's 113 river basins are categorized into three groups (Table 1.1).

Table 1.1: Classification of river basins in India

River basins	Catchment area (km^2 / percent)	No. of basin
Group 1 - Major	More than 20,000 (82.4)	14
Group 2 - Medium	Between 2000-20,000 (8)	44
Group 3 - Minor	Less than 2000 (9.6)	55

1.6 River pollution

Human activities often result in environmental devastation. Domestic, industrial, and agricultural activity typically falls under this category of human activity. Megacities are expanding due to the fast industrialization and urbanization of some regions. This development has put the surrounding cities' natural ecosystems under strain (Palmer et al., 2008; Fuller et al., 2015). Mass rural-urban migration is a result of rapid industrialization. These people go from small towns or villages to megacities in search of better opportunities to raise their standard of living. Freshwater bodies are particularly under strain from these developments because they are crucial to the growth of any metropolis. The prevention and reduction of pollution and any residential or industrial activities that damage the local ecosystem are essential for successful city governance. More than a billion people are thought to live without access to clean drinking water, mostly in emerging and poor countries. The water is utilized for industrial and commercial purposes, and the garbage from these operations is dumped straight into the natural water bodies without adequate or effective treatment. The majority of rivers in India are treated like exposed drains (Singare et al., 2012; Kamboj and Choudhary, 2013).

Approximately 70% of India's river water is polluted due to elevated levels of pollutants (ICMR, 1975; CPCB, 2000; WHO, 2011; BIS, 2012). Consequently, the water quality standard directly impacts both the health of human civilization and the health of aquatic and environmental organisms (Kamboj and Kamboj, 2020). Due to that, the water quality is very poor for human use and agricultural purposes and even harmful for animal intake (Jindal and Sharma, 2011).

There are requirements for water quality set by various national and international organizations (ICMR, 1975; CPCB, 2000; WHO, 2011; BIS, 2012). If the water quality in rivers and other bodies of water meets these standards, it is suitable for human eating and drinking. Since water is a necessary component of daily life, it is crucial to guarantee a consistent water supply of the right quantity and quality for home and agricultural usage (Khan et al., 2021a). The availability of sufficient water for domestic as well as industrial use is essential for the sustainable progress and improvement of human civilization.

Both point sources and non-point sources of water pollution have been identified. Point sources are characterized by the Environmental Protection Agency (EPA) as a single, recognizable source of water pollution, while non-point sources are described as scattered sources that cannot be linked to a single or point source (Sutadian et al., 2016; Jadeja et al., 2022). The discharges from wastewater treatment facilities in municipalities and industries are considered to be the point sources of wastewater pollution. On the other hand, urban runoffs, agricultural runoffs, and livestock runoffs are considered substantial non-point sources (Khan et al., 2021b). The current government standard concentrates on treating wastewater from point sources, while discharges from non-point sources are commonly ignored. Urban and rural runoffs, atmospheric depositions, and agricultural runoffs all considerably contribute to water pollution but are not yet taken into account in the wastewater management plan (Chakraborty et al., 2021; Maity et al., 2022).

Anthropogenic activities have a greater effect on the physical, chemical, and biological characteristics of river water quality than natural forces. Without talking about the exchanges and reciprocal relationships between man and nature, the environmental study of the river basin would be lacking. Agricultural activities, urban development, mining, power production, deforestation, industrial pollution, sewage issues, and tourism that outpaces available resources are some of the anthropogenic factors affecting river water quality (Maity et al., 2022).

Any natural water body can somewhat remove pollutants from wastewater. Every water system has the ability to degrade pollutants with the aid of naturally occurring aquatic creatures and plants, as well as chemical, physical, and biological reactions (El-Jabi et al., 2014). However, the effectiveness of the water bodies' natural cleansing mechanism is limited, and they cannot manage significant amounts of pollutants on their own (Egbe et al., 2018; Chapra et al., 2021). The water cycle and the equilibrium of the environmental water cycle are changing as a result of the expansion and growth of industry, as well as numerous human activities like deforestation, global warming, climate change, and other ones, as well as growing population (Danladi Bello et al., 2017; Abeysingha et al., 2020; Rajesh and Rehana, 2022). Water suitable for drinking and cooking is accessible in tiny quantities in all of India's several states. Only a small percentage of the population in India has access to clean, safe water. The remaining Indian population consumes tainted or chlorinated drinking water, which can lead to various health issues (Khan et al., 2021a).

Various domestic and commercial operations, such as sewage, wastewater, effluent discharge, rubbish, etc., are poured into rivers either directly or improperly treated wastewater (Sunar et al., 2020). This negatively impacts the physiochemical characteristics of river waters. BOD, COD, DO, TDS, TC, WT, TA, Cl, TH, pH, etc., are among the physiochemical characteristics of river water that have the most impact. These physiochemical characteristics determine the water quality and how well the aquatic ecosystem is doing (Gazzaz et al., 2012).

Due to limited resources and the need for increased farming due to the growing population, a significant portion of the world's forests are being cleared, which causes land degradation. Increased use of pesticides and fertilizers harms the quality of drinkable water and adds to the direct discharge of harmful substances, increasing the amount of nitrates and phosphorus on the water surface (Solangi et al., 2018; Lkr et al., 2020). The concentration of various nutrients, coliforms, and sediment loads is increased by grazing, forestry practices, and poor agricultural practices, which harm the aquatic ecology significantly by generating the eutrophication of waterbodies (Roy et al., 2021). Increased sediment load causes issues for marine life. As a result, spawning grounds are harmed, and dissolved nutrients like nitrates and phosphates, which encourage the growth of aquatic plants and stress DO, are increased (Somura et al., 2012). Farmers are forced to use filthy river water that hasn't been cleaned for farming uses like irrigation. Water availability for agricultural needs is decreased globally due to inefficient water management and unequal water distribution (Khan et al., 2021b).

Feces, urine, laundry waste, and oxygen-depleting organic chemicals are among the untreated municipal trash produced by home activities and poisonous and unstable inorganic materials (Goel et al., 2018). The increase in phosphate and nitrates caused by this untreated residential sewage and organic waste is hazardous to water bodies and negatively impacts rivers' ecosystems and water quality (Norah et al., 2015). It has been acknowledged that non-point sources of water pollution frequently have a higher effect than point sources, especially in rural catchments.

Waste produced by industry, such as effluences or garbage, is significant. The main sources of industrial wastewater are mines and quarries, iron and steel industries, food industries, chemical, nuclear, and radioactive industries, tanneries, and the cleanup of petroleum and chemically polluted sites. Due to authorities' dwindling and fraudulent actions, these industrial effluences contain substantial chemical and inorganic pollution that enters the river (Jadeja et al., 2022).

Another factor affecting river water quality is mining. Sulphuric acid is created when the sulfide mineral in rocks combines with oxygen and enters the water drainage system. Similar to how arsenic, cobalt, cadmium, lead, silver, and zinc react with water, harming human health and waterways (Florea and Busselberg, 2006; Jaishankar et al., 2014). Mining businesses utilize chemicals like cyanide and sulfuric acid to remove the desired mineral from their ores. Due to the failure to follow regulations when building and maintaining roads, garbage impoundments, holes, and pits degrade the land and add a significant quantity of silt to the river, clogging the riverbeds and disrupting the aquatic ecosystem and species in the watershed (Kamboj and Kamboj, 2019).

Using artificial flow control, advanced hydroelectric projects and dams disrupt the river's physical and biological components and lessen its natural flow. Hydropower plants alter the flow of water downstream. While run-of-river operations are used for small projects, increasing the state's hydropower capacity promotes economic growth and harms the environment. These activities alter the WT and DO content, upsetting the river's aquatic life (Rajesh and Rehana, 2022).

The quickest and least expensive way to dispose of garbage produced by industries is to dump it in rivers or other aquatic bodies. However, this effluent dumped into the river negatively impacts the health of people and aquatic species. Both developing and developed countries today are dealing with the problem of wastewater disposal. A significant issue is presented by disposing of wastewater from the home and industrial sources (Jadeja et al., 2022).

A pristine, unpolluted river guarantees a great crop and a healthy country. However, paradoxically, this foundation of human civilization has been savagely attacked for the sake of senseless economic gain. Unplanned modernization and industrialization, disregard for religious beliefs, overuse of natural resources, a lack of ecological education, and population explosion have all contributed to the global degradation of aquatic ecosystems (Jadeja et al., 2022).

1.7 River pollution in India

The foundation of India's agricultural economy has always been its rivers. The main elements that substantially impact surface water quality are human activities, chemical fertilizer use, and land use changes (Hussain et al., 2008; Azhar et al., 2015). Rivers provide water for home, industrial, and agricultural purposes. India is fortunate to have many rivers, but the current situation is on the verge of declension due to pollution and overuse. Rivers' identity and existence are in danger due to heavy pollution load. In India, open defecation, holy bathing, and other religious practices are among the leading causes that affect and directly impair river water quality (Matta et al., 2020).

One of India's major problems is river water pollution. The river water quality gradually deteriorates due to hazardous compounds (heavy metals, pesticides, and polychlorinated biphenyls) and organic substances. The degree of degradation has grown to the point where it is now dangerous for use in agriculture, industry, and even human intake. In India, CPCB has acknowledged significantly polluted sections of 18 key rivers, mostly in and around the country's major urban and industrial hubs. Due to the extreme pollution throughout urban areas, it may be concluded that home and industrial water pollution is more detrimental to India's economy than its respective importance and advantages. Additionally, agricultural practices significantly harm the overall river water quality (Goel et al., 2018; Iqbal et al., 2019).

The capacity of sewage treatment, according to CPCB (2015) statistics, was 66% of its total urban sewage discharge in 2013, but that capacity has reduced to 38% due to rising municipal sewage and a shortage of sewage treatment facilities. It suggests that a significant volume of untreated waste-roughly 38 billion liters was entering waterways, with a substantial portion coming from industrial sources. There is yet no data available regarding untreated sewage from rural regions, which is also a major concern (Table 1.2).

Table 1.2: Mean annual surface runoff and wastewater generation of the major river basins of India

Name of the river basin	Basin area (km^2)	Mean annual runoff (km^3)	No. of class I cities	Wastewater generation (MLD)	No. of class II cities	Wastewater generation (MLD)
Indus	3,21,290	80	15	624	20	142
Ganga	8,61,404	550	103	5812	119	628
Brahmaputra	1,87,110	591	7	179	9	54
Sabarmati	21,674	4	7	652	6	32
Mahi	34,842	41	3	161	4	19
Narmada	98,796	40	4	44	5	25
Tapi	65,145	20	8	275	5	18
Subarnarekha	19,300	12	2	280	2	7
Brahmani	39,033	29	1	17	1	3
Mahanadi	1,41,600	67	9	413	9	35
Godavari	3,12,812	116	25	635	37	168
Krishna	2,58,948	68	27	1314	22	90
Pennar	55,213	7	6	61	5	15
Cauvery	87,900	21	16	727	18	51

To stop untreated sewage from entering the waterways, the CPCB issued directives to the nation's SPCB and pollution control commissions in April 2015, leading them to establish sewage treatment facilities (STPs) in their respective states. In October 2015, the CPCB issued directives to all 69 local authorities of major cities and metropolitan areas about reducing pollution. The water quality of the river has not changed much, though. Based on BOD, there are approximately 302 polluted stretches on 275 rivers. Additional priority classes were assigned to these filthy river segments. Three hundred two (302) river segments were divided into five priority segments, i.e., 34 into I priority, 17 into II priority, 36 into III priority, 57 into IV priority, and 158 into V priority river segments (CPCB, 2017).

Over 12,000 km of riverine areas are polluted, which is nearly five times the length of the river Ganga. There is no evidence to support any improvement in these 4-5 years, as the CWC reports reporting the maximum BOD of river water between 2012–2013 and 2016–17. Sixty-seven (67) places' water quality is deemed to be dangerously low. Out of 67 sites, 14 had BOD values over 30 mg/l (extremely polluted), 12 had levels between 10-30 mg/l, and 30 had levels between 3-10 mg/l, indicating extremely high levels of pollution (CPCB, 2017). Eleven additional locations are likewise moving into a serious situation. The organic and bacterial pollution brought on by untreated industrial and domestic effluent is critical for water bodies, according to CPCB data.

It is time for India to take the problem of river water pollution seriously. Due to rising industrial activity, unplanned urban growth, and agricultural activity, several cities have been experiencing groundwater scarcity (Deshmukh, 2013). This scarcity, which severely impacts the temperature and hydrological cycle, is made worse by population growth and irrigation. To protect the public's health and priceless yet delicate freshwater resources like rivers, there is a need for assurance and sustainable development of rivers with proper waste management and complete river water quality management strategies and plans (Parmar and Bhardwaj, 2015; Dutta et al., 2018a).

Globally, there is a greater need for non-conventional water resources because of the scarcity of fresh water. India has moved up to position 13 on the list of water-stressed nations, with 21 big cities on the verge of running out of water and numerous cities experiencing water supply cuts (Jadeja et al., 2022). With 1.3 billion inhabitants and wastewater generation ranging from 15-135 l/person/day, this second-most populous nation provides significant hurdles to creating economic wastewater treatment systems that adhere to current discharge regulations (Ministry of Water Resources, 2000; MoEF&CC, 2020).

Domestic and commercial wastewater discharge into waterways causes health concerns, ecological harm, and monetary loss. Wastewater is dumped into water bodies indirectly in around 118 Indian towns, and it is routed into rivers in 41 cities (CPCB, 2000). MoEF&CC, the ENVIS Centre on Hygiene, Sanitation, Sewage Treatment Systems, and Technology, collects and compiles information regarding the current national status of wastewater generation as well as wastewater treatment in all of India's states (ENVIS, 2021). Our nation's marine water bodies get about 25% of the industrial effluent dumped there. According to reports, 6614 MLD of wastewater, or 426 TPD of organic pollutants, are thrown into the Ganga River (CPCB ENVIS, 2008). Due to a capacity deficit for sewage treatment, there is currently a discharge of 38791 MLD of untreated sewage into aquatic bodies. This accounts for 62% of the total sewage (CPCB, 2021). According to the CPCB's most recent National Inventory Report (2019), more than 55,000 industrial facilities produced 7.17 MT of hazardous garbage between 2016 and 2017, the vast bulk of which was liquid trash (CPCB, 2019).

1.8 River pollution in Uttar Pradesh

Uttar Pradesh is home to several of the nation's largest rivers, including the Betwa, Chambal, Dhasan, Gandak, Ganga, Ghaghara, Gomti, Ken, Ramganga, Son, Tons, and Yamuna (UP). Along with these big rivers, smaller rivers like Kali, Krishni, Dhamola, and Hindon also flow around UP's largest cities and meet the needs of those living there. However, the UP's growing industrialization and urbanization have led to an alarming pace of decline in river status (Singh et al., 2005; Tiwari and Kisku, 2016; Kumar et al., 2020b; Khan et al., 2021a, b, c; Kumar et al., 2022a). River water quality is continuously declining, which has prompted numerous government agencies, NGOs, and scholars to conduct numerous studies to address the issue. As per CPCB (2017), the most polluted rivers in India are some of the rivers in Uttar Pradesh. The Gomti, Hindon, Kali, Krishni, Dhamola, and Yamuna rivers' water quality is considered to be gravely worrying. Thirteen detected polluted river sections are near 37 of the main UP towns and cities (CPCB, 2017).

The Gomti River is an example of a river in India that routinely transports garbage from agriculture, sewage from homes and offices, wastewater from industrial facilities, and other sources from both point sources and non-point sources across the river basin (Singh et al., 2005; Kumar et al., 2020b; Kumar et al., 2022a). Traditional religious processes, for instance, idol immersion at festivals, the disposal of pathogenic biomedical waste and fecal matter, the release of surfactants and color from nearby chikankari, the release of oil and grease from auto repair shops, and agricultural runoff from farmlands all negatively affect water quality and pose a serious hazard to the fauna and flora of the river system (Tiwari and Kisku, 2016; Chakravarty and Gupta, 2021).

Based on the last three years (2017-2019) of monitoring data of water quality of river Gomti in the identified polluted stretch, the river water quality analysis shows that the average DO was found to be 5.05 mg/l and BOD lies in the range of 2.25 mg/l to 17.33 mg/l (UPPCB, 2019). This falls under category E as per water quality standards IS 2296-1982. The river's water quality degrades due to the large volumes of wastewater discharged daily from the businesses and sewage systems that run from Lucknow, Sitapur, Hardoi, Barabanki, Sultanpur, Jaunpur, and Kerakat (Jaunpur).

1.9 Need of the study

The need to study the water quality of river Gomti is identified in the background of its continuously deteriorating water quality. Although many studies to evaluate the state of the river Gomti's water quality are available in the literature, but no studies have been found that provide prior knowledge of integrated GIS, WQIs, Assimilative Capacity, and Climate Change on the efficacy of its water quality management plan.

Since there are many studies about the river Gomti, this study is a pioneer in terms of determining the river's vulnerability using a cutting-edge methodology. In addition, there is no prior work done on the Gomti water quality modeling. In order to facilitate a water quality management plan, the current work uses an integrated strategy by using MSTs, WQIs, GIS, and Statistical Modeling in reference to assimilative capacity and climate change (impact of rising temperature). The combined use of these techniques is anticipated to provide a first thorough picture of the current conditions affecting the water quality of the Gomti River in Lucknow (UP). The study's findings will be of significant use to academics and those who determine policy.

1.10 Statement of problem

An increase in anthropogenic activity due to economic growth and decreased river releases over the past few decades have multiplied pollution loads in Indian rivers, which adversely affected the water quality. Numerous research has been conducted to assess the water quality in various Indian rivers (Singh et al., 2005; Jindal and Sharma, 2011; Katyal et al., 2012; Rajkumar and Sharma, 2013; Kumarasamy et al., 2014; Kumar et al., 2015; Bhutiani et al., 2016; Bora and Goswami, 2017; Dutta et al., 2018a, b; Jaiswal et al., 2019; Matta et al., 2020; Lkr et al., 2020; Ali et al., 2021; Kumar et al., 2022a). According to the CPCB (2017), some of the most polluted rivers in India are in Uttar Pradesh. The Gomti, Hindon, Kali, and Yamuna rivers' water quality is considered to be gravely worrying. Gomti stretch from Sitapur to Varanasi is classified as Priority Class – I (Sitapur, Lucknow, Sultanpur) according to CPCB (2017).

Based on the aforementioned justification, the primary objective of this study is to evaluate the current status of Gomti river water quality and to predict the future condition of overall water quality that flows through Lucknow, UP (India). This study has also developed long-term water quality management strategies and plans for the region. Being the nation's largest state and fastest growing economic center, Lucknow (capital of Uttar Pradesh) has been selected as a study location. The capital city is seeing fast urban and economic growth. Unhealthy water environments result from significant economic growth combined with unplanned, rapid urbanization, especially in areas surrounding water bodies such as the Gomti River basin. Despite its significance, relatively little information is available regarding its current state and management plans for the future.

1.11 Objectives of the study

This research aims to determine the most appropriate strategy for administering a program to control water quality and to analyze data sets collected to deliver valuable and accurate information. This research study has the following objectives:

1. To identify and quantify the point and non-point sources of pollution.
2. To study the effects of future temperature change scenario on river water quality.
3. Modeling and simulation of water quality and prediction of pollution status in the river.
4. To estimate the assimilative capacity of the river for different seasons.
5. Formulation of river water quality management strategies and plan.

1.12 Organization of the Thesis

There are six chapters in the thesis. Each chapter covered distinct research objectives and defined features of those objectives:

Chapter 1: The introduction provides background information with the primary goal of introducing the relationships between human civilizations and the significance of river water in their growth. The chapter discusses concerns over river water quality and its causes. It is crucial to discuss anthropogenic activities and how they affect the river basin's environment. The chapter covers the need for the study, the problem statement, and the objectives.

Chapter 2: The study area provides specific information about the physiology, drainage, climate, geology, land use, and pollution sources. To comprehend anthropogenic activities in the watershed, the Gomti River and its major urban centers are described in detail in this chapter.

Chapter 3: A thorough review of the pertinent literature is provided for determining the state of knowledge on MSTs, different WQI types, assimilative ability, climate change (effect of rising temperature), and statistical modeling. This chapter also examines how the results of the WQIs were included in the river water quality management plan and GIS, highlighting the gap that this study aims to fill.

Chapter 4: Materials and techniques provide a comprehensive research framework that was employed to accomplish the thesis' goals. It also details the study area, sampling sites, and data analysis. It offers a thorough methodology for descriptive statistics, multivariate statistical approaches, the evaluation of WQIs and their integration with GIS, statistical modeling of WQIs, the effect of climate change (rising temperatures), and the evaluation of the assimilative capacity of water quality variables in rivers.

Chapter 5: Results and discussion include a description and analytical discussion of the physiochemical study, descriptive statistics, multivariate statistical analysis, specifics of the WQIs analysis, data visualization using GIS maps, the effect of climate change, and the assimilative capacity of rivers. Figures and tabular representations of all the results have been provided. The chapter outlines the recommendations for the management strategy for river water quality.

Chapter 6: The current research results are summarised in the section under "Conclusion, Significance and Scope." The chapter also highlights the present study's key contributions and potential scope. With a few comments about the limitations of the current work, the chapter and thesis come to a close.

CHAPTER - 2

STUDY AREA

2.1 Gomti river basin

According to Census 2011 data, Uttar Pradesh, which has a geographical area of 24.12 MH and a population of roughly 199.81 million, is India's fourth-largest state by area. However, it is the most populous (Census of India, 2011). It is also blessed with abundant water resources, fertile land, and a favorable climate. Agriculture dominates its eight most important river basins: Yamuna, Ganga, Ramganga, Gomti, Ghaghra, Rapti, Gandak, and Sone (Figure 2.1), contributing to 27% of the state's GDP and 63% of employment (Abeysingha et al., 2015).

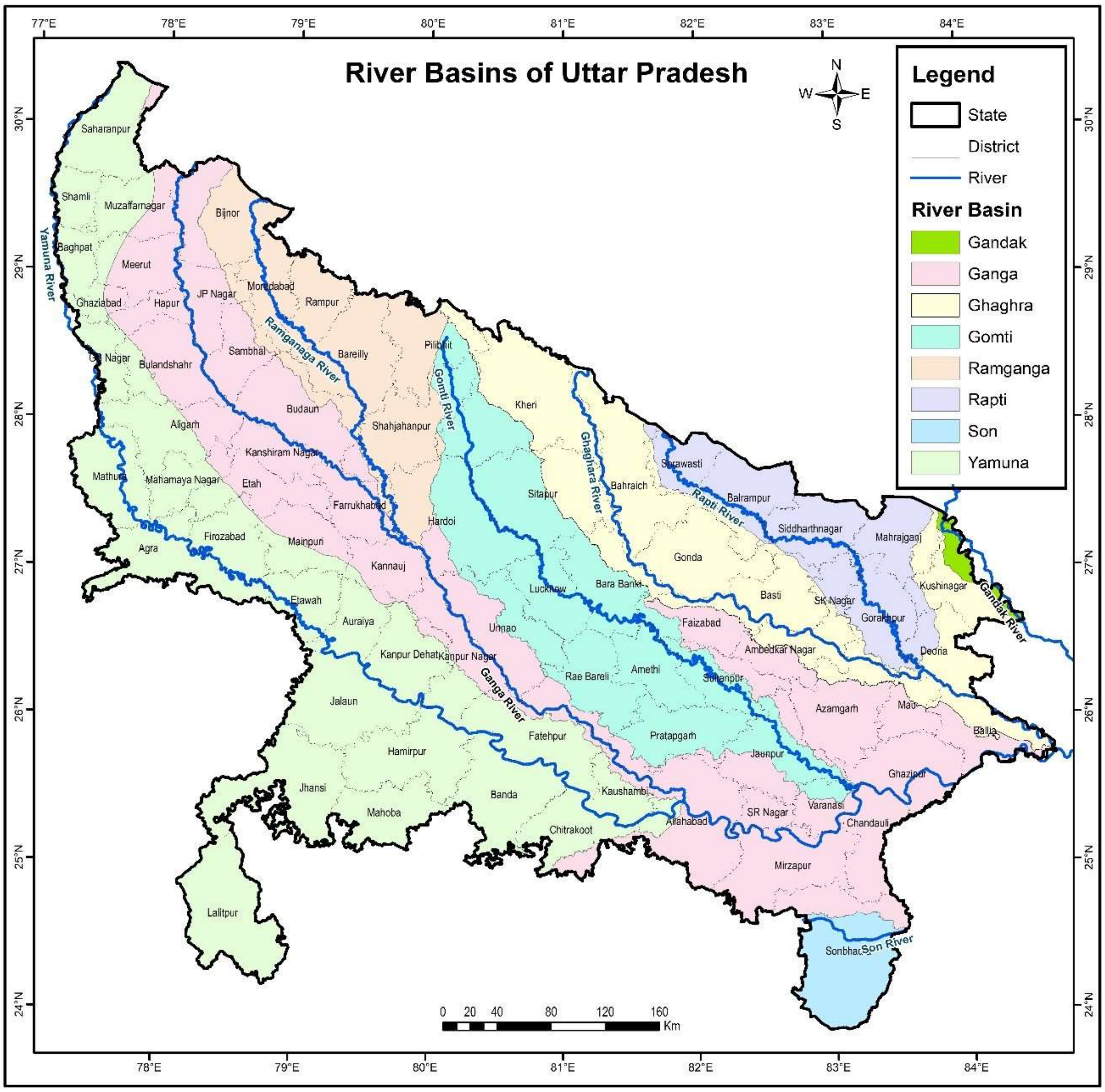


Figure 2.1: River basins of Uttar Pradesh

The Gomti, an important Ganga tributary and an alluvial river of the Ganga plain, rises at an elevation of 190 m in Madhotanda, approximately 30 km to the east of Pilibhit in UP, near Mainkot (55 km to the south of the foothills of the Himalayas) (Dutta et al., 2011, 2015, 2018a). The river completely flows within the UP and drains the region between the Ramganga and Ghaghara systems (Krishan et al., 2022a). The Gomti basin, which encloses an area of 31,433.67 km^2 in UP, is located between the East longitudes of 79°57' and 83°11' and the North latitudes of 25°23' and 28°42' (Figure 2.2) (Khan et al., 2021a, b, c). It is bordered on the north and west by the Ramganga Basin, the north and east by the Ghaghara Basin, and the south and east by the Ganga Basin. Lower Gomti, Sai, and Upper Gomti are the names of the three sub-basins that are identified within the Gomti basin. These sub-basins drain portions of UP that are 5,659.16 km^2 (18%), 12,188.39 km^2 (39%), and 13,586.12 km^2 (43%), respectively (Dutta et al., 2011).

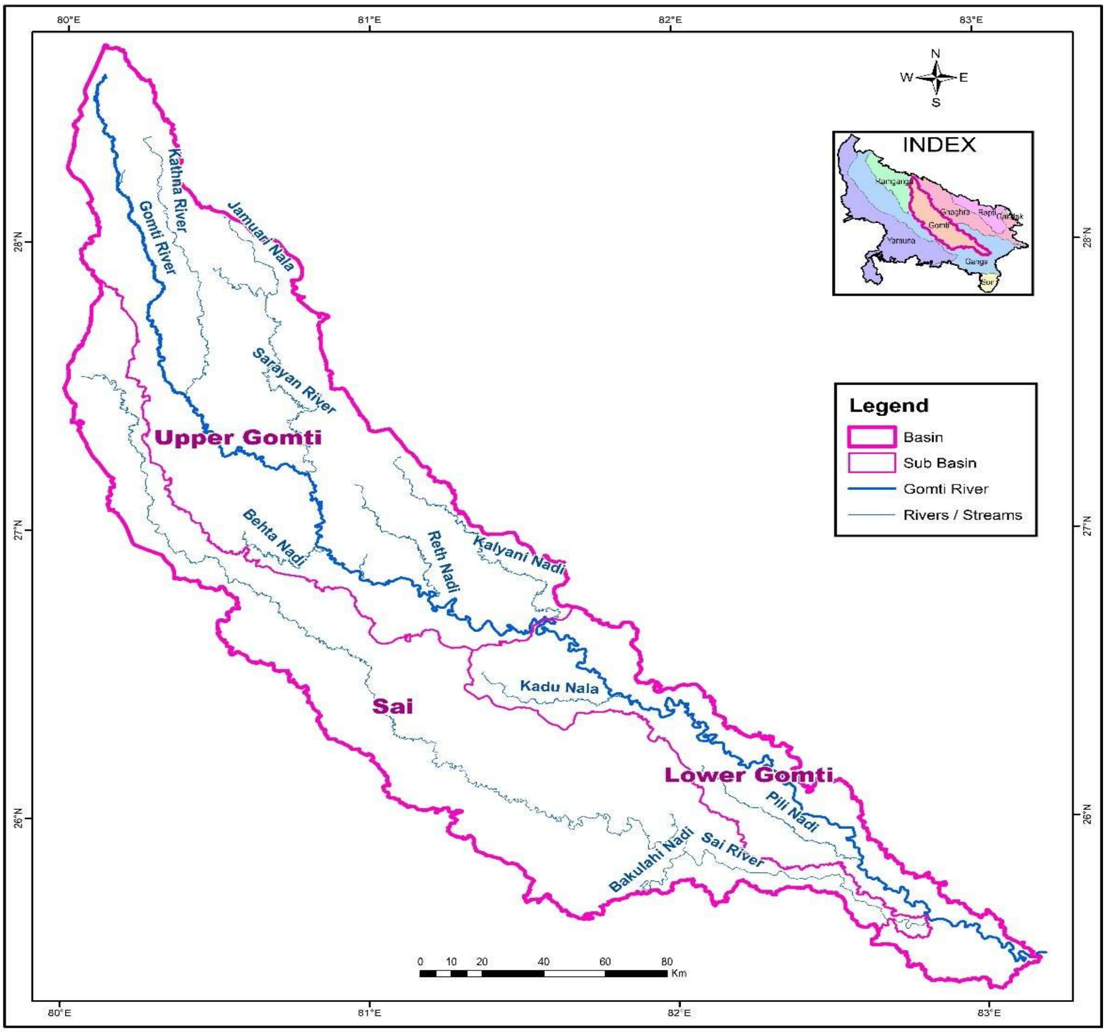


Figure 2.2: Location map of the Gomti basin

This river basin, which flows through both rural and urban regions, largely or entirely comprises 14 districts (Table 2.1). The river travels approximately 960 km in a south-southeast direction, passing through or bordering the districts of Pilibhit, Shahjahanpur, Kheri, Hardoi, Sitapur, Lucknow, Barabanki, Faizabad, Amethi, Sultanpur, Pratapgarh, and Jaunpur before coming together with the Ganga River near Kaithi village, Varanasi district bordering Ghazipur district (located 61 m above sea level) (Sharma et al., 2021a). The three largest urban areas on the river's banks are Lucknow, Sultanpur, and Jaunpur (Singh et al., 2004; Dutta et al., 2011). All major and minor tributaries of river Gomti confluence points are given in Table 2.2.

Table 2.1: The Gomti River's length by district

District (s)	Length of the river (km)	Area falling in Gomti Basin (km^2)
Pilibhit	30.03	894
Shahjahanpur	68.18	974
Kheri	85.12	2230
Hardoi & Sitapur	160.82	3572 (Hardoi) & 3076 (Sitapur)
Unnao	0	1856
Lucknow	98.75	2538
Barabanki	129.67	2960
Raibareli	0	3577
Faizabad	57.87	228
Sultanpur & Pratapgarh	163.18	3466 (Sultanpur) & 2878 (Pratapgarh)
Jaunpur	112.5	2230
Varanasi	10.39	492
Ghazipur	24.98	38
Total	960	31009

Recently, the Gomti riverfront neighborhood in Lucknow city has been built. The Lucknow Development Authority is developing recreational amenities here (Dutta et al., 2018a; Khan et al., 2022). The Gomti River has traditionally been revered. Nemsharanya Tirth, which, according to Hindu mythology, serves as a residence for saints and rishis, is located on the river's bank in Sitapur district, some 80 km southwest of Lucknow. Hindus hold this location in the highest regard and bathe in the river on holy days (Dutta et al., 2011).

Table 2.2: Confluence points of all major and minor tributaries of river Gomti

S. No.	Tributary Name	District	Length (km)	Place of Confluence
1	Gachai River	Pilibhit	14.9	28°29'42.16"N, 80°5'15.91"E
2	Joknai River	Shahjahanpur	52	28°12'22.09"N, 80°10'14.99"E
3	Bhainsi River	Shahjahanpur	41	28°5'17.69"N, 80°12'10.10"E
4	Chuha Nala	Kheri	44	27°44'30.64"N, 80°16'0.14"E
5	Andi Nala	Hardoi	10	27°30'53.23"N, 80°20'18.79"E
6	Kathina River	Sitapur	176	27°28'23.89"N, 80°23'29.62"E
7	Chitwa Nala	Sitapur	12	27°24'12.75"N, 80°26'52.56"E
8	Gharera Nala	Hardoi	18	27°21'34.27"N, 80°27'12.27"E
9	Sarayan River	Sitapur	274	27°11'58.67"N, 80°47'20.88"E
10	Nakha Nala	Lucknow	10	27°3'5.23"N, 80°50'39.06"E
11	Akraddi Nala	Lucknow	19	27°1'0.81"N, 80°49'12.53"E
12	Behta River	Lucknow	134	26°56'8.03"N, 80°51'25.45"E
13	Kukrail River	Lucknow	20	26°51'34.00"N, 80°58'0.75"E
14	Loni River	Lucknow	2	26°48'59.66"N, 81°0'30.53"E
15	Asaina Nala	Lucknow	6	26°50'15.02"N, 81°5'36.15"E
16	Reth River	Barabanki	103	26°46'5.03"N, 81°11'20.70"E
17	Kalyani River	Barabanki	190	26°41'33.77"N, 81°35'49.73"E

S. No.	Tributary Name	District	Length (km)	Place of Confluence
18	Arahi Nala	Amethi	28	26°35'0.70"N, 81°39'10.61"E
19	Betwa River	Barabanki and Faizabad border	19	26°35'17.18"N, 81°42'9.59"E
20	Kandu Nala	Amethi	69	26°25'26.41"N, 81°49'29.95"E
21	Gobaria Nala	Sultanpur	23	26°17'2.04"N, 82°3'48.71"E
22	Sewai Nala	Jaunpur	31	25°57'46.55"N, 82°32'23.89"E
23	Pili River	Jaunpur	95	25°51'6.47"N, 82°35'24.40"E
24	Sewai Nala	Jaunpur	31	25°42'9.36"N, 82°46'33.88"E
25	Balohi Nadi	Jaunpur	11	25°40'42.38"N, 82°48'20.82"E
26	Sai River	Jaunpur	695	25°39'7.76"N, 82°48'7.69"E
27	Nand River	Varanasi	47	25°37'21.43"N, 82°57'15.65"E

Groundwater provides domestic water supply in the Gomti basin (Sharma et al., 2021a). However, water from the Gomti River is being used to meet Lucknow's rising water demand (Abeysingha et al., 2016). The river almost completely dries up throughout the summer. Therefore, during the months of May and June, 4.25 m^3/s of water are made available from the Lucknow branch of the Sarda canal system through the Mahdoiya escape into the Gomti river to meet the residential water supply needs of Lucknow city. To lift this water and provide it to the ancient city area, a pumping station was constructed at Gaughat on the Gomti River. 1.42 m^3/s of water are pumped from Sharda Sahayak Feeder to Kathauta Jheel for the trans-Gomti area of Lucknow city. Water is delivered to this area from this location (Tangri et al., 2018). In addition to Lucknow, the Gomti River also delivers domestic water to the nearby town of Jaunpur. Groundwater is mainly used for industrial water supplies (Dutta et al., 2018a).

2.2 Basin morphology and sub-surface geology

The Indian subcontinent is home to the Ganga-Brahmaputra-Meghna (GBM), one of the biggest fluvial sedimentary basins in the world. The two regions of the world with the most tectonic activity are the Himalayas to the north and the stable Indian Craton to the south. The GBM, which dates back to the Pleistocene and Holocene, is traversed by the Gomti River, which also redistributes the GBM's weathered sediments from the Himalayas (Dutta et al., 2011; Sharma et al., 2021a). The most notable geomorphic features displayed by the GBM's active rivers are those involving fluvial incision (Dutta et al., 2015). Rainfall collected by the GRB and river discharge in the GBM are both regulated by the monsoon. The river travels 960 km southeast before joining the Ganga River near Kaithi, Ghazipur, adjoining Varanasi (located 62 m above sea level) (Dutta et al., 2011). With an altitude range of 200 to 62 m AMSL, most of the GRB's surface area is fairly flat and slopes toward the south and southeast. Before encountering the Ganga in the city of Kaithi in Ghazapur, which is close to Varanasi, it travels through the districts of Sitapur, Lucknow, Barabanki, Sultanpur, and Jaunpur as it makes its way south (UPPCB, 2019; Sharma et al., 2021a). Based on changes in the river's slope and its tributaries, the GRB is separated into upper and lower portions. The variation in height for 450 km from the starting point is around 100 m AMSL. There is a 25 m variation in height for the next 805 km (Dutta et al., 2015).

According to Plate 1(b), the Gomti River's valley edges have noticeable escarpments or bluffs, which are also known as banks. The height of the escarpment is essentially the elevation of the vertical cliff that outlines the river channel and valley. The Ganga River's base level being lowered is principally responsible for controlling the increasing downstream tendency of the cliff heights of both river borders. The Gomti River's longitudinal profile spans from 200 m to 62 m AMSL and has three breaks in the slope. The profile's noticeable convexity, situated above the subsurface Faizabad ridge, might be connected to movement over this ridge (Dutta et al., 2015).

The upper segment of the Gomti River has a highly sinuous active channel. The middle segment has river valley edges with a disconnected and steep escarpment. Before joining the Ganga at Kaithi, the lower segment had a meandering river valley with a 10–12 m–deep incision on the Ganga plain (Plate 1(d)). The effects of tectonics and climate change are notable and significant, and in the past, they may have caused river channel incisions and the renewal of the entire drainage network (Dutta et al., 2011, 2015).

According to the observation of the authors, groundwater and surface runoff contributed to a rise in the Gomti River's downstream discharge. The Gomti River's top part experiences little incision when experiencing high rainfall; in contrast, the middle and lower segments have high incision while experiencing low rainfall. Water output is lower in the middle segment than in the lower portion, yet the incision is at its greatest. Furthermore, the Gomti River's incision pattern is wave-like, indicating that rainfall is insufficient to account for it (Dutta et al., 2011, 2015).

The groundwater in the GRB is connected to the surface of the local uplands, rivers, and lakes, forming an integrated groundwater flow system (Singh et al., 2013). The quaternary alluvium strata include large aquifers at different depths. The hydraulic slope in the plain alluvial region is 2.5–3.5 m/km, whereas, in the river valley region, it is 6.5–7.5 m/km. The Gomti River valley has a groundwater depression, and groundwater flows from the valley edges to the active river channel toward this depression (Singh et al., 2013).

2.3 Sediment profile of Gomti river

The entire GRB sits atop thick alluvial sediment that dates back to the quaternary period. The alluvial deposits are made up of boulders, pebbles, gravel, sand, silt, clay, and occasionally kankar bands. Younger alluvium may be separated from the unconsolidated unit. The younger alluvium is found on the current floodplains, while the older alluvium is found in elevated areas, primarily the doab areas. The deeper kankar nodules in the older alluvium set it apart from the younger alluvium. Maximum sediments are carried during the monsoon season when rivers are discharging heavily. Sandbeds have a large aquifer system due to their structure and thickness (Dutta et al., 2015). Sand bars and sinuous-crested dunes deposit sets of trough cross-beds floor the waterways of the Gomti—inadequately defined trough cross-bedding results from the fast migration of sinuous-crested dunes with a coarse bed-load. During flood occurrences, coarse sediments are conveyed in the channels as depth and flow velocity rise significantly. Therefore, the deep channel deposits are composed of coarse sandstones with trough cross-bedding comparable to what is seen beneath the Siwalik sequences (Dutta et al., 2015).

Due in large part to the homogeneous distribution of alluvium dun gravels spread across the entirety of the basin, an almost monotonous spatial distribution of different chemical species is seen in the sediments. The river yearly conveys 3.0×10^6 tonnes of total dissolved solids and 0.34×10^6 tonnes of total suspended material, of which only bicarbonate ions account for 69%. A significant amount of anthropogenic loadings were detected in river water in samples taken downstream of Lucknow city. Concentrations of Na^+, Cl^-, and SO_4^{2-} increase downstream. With detrital quartz accounting for around 74% of the mineral composition of the bed sediments in the river, Si (36%) dominates the bed sediment chemistry. The percentage of organic stuff that can be found in the sediments was indirectly inferred by the average Kjeldahl nitrogen concentration (234 g/g). The Hg concentration in sediments has been found to be greater than background levels (on average, 904 µg/l). The Gomti River flows at a low energy level, as evidenced by the well-sorted, very leptokurtic, and finely skewed suspended sediments (Dutta et al., 2015).

2.4 Climate

Koppen classified the whole Indo-Gangetic Plain into the humid subtropical climate (Cwa system). The Cwa system is a unique classification, and it is applicable for Indo-Gangetic Plain only (Tangri et al., 2018). Winter, summer, and monsoon are the three main seasons the river basin experiences yearly. Beginning in November and lasting until February, winter brings temperatures down from 2°C to 22°C. Siberian-born frigid winds and relatively little precipitation are characteristics of the winter season. Most of the rainfall during this season is caused solely by westerlies or cyclonic disturbances. Erosion and chemical or mechanical weathering are slowed down by the winter season.

The summer season begins at the beginning of March and lasts until mid-June. The temperature in the summer varies between 28°C and 44°C, and most of the basin is subject to the loo, a hot local breeze. Humans in the summer receive some relief from cyclonic rain. At this time, the wind's action primarily controls the processes of weathering and erosion. June begins the monsoon season, which lasts until September (Das et al., 2019). The humidity is extremely high at this time, and the majority of the basin sees severe rain. Most of the geomorphic characteristics of the basin are developed and altered by weathering and erosion, influenced by heavy rain and increase the river's velocity and sediment supply.

The basin experiences annual rainfall ranging from 850 to 1,100 mm, with the southwest monsoon responsible for around 75% of the total precipitation falling between June and September (Abeysingha et al., 2015). The strength and duration of the monsoon rainfall significantly impact the Gomti River's flow (Abeysingha et al., 2020).

2.5 Land use cover in the Gomti river basin

In the Gomti watershed, declining wetlands and forest cover are key concerning causes. Due to rising demand and urbanization, forest cover has significantly declined during the past 100 years. This has negatively impacted the Gomti River's water flow. A decrease in their density has reduced the amount of water available in the river, as most tributaries come from woods and water sources. The majority of the woods in the river basin are open-type and less thick (Dutta et al., 2011). All of the districts within the basin, except for Pilibhit and Kheri, have insufficient greenery. The overall quantity of forest cover in the river basin is only 4.10%, compared to 9.01% of the geographical area in UP. In the Gomti basin, it is visible that 64.35% of the area is under agriculture, and harvesting intensity is 163.12% (Dutta et al., 2011). Surface and groundwater sources are used to irrigate about 88.7% of the gross planted area. According to data from the agriculture department for 2014–2015, the yearly per capita food output (cereal and pulses) in the Gomti basin is 170 kg/person (Sharma et al., 2021a). The land use and cover pattern of the river basin were studied to identify the kinds of land use in the basin. A land use and land cover pattern in the GRB has been shown in Table 2.3 (Dutta et al., 2011, 2015).

Table 2.3: Land use and land cover pattern in the Gomti river basin

Field	Area in km^2	Percentage share in the basin
Built-up	1743.014	5.62
Kharif crop only	1828.539	5.9
Rabi crop only	2527.707	8.15
Zaid crop only	8.799616	0.03
Double/triple crop	17384.9	56.06
Current fallow	833.6241	2.69
Plantation	2119.563	6.84
Evergreen forest	2.119936	0.01
Deciduous forest	1068.777	3.45
Degraded/ Scrub forest	21.97709	0.07
Wasteland	2489.783	8.03
Deep water bodies	970.5042	3.13
Shallow water bodies	9.696512	0.03

2.6 Socio-economic status

According to the 2011 Census, there are 27.71 million people living in the Gomti basin, of which 22.59 million (81.5%) live in rural areas and 5.13 million (8.5%) live in urban areas. The population comprises 14.33 million males and 13.39 million females. According to statistics from 2012, 43% of the basin's population lives in poverty (Census of India, 2011).

Most of the land in the Gomti basins is owned by marginal laborers, who have agricultural fields with a total area of less than 1 Ha. According to the agriculture census 2010–11, of the total operational holdings in the Gomti basin, marginal land holdings (<1.00 Ha) are made up of 84.58%, which was followed by small (1 to 2 Ha), semi-medium (2 to 4 Ha), medium (4 to 10 Ha), and large (above 10 Ha) land holdings (10.59%, 3.96%, 0.85%, and 0.03%), respectively. In comparison to the national average (67.10%) and the state average (13.01%), the fraction of marginal land holdings in the Gomti basin is higher (79.48%) and lower (17.91%), respectively (Census of India, 2011). This shows that the region has a huge number of minor agricultural fields, which has led to a low level of crop intensification, crop diversity, agricultural mechanization, and low economic growth. The repeated rice-wheat cycles may also have additional unfavorable effects, such as low farmer income, agriculture focused on subsistence, loss of soil health, and many others. According to the 2011 census, of the total number of workers in the Gomti basin, 31.8% are agricultural laborers, and 30.7% are cultivators, making up 62.5% of the working population in the region (Abeysingha et al., 2016).

2.7 Water availability in the river

The Gomti River's water is annually released into the Ganga River at about 7390 x 10^6 m^3. The monsoon season sees about 80% of the discharge flow (Tangri et al., 2018). According to research, the Gomti basin's average annual water output from rainfall is 7390 million cubic meters, with a specific yield and discharge of 244,000 m^3/km^2 and 234 m^3/sec (Abeysingha et al., 2020). Individual basin runoff might vary significantly from the national average. For instance, the runoff in the upper Gandak is about 1600 mm/yr compared to about 250 mm/yr in the Gomti basin. According to estimates, the river has an average daily flow of 1,500 MLD. It rises to 45,000 MLD after rains and drops to 500 MLD during the summer (Dutta et al., 2018a; Khan et al., 2022; Krishan et al., 2022a). In fact, there have been instances during the dry season when it has been necessary to ask the state irrigation department to increase supply in order to fulfill drinking water demand. The river is known for its slow flow year-round, except for the monsoon season, when excessive rainfall produces a manifold spike (20 to 50 times) in the discharge (Singh et al., 2013). The 75% predicted flow in September was recorded as 450 m^3/s in Maighat (after the Sai-Gomti confluence), and 125 m^3/s. were recorded at Hanuman Setu, Lucknow (Abeysingha et al., 2020).

For Lucknow, Jaunpur, and other communities downstream, including many farmers, the Gomti River is their primary water source. Many tube wells have been drilled close to the riverbed to access groundwater. Around 250 MLD of water is taken out of the Gomti river daily for Lucknow, while 300 MLD is taken out of the groundwater. There is practically little recreational use of rivers and waterways. Another barrier to the construction of recreational amenities is low river discharge (Dutta et al., 2018a; Goel et al., 2018).

Through escapes to 2.83 m^3/s the Sharda canal system occasionally increases Gomti flows through the Kheri branch, which is on the left, and the Lucknow branch is on the right. According to the roaster, the branches in Lucknow and Kheri operate concurrently and alternately. In the highest reaches, Sharda flows can be pushed into Gomti.

However, as all flows are channeled into the Sharda canal at Banbasa during non-monsoon, there won’t be enough flow in the Shards during that time (Tangri et al., 2018).

In the Gomti basin region, neither thermal nor hydroelectric power is produced. Intracoastal navigation is not possible because of low discharges. However, at its confluence with the Ganga River close to Varanasi, the river serves as a platform for inland shipping. There are 111 officially notified Inland National Waterways (NW) in India identified for the purposes of inland water transport, as per The National Waterways Act, 2016. Out of 111 NW, 106 were created in 2016. The 518 km long Gomti River (NW42) is one of the 106 newly designated NW.

2.8 Major canal network in the Gomti river basin

The Sharda River's water accumulated at the Banbasa barrage in the Uttarakhand region of Nainital, where the main Sharda canal begins. In the district of Pilibhit, the main Sharda canal is divided into three additional branches (Tangri et al., 2018).

- Main Hardoi branch
- Kheri branch
- Feeder channel which feeds the Sharda Sagar

Water from the Sharda River is held in the Sharda Sagar, and Hardoi, a branch canal, is pulled out of the Sharda Sagar's zero point. The Sharda Sagar reservoir's "Zero Point" is where the feeder canal meets the reservoir, and the subsidiary Hardoi branch emerges. The tail end of the Sharda Sagar reservoir is its upstream side. A second feeder channel is drawn out from the main Sharda canal's tail point, feeding water into the Sharda Sagar reservoir. The Sharda Canal's branches, such as Hardoi, Kheri, Sitapur, Sandila, Sultanpur, Jaunpur, Lucknow, and Mariyahau, make up most of the Gomti river basin's primary canal network. These branches are divided into a variety of distributaries, including the Maholi distributaries, Misrikh distributaries, Banaura distributaries, Bharawan distributaries, Jindana distributaries, Nawabganj distributaries, Chilbila distributaries, Chanda distributaries, Ramganj distributaries, Peng distributaries, Pihani distributaries, Bhadaicha distributaries, Pandarwa distributaries (Dutta et al., 2011; Tangri et al., 2018). The entire Gomti river basin is drained in addition to these large canal networks by numerous lesser ones. As a result, the vast system of canals, along with its distributaries and minors, completely encloses the basin of the Gomti River.

2.9 Flood and Drainage Management

The Gomti River and Sai, its principal tributary, serve as the basin's primary drainage systems. The river runs over 960 km in a south-southeast direction. The river's overall drainage area is 31,434 km^2, whereas Sai River's drainage area is 12,188 km^2 or 39% of the Gomti basin's total catchment area. The Gomti basin's surface area is primarily flat and slopes south and southeast, with elevations ranging from 200 m to 61 m AMSL. The height difference is around 90 m for the first 425 km from the starting point and 49 m for the final 500 km. Due to drainage congestion, the lower, flatter slope causes occasional flooding in Jaunpur and some areas of the Pratapgarh district. In Jaunpur town, several low-lying regions experience brief flooding during the monsoon season. Flooding of the Gomti River has no effect on the population (Dutta et al., 2011; Tangri et al., 2018). The Gomti River caused flooding in Lucknow city in the 1980s. Embankments were built to protect the city from the intensity of the Gomti floods. These are:

- U/s of Hardinge bridge on the left bank
- U/s of a confluence of Kukrail Nala and Gomti River, along Kukrail Nala on both banks.
- Gomti barrage to the railway bridge in the d/s, on both banks, to save La Martiniere College and Gomti Nagar.

2.10 Water quality deterioration

Surface runoff is a seasonal occurrence strongly influenced by the basin’s climate, whereas human discharges are a continuous polluting source. Domestic sewage from Class-I cities, Class-II cities, and many towns, effluents from various industries, are discharged into the river Gomti throughout its length. About 78% of the pollution is caused by raw sewage, effluents, and sludge disposal. The major sources of river Gomti pollution are given below:

- Small and major drains carrying sewage from adjoining areas.
- Untreated industrial effluents.
- Chemical fertilizers, pesticides, and insecticides as surface runoff from nearby agricultural fields.
- Surface runoff from areas on which urban solid wastes are dumped.
- Disposal of dead animal bodies.

A total of 865 MLD of sewage has been dumped into the river Gomti through 68 major drains. In the river's catchment region, there are seven major towns – Sitapur, Sandila, Lucknow, Barabanki, Jagdishpur, Sultanpur, and Jaunpur town – as well as one smaller town—Kerakat (Jaunpur). The sewage and other industrial effluent produced by these cities increase the organic load on the river. Given that the installed capacity of the sewage treatment plants is 443 MLD and that they are operating at 100% of their capacity. Sewage treatment is a major source of concern. About 422 MLD of untreated sewage enters the river Gomti each year. This suggests that the available treatment facility is insufficient. The river Gomti and the 345 MLD Bharwara STP's treated sewage meet just downstream of Lucknow city, close to Khaledeoria. Upstream of Lucknow city, close to Kudiyaghat, the river Gomti is where the 56 MLD treated sewage from Daulatganj STP meets (UPPCB, 2019; Krishan et al., 2022 a, b).

Within the catchment region of the Gomti River's pollution section, there are 30 water-polluting enterprises. These businesses have wastewater treatment facilities, and the processed wastewater is released through 10 mixed drains, where the treated industrial wastewater is mixed with sewage. The industries related to sugar, distilleries, textiles, electroplating, slaughterhouses, and other unrelated businesses are extremely polluting (UPPCB, 2019).

According to CPCB river water quality monitoring, the river Gomti is not appropriate for drinking purposes or outdoor bathing between Kudiaghat and Jagdishpur due to the detected polluted length of the river between Sitapur and Jaunpur. It can only be used for controlled waste disposal, industrial cooling, or irrigation (Class-E, specified as per IS 2296-1982) (UPPCB, 2019).

2.11 Gomti River in Lucknow

The Gomti River approaches Lucknow after traveling 240 km from its source. Here, it meanders. Lucknow is located at 26°52′ N latitude, 80°56′ E longitude; it is situated above mean sea level at the height of 124 m (Tangri et al., 2018). The city experiences a hot, humid subtropical climate from April to June, with chilly, dry winters from December to February. The extreme temperature ranged from 1.67^{O}C in the winter to 48.9^{O}C in the summer. About 900 mm of rain falls on the city each year, primarily from the southwest monsoon in July, August, and September (Goel et al., 2018). The city is between 100 and 130 m above mean sea level and slopes east (Khan et al., 2020). With a projected population increase from 2.8 million in 2011 to 4.7 million in 2031, Lucknow is one of the cities in the nation that is expanding very fast (LDA, 2016; Kumar, 2018). The urban core has a surface area of around 250 km^2, growing each year exponentially. As it enters Lucknow, water is drawn from the Gomti River at the Gaughat pumping station for the city's water supply. In the Lucknow region, up to 28 city drains discharge untreated sewage water into the Gomti, severely polluting it. The Gomti barrage impounds the river, turning it into a still lake at Gomti's downstream end in Lucknow city (Tangri et al., 2018).

Due to the daily release of millions of gallons of untreated residential garbage, the Lucknow population's primary source of drinking water, the river, is the filthiest. The river not only feeds water to Lucknow but also to 14 other towns that are located along its banks, such as Lakhimpur Kheri, Sultanpur, and Jaunpur (Krishan et al., 2022a, b).

The Lucknow urban center receives the majority of its water from the Gomti River. At Lucknow, the Gomti River's available discharge ranges from 500 MLD during the lean season to 55,000 MLD during the monsoon season. The typical discharge for most of the year is only about 1500 MLD. The urban region of Lucknow has about 407 tube wells. About 190 MLD of water is produced by these 407 tube wells. Several private colonies and organizations have set up about 100 tube wells to meet their water needs. Due to low water discharge, the post-monsoon season is connected to the river's depositional phase (Tangri et al., 2018).

Lucknow had its highest flood level in 1960 at 113.2 m, with significant portions of the city submerging. Earthen embankments have been built up to a high level of 114.4 m along the riverbank and atop Kukrail nala to safeguard the homes. To avoid water logging in the city during flooding and severe rain, pumping stations transport stormwater across an embankment and into a river. The Gomti Nagar settlement, a component of the Lucknow urban area, is located on the flood plain of the Gomti river; as a result, water logging happens in various places during rainy seasons. The Gomti does not create any problems unless there is hefty rainfall; however, harm is frequently brought on by floods and their aftereffects (Tangri et al., 2018).

There are 28 important drains in Lucknow; 14 are in the Cis-Gomti area, which is the southern half, and 14 are in the Trans-Gomti area, the northern section (Figure 2.3). Some of these large drains can discharge up to 78 MLD of sludge, whereas the smaller drains can only discharge 0.5 MLD (Table 2.4) (Krishan et al., 2022a, b).

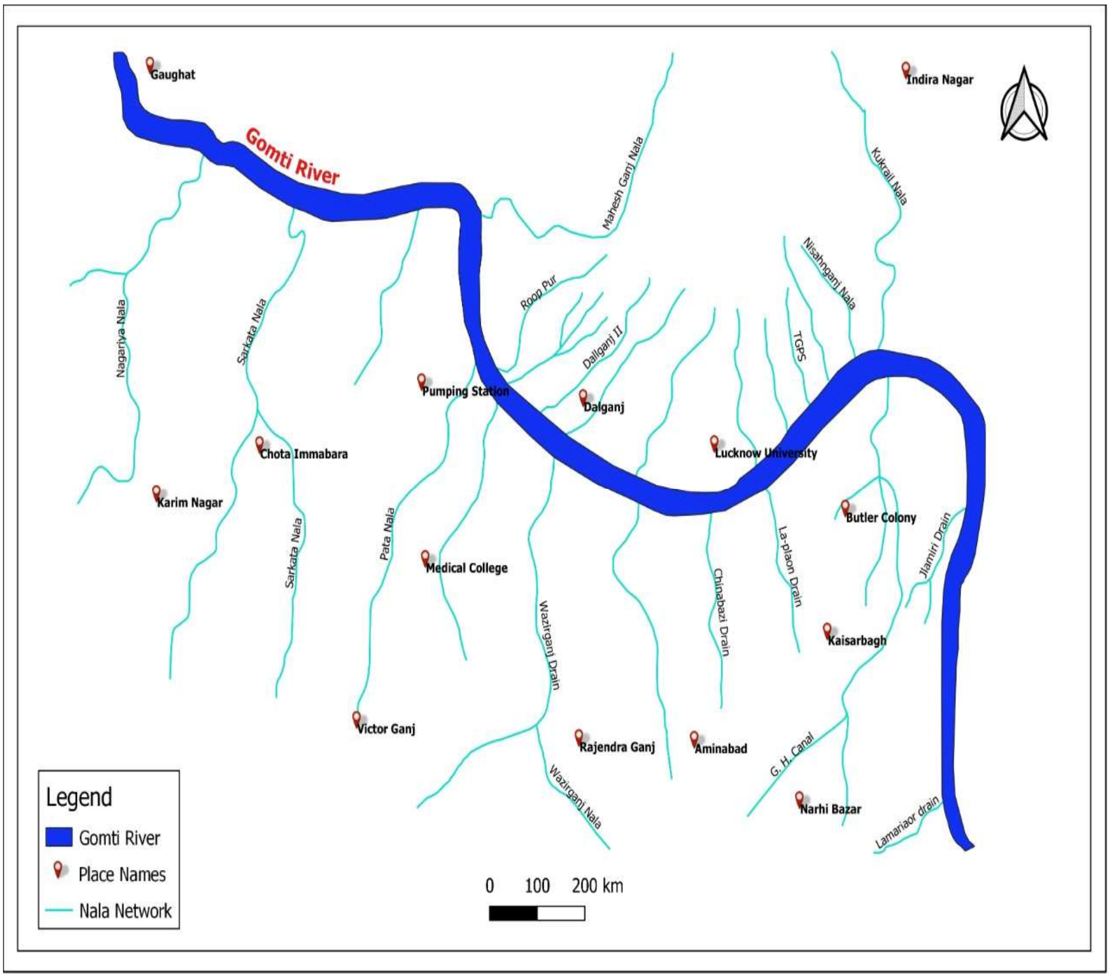


Figure 2.3: Map showing the sewerage network joining the right and left banks of the Gomti River at Lucknow

A few of the major polluting industries that significantly contribute to the Gomti River are M/s. Hindustan Aeronautics Ltd., Tata Motors, Railway Carriage and Wagon Shop, battery industry, many small/medium scale industries, bakeries, vehicle workshops, dairy farms. In spite of these industries, other notable polluters are vegetable waste, oil and grease, surfactants used for cloth washing at river sites, biomedical/animal waste, fish/meat markets, and cattle sheds along the river banks that considerably contribute to the Gomti River. Between 1993 and 2019, Lucknow city's built-up area increased by 43.8%, along with the city's population growth, which had an even greater influence on the river's water quality. Newly built structures and infrastructural growth have also influenced the water quality (Kumar et al., 2022a).

Table 2.4: Wastewater load at different outfall drains, Lucknow

S. No.	Name of the drain Cis-Gomti (right bank)	Discharge (MLD)
1	Nagariya drain	10
2	Sarkata drain	34.57
3	Pata drain	18.54
4	Drain downstream of NER	1
5	Wazirganj drain	75.6
6	Ghasiyari mandi drain	19.53
7	China bazar drain	7.01
8	La-place drain	3
9	Cis-Gomati Pumping Station	19.64
10	Joppling road drain	3
11	G. H. canal	106.2
12	Jiamau drain	3
13	Lamartenier	1
14	Drain upstream of rail bridge	3
Total		**305.09**
S. No.	**Name of the drain Trans-Gomti (left bank)**	**Discharge (MLD)**
1	Maheshganj drain	4.57
2	Rooppur drain	0.66
3	Mohan meakins drain	5.19
4	Daliganj drain I	12.28
5	Daliganj drain II	6.95
6	Arts college drain	8.89
7	Hanuman setu drain	0.83
8	Trans-Gomti Pumping Station	1.64
9	Kedernath drain	3.4
10	Nishatganj drain	1.7
11	Babapurwa drain	0.65
12	Kukrail drain	50
13	Weeping sewers of city	34.5
14	Gomti N. drainage	25
Total		**156.24**
Grand total: 461.33 MLD		

CHAPTER - 3

LITERATURE REVIEW

3.1 General

A review of every facet of this research project is presented in this chapter. The first part reviews the management of water quality and the river water quality conditions in India and the rest of the world. The use of multivariate statistical analysis, the water quality index, assimilative capacity, water quality modeling, and the impact of rising temperatures on water quality, as well as the integration of GIS with WQIs, are covered in this section.

3.2 River water quality management

All life depends on water, an essential natural resource (Semy and Singh, 2021; Kumar et al., 2022a). The two categories of natural water resources are surface water and groundwater. Rivers, lakes, ponds, and oceans are surface water resources (Markandeya et al., 2021; Pandey et al., 2021). Rivers are a significant part of the natural environment, and their quality must be preserved for various water uses (Arora and Keshari, 2021; Kumar et al., 2022b). A measurement of the water status concerning the needs of one or more aquatic biota and/or any human need is known as water quality (Singh et al., 2019). The primary water quality metrics include temperature, pH, sediment load, BOD, TDS, DO, nitrogen, phosphorus, heavy metals, radionuclides, and pathogenic microbes (Kumar et al., 2022b). To maintain water quality, several strategies have been used nationally and worldwide (Parmar and Bhardwaj, 2014, 2015; Kumar, 2018; Ali et al., 2021). To keep water quality at an acceptable level for the intended use, water quality management comprises monitoring, evaluating, identifying, and controlling potential sources of pollution (Kumar, 2018; Arora and Keshari, 2021). Since the turn of the century, efforts have been made in Germany to manage and regulate surface water quality. For the German Emscher River basin, an institution responsible for basin-wide water quality control was established in the middle of 1900. Later, six more river basin authorities were founded in Germany's highly industrialized and urbanized Ruhr region. An innovative project to measure rivers' ability to absorb garbage was initiated on the Ohio River in the 1920s. No effort was made after World War II to regulate wastewater discharge and improve river water quality. A complete sewerage system had been built in the USA and Europe by the middle of the 1880s (Council, 2002). Later, a global network of STPs was set up to enhance the wastewater's quality before disposal in surface water bodies.

Several environmental laws have been created and put into effect around the globe to preserve the purity of water. The Water (Prevention and Control) Act of 1974 was passed by the Indian government. The CPCB and SPCB were given significant duties and powers under the act, which was focused on maintaining the water quality of aquatic resources. Each SPCB is required by this legislation to establish a water and wastewater laboratory in cooperation with the CPCB. Both SPCB and CPCB contribute to the nationwide monitoring of water quality.

Recent decades have seen a significant decline in the ecological health of the Ganga River due to unchecked and unplanned rapid urbanization, discharge of both partially treated wastewater and untreated wastewater, inappropriate patterns of land use, excessive numbers of people participating in religious bathing, and the dumping of solid waste along the river stretch (Nandi et al., 2016; Singh et al., 2020). The government of India has implemented a number of mitigating measures as part of GAP- I and II with the primary goal of reducing the pollution load into the national river Ganga (Ching and Mukherjee, 2015; Kumar et al., 2021a).

The Indian government initiated the GAP-I in 1985 and collaborated technologically with local and foreign (United Kingdom, Netherlands, and other) non-profit organizations (Chaudhary et al., 2017). The GAP-I mainly concentrated on building bands to control nonpoint pollution inputs from agricultural runoff, a new electric crematorium to prevent the mixing of partially and fully burned dead bodies at river banks, STPs to prevent untreated urban discharge of wastewater in rivers, diverting drains that directly discharge wastewater, and developing sewerage systems in the surrounding areas (Birol and Das, 2010; Matta et al., 2020). GAP-I had a significant role in the significant decrease of wastewater discharged directly, which improved the quality of the Ganga River's water (Trombadore et al., 2020). Nevertheless, despite significant enhancement, river water quality was unfit for various uses, including human bathing (Kumar et al., 2021a). Based on this information, the Indian government implemented GAP-II in 1993 with the assistance of indigenous and Japanese environmental organizations. The main goal of GAP-II was to reduce the pollution load in the three major tributaries (Yamuna, Damodar and Gomti) of the river Ganga, which was not taken into account in GAP-I (Das and Tamminga, 2012; Kumar et al., 2021a).

Despite being a top priority for the government and involving governing authorities, specialists, and regulatory systems, the river's water quality has not improved but rather deteriorated and has become inadequate for supporting biodiversity (Tripathi and Singal, 2019; Kumar et al., 2020a).

Several researchers have restored riverine environments in the UK, US, and Europe (Helfield et al., 2007; Newson, 2010; Raven et al., 2010). The main points are that these initiatives are long-term, technically sound, depend on separate financing for habitat changes, and use river segments with designated special protection areas for wildlife as a "springboard for a systematic approach to river restoration" (Philip and Paul, 2012). Restoration initiatives also focus on a river system's geomorphic structure, purpose, and historical development (Brierley et al., 2010). For the Gomti River, there is a need to implement a restoration plan that is technically and scientifically sound, extensive, long-term, and economically sustainable (Dutta et al., 2018a).

For the preservation of desired water quality, a variety of water quality management systems have been created to date (Sharma and Kansal, 2011; Gupta et al., 2014; Parmar and Bhardwaj, 2014, 2015; Kumar et al., 2015; Kumar, 2018; Ali et al., 2021). Traditionally, water quality regulation is used to assess the quality of tested surface water for various parameters (Debels et al., 2005; Zhang et al., 2010; Arora and Keshari, 2021; Kumar et al., 2022b). Monitoring does not determine how one parameter affects another, but it does lay the groundwork for using MSTs, WQIs, assimilative capacity, and water quality models (WQMs) to improve management and comprehend underlying concerns and issues. The development of contemporary computational approaches such as WQIs and WQMs for evaluation and management of water quality can be applied to the data on water quality (Parmar and Bhardwaj, 2014, 2015; Kumar et al., 2015; Arora and Keshari, 2021).

Water quality monitoring, water quality assessment using MSTs, WQIs, assimilative capacity, and design of pollution control plans using WQMs are the primary components of surface water quality management. The following sections describe and evaluate essential aspects of surface water quality management systems.

3.3 Water quality monitoring

The main method for gathering initial data and evaluating the water quality of any body of water is water quality monitoring. Primary monitoring is essential for determining the water quality of the bodies. For this objective, several primary monitoring studies have been conducted globally (Sargaonkar and Deshpande, 2003; Nikoo et al., 2011; Rizvi et al., 2016; Bora and Goswami, 2017; Chabuk et al., 2020; Lkr et al., 2020; Kharake and Raut, 2021; Kumar et al., 2022a).

Numerous water quality management studies have been conducted on various water bodies in India and overseas to evaluate the water quality (Meme et al., 2014; Kumar et al., 2015; Jaiswal et al., 2019; Kumar et al., 2020a; Khan et al., 2021d; Kumar et al., 2022b). It has been discovered that the presence of industrial operations close to water bodies, the discharge of untreated sewage, and runoff from agricultural fields are the leading causes of these water bodies declining water quality (Jaiswal et al., 2019; Kumar et al., 2020a; Khan et al., 2021d). In India, the CPCB, SPCB, and CWC have already established monitoring stations on rivers nationwide for water quality assessment (Arora and Keshari, 2021; Kumar et al., 2021a).

Apart from these, various researchers and scholars (Suthar et al., 2010; Gupta et al., 2011; Tyagi et al., 2013; Bhutiani et al., 2016; Singh et al., 2018; Kamboj and Kamboj, 2019; Sharma et al., 2020; Ali et al., 2021; Kumar et al., 2021a; Khan et al., 2022a; Kumar et al., 2022b) have examined the water samples taken from several Indian rivers physiochemically and microbiologically. Untreated sewage disposal, urban runoff, fertilizers, industrial effluent, and the use of both agricultural and forest land for development are the primary factors identified as degrading the water quality of various rivers in India, including the Ganga, Cauvery, Hindon, Chambal, Mahanadi, Yamuna, Narmada, Gomti, Brahmaputra, Godavari, and Krishna.

Designing different implementation techniques to improve water quality and allocate water distribution schemes requires regular and ongoing monitoring procedures (Singh et al., 2004; Shrestha and Kazama, 2007; Pati et al., 2014; Arora and Keshari, 2021). Designing, establishing, and planning a water quality system based on the goals of the water monitoring program is one of its key components (Arora and Keshari, 2021). In order to preserve the quality of surface water, many water quality networks exist all around the world.

Numerous water-quality networks were established in the USA in the 1970s due to the growing public concern over the condition of aquatic ecosystems and conventional public health worries. NASQAN was developed by the USGS in 1973. The network aids in identifying the factors contributing to the spatiotemporal variability in water bodies. The NASQAN continuously updates information on the water quality of bodies present inside or beyond borders. In New York, water quality is routinely checked in smaller streams and rivers in southern New York and northern Pennsylvania by the Remote Water Quality Monitoring Network (RWQMN) under the Susquehanna River Basin Commission (SRBC). This network aids in alerting water management about the current state of water quality while also foretelling changes that may occur in that quality (<http://mdw.srbc.net/ remotewaterquality/>). River water quality is regularly monitored in Hong Kong. This program has 82 monitoring sites and covers 30 major rivers and streams. The Environmental Protection Department (EPD) oversees the initiative (<http://wqrc.epd. gov.hk/en/water-quality/river-1.aspx>).

The National Water Research Center and Egypt's Ministry of Water Resources and Irrigation monitored the water quality at 69 sites along the Nile River. Every two years, the water quality is monitored (Abdel-Gawad and Khalil, 2003). The Chinese national monitoring network comprises 759 surface water stations, 45 international river stations that traverse international borders, and 149 involuntary monitoring stations. This network includes China's ten largest watersheds (Wang et al., 2014).

The CPCB in India has already established monitoring stations on rivers nationwide (Bhargava, 2006). The CPCB monitors hazardous metals As, Cu, Cd, Cr, Ni, Hg, and Pb in 120 rivers in addition to water quality in 206 rivers. The BIS on Drinking Water standards (http://wqaa.gov.in/Content/SWQStatus.aspx) has determined that the metal levels in various rivers, except for Cr, Cu, and Cd, are within allowed limits.

With the help of the National Water Quality Monitoring Program, CPCB India is in charge of eliminating water pollution in rivers (CPCB, 1980-1981; CPCB, 1982-1983; CPCB, 1999-2000; CPCB, 2003, 2006). The CPCB of India seeks to assess environmental problems relating to water and restore and preserve aquatic resources' health. The Indian government created plans to determine the optimal use for each class after classifying the country's water bodies according to their quality and pollution status (Arora and Keshari, 2021). Additionally, to determine if water is suitable for drinking, the BIS has set the acceptable and desirable limits of several water quality criteria (IS: 10500:2012). In addition, according to IS: 2296:1992, a number of classifications have been established, including classes A, B, C, D, and E, to designate distinct applications of water resources. These guidelines have been applied to outline sampling techniques and evaluate the water quality in Indian rivers (Arora and Keshari, 2021).

The monitoring network for inland water quality in India is run through a three-tier program called Yamuna Action Plan (YAP), Monitoring of Indian National Aquatic

Resources System (MINARS), and GEMS (Bhargava, 2006; Kumar et al., 2021a). According to the CPCB, monitoring water quality helps determine trends in water quality, which in turn aids in determining the order of importance of pollution management initiatives. The CPCB has created a network of monitoring stations for efficient river water quality monitoring. CPCB, under the auspices of a World Bank-funded initiative, is developing a network of 113 real-time monitoring facilities on the Ganga across Uttarakhand, Uttar Pradesh, Bihar, Jharkhand, and West Bengal in order to have a clear image of river water quality. Additionally, several prestigious organizations, including the CWC, CGWB, and SWARDA, independently monitor the quality of river water through their extensive and pricey networks of monitoring stations (<http://cwc.gov.in/main/HP/>).

Since 1963, the CWC has been a significant player in monitoring river water quality. As of January 2021, 764 sites along significant rivers in India are being monitored by CWC for river water quality. In August 2011, the first edition of "REPORT ON WATER QUALITY HOTSPOTS IN RIVERS OF INDIA" was released. Data on water quality for ten years (2001–2010) was collected at 371 CWC water quality monitoring sites. A report titled "WATER QUALITY HOTSPOTS IN RIVERS OF INDIA OTHER THAN GANGA, INDUS & BRAHMAPUTRA BASIN" was released in November 2017. The only parameter BOD, the most often used criterion for measuring the amount of pollution caused by organic material present in river water and determining the overall health of the river, was considered for this study. The analysis was conducted using BOD data from 429 CWC water quality stations from 2012 to 2017 for all Indian river basins other than the Ganga, Brahmaputra, and Indus basins. This report was created to evaluate the potential of STPs. This third version of the study on "WATER QUALITY HOTSPOTS IN RIVERS OF INDIA" is based on data from 10 different water quality metrics that were observed between 2010 and 2020 at 588 of the CWC's 764 water quality monitoring stations.

Early indicators of declining water quality are identified so that subsequent corrective measures can be taken to manage its quality through water quality monitoring, providing the necessary baseline data. As a result, any program for managing water quality must have water quality monitoring as a key component.

3.4 Multivariate statistical techniques

To gather reliable water quality statistics, routine and continuous monitoring programs are required (Singh et al., 2004; Shrestha and Kazama, 2007; Pati et al., 2014; Arora and Keshari, 2021). These programmes generate enormous amounts of complex data. These data include unpublished information on the area as well as behavioral characteristics of the surface water body. Interpreting this concealed information is crucial for managing water quality (Saha and Paul, 2019; Ali et al., 2021). Advanced and complex analytical tools and procedures, such as MSTs, are required to analyze these data (Singh et al., 2005). The MSTs, such as PCA and CA, aid in exposing the concealed information found in sizable matrices of high-quality data. The usage of MSTs is necessary for the assessment of river water quality in order to increase the scope of the evaluation and accuracy based on the vast amount of data inputs (Chakravarty and Gupta, 2021). Since the past decade, MSTs have been employed to analyze and characterize surface water quality (Kumarasamy et al., 2014; Sharma et al., 2015; Pandey and Dikshit, 2016; Bonansea et al., 2018; Shil et al., 2019; Gyimah et al., 2021; Arora and Keshari, 2021; Maity et al., 2022). Below is a brief summary of the literature on using several relevant MSTs, including CA, PCA/FA, DA, MANOVA, and MLR, in determining surface water quality.

Unsupervised pattern recognition techniques, such as CA, group samples into clusters where the items are similar to one another but distinct from other clusters. Many researchers and scholars (Kazi et al., 2009; Li et al., 2014; Barakat et al., 2016) have employed CA to comprehend the temporal and spatial pattern of water quality changes brought on by anthropogenic or natural sources. CA was utilized to evaluate the chemical water types and their geographical variations in Queens lands streams in 2005 (McNeil et al., 2005). Li et al. (2007) considered twelve lakes on the Yunnan plateau (China) and used CA to evaluate the water quality. CA categorized lake water quality into low, medium, and high-polluted. The differences in these plateau lakes' water quality were caused by their basin sources, morphometry, and human perturbations.

Gupta et al. (2009), Gazzaz et al. (2012), and Khan et al. (2017), based on the level of pollution, the hierarchical CA has been utilized to categorize the water quality characteristics of various sampling locations. By combining the information that appears to be similar, the CA aids in constructing the best sampling approach. Additionally, it lowers the cost of sampling by reducing the number of sampling locations without losing any relevant data (Gholikandi et al., 2011; Gazzaz et al., 2012; Ling et al., 2017).

Surface water quality variation has been characterized spatially, and potential sources of variance have been categorized using CA based on a relatively small and short-term dataset (Zhang et al., 2010; Haque et al., 2016). Only a few studies have combined ANOVA and CA to identify statistically significant factors driving data variability and enhance the studies' overall results (Noori et al., 2010; Varol et al., 2012; Bu et al., 2014).

It has proven quite challenging to reduce the dimensionality of a dataset without losing intrinsic information. Multivariate statistical methods like PCA, FA, and CA have been used to address this problem. Using PCA and FA to reduce the dimensionality of big datasets without sacrificing information has become increasingly common in assessing water quality. Many researchers have used PCA approaches to find fewer hidden factors associated with pollution sources that affect the hydrochemistry and quality of water resources. These elements are further distinguished and attributed to sources of pollution (Juahir et al., 2011; Ayeni and Soneye, 2013; Li et al., 2014; Voza et al., 2015). A statistical model based on the PCA was created by Iyer et al. (2003) to evaluate the water quality of coastal areas. This model shows the connections between the many physicochemical variables under observation and the environmental factors that affect the quality of the coastal waters.

Contrary to traditional PCA, Praus (2005) used PCA based on singular value decomposition (SVD) to analyze the quality of the water. It was discovered that SV-based PCA is a highly useful method for evaluating water quality since it aids in obtaining an objective understanding of the water's composition. Despite the claimed benefits, researchers have not yet applied SV-based PCA. Felipe-Sotelo et al. (2007) used physicochemical parameters and chemometric techniques to characterize the temporal characteristics of river waters in urban and semi-urban regions, applying three models: PCA, MA-PCA, and PARAFAC (PARAllel FACtor analysis). It was later determined that MA-PCA outperformed the other two models. Compared to the individual PCA, the MA-refolding PCA's scores offered a more accurate and direct perspective of the sample's temporal and geographic fluctuations. It has been discovered that MA-PCA is more adaptable and versatile to environmental investigations than PARAFAC.

Zhang et al. (2010), to determine the virtual contribution of spatiotemporal variation to every PC, combined PCA with ANOVA. To distinguish the leading causes of pollution in the Jakara Basin, Nigeria, Mustapha and Abdu (2012) employed Pearson's product moment of the correlation matrix and PCA. It was discovered that home wastewater is to blame for the deterioration of the water quality in this area.

Zeinalzadeh and Rezaei (2017) used PCA to analyze the temporal and spatial variations in surface water quality in the Shahr Chai River. It was discovered that rural and agricultural have an impact on the river's water quality.

The PCA and FA cannot provide quantifiable contributions of sources to each variable and only provide qualitative information about the sources of pollution (Pekey et al., 2004). However, this issue can be resolved by utilizing a receptor-based model, such as APCS-MLR (Singh et al., 2005). This technique was initially applied to the air environment to locate and allocate pollution sources (Miller et al., 2002). Later, because it is least dependent on the kind and quantity of sources, many researchers began to utilize the APCS-MLR technique for apportioning the causes of pollution in water bodies (Singh et al., 2005; Su et al., 2011; Chen et al., 2015; Gholizadeh et al., 2016). While this happened, multiple studies looked into the spatio-temporal variations in several surface water bodies using three-way PCA (Singh et al., 2004; Giussani et al., 2008; Pardo et al., 2008; Dong et al., 2010). By discovering and extracting the hidden data structure and its linkages, three-way PCA aids in demonstrating the multi-dimensional nature of water quality data.

Canonical correlation analysis (CCA), an extension of PCA, was created to determine how one set of measurements relates to another and which specific trait is responsible for this association. This method was initially used in an atmospheric setting to forecast air temperature using sea level pressure and temperature. CCA has been utilized by Noori et al. (2010), Chan et al. (2013), and Sakelarieva and Varadinova (2013) to determine the link between several physicochemical characteristics of the quality of surface water.

DA is a crucial prediction tool for determining the reasons behind spatiotemporal variations in the quality of surface water (Boyacioglu and Boyacioglu, 2010; Varol et al., 2012; Gholizadeh et al., 2016). The DA also assists in creating a proper pollution abatement plan for preserving water quality. Canonical discriminant analysis (CDA), a kind of DA, was employed in 2008 to locate the source of pollution in nearby rivers beyond the Tapeng Lagoon (Liao et al., 2008). The CDA aids in identifying crucial distinctions between the predetermined groups while considering the intricate link between several features, which is not achievable using univariate statistical techniques. To begin with, the researchers used CDA to comprehend how bio assemblages with various environmental characteristics are distributed spatially (Comber et al., 2005).

The DA was applied to data on water quality to determine the impact of the most important factors for differentiating water qualities. The water quality data gathered from Yliki Lake, Athens, was recently subjected to DA, classification, and regression tree applications by Smeti et al. (2016). This method assisted in identifying the variables that were most effective at differentiating between clusters. Stepwise DA has only been employed by Bhat and Pandit (2014) and Hajigholizadeh and Melesse (2017) to determine the reason behind spatial changes in surface water bodies.

MRA/MLR is a predictive tool that has frequently been used to forecast the dependent variable, which is typically a parameter of water quality, as well as to study the relationship between a dependent variable and a group of independent variables. For example, Singh et al. (2005) employed MRA to examine the link between landscape features and water quality metrics (physical, chemical, and biological). MRA was utilized by Mallin et al. (2000) and Crowther et al. (2001) to show the connection between pathogen indicators and water quality. Later researchers Simeonov et al. (2003) and Mustapha and Abdu (2012) employed PCA and MLR to identify the most important factor causing water quality variations in Malaysia's Tunggak River. To recognize the complicated correlations between the water quality metrics in the Klang River in Malaysia, Nasir et al. (2011) coupled multivariate linear regression (MLR) with PCA. They concluded that PCA aids model prediction by bringing the complexity of the parameters down. Additionally, Isiyaka and Juahir (2015) used MLR and PCA to apportion the mass source category in the Kinta River, Malaysia. The river's water quality has been deteriorating recently and was determined to be caused by weathering of rock, wastewater, waste discharge by a point source, surface runoff, feces, erosion, and weathering.

MANOVA, a common MST, aids in identifying the existence of any significant differences across several groups of multivariate data (Garizi et al., 2011). MANOVA was used by Salih et al. (2013) to assess surface water quality. Tanty et al. (2014) utilized MANOVA to examine inorganic chemicals in groundwater in Indonesia. To analyze the health effects of river water pollution, Basu and Lokesh (2014) utilized MLR and MANOVA to data on the water quality of the Cauvery River gathered from the Srirangapatna section. In order to evaluate the interrelationships between the various analyzed environmental factors and their seasonal change, Banerjee et al. (2015) performed correlation coupled with MANOVA.

Geographical information systems (GIS) and MSTs have been combined in some studies to regulate water quality because GIS tools can govern the multivariate analysis process by giving an understanding of the underlying components (Li et al., 2004; Arslan, 2009; Zhao et al., 2011).

Several researchers in India have employed MSTs (PCA, CA, and DA) to determine the reasons for spatiotemporal variation in water quality and to allocate sources (Kaur and Dua, 2012; Hema et al., 2014; Sharma et al., 2015; Chaturvedi et al., 2016; Herojeet et al., 2017; Dutta et al., 2018b; Shil et al., 2019; Gupta et al., 2020; Pramanik et al., 2020; Ali et al., 2021; Maity et al., 2022). Kaur and Dua (2012) performed PCA and CA on samples of surface water taken from the Chamera I reservoir near the river Ravi. While domestic sewage and naturally occurring soluble salts were indicated to be the main causes of fluctuation in most water quality measures, CA divided sample seasons into two clusters based on inorganic runoff. Hema et al. (2014) used FA on water samples taken from the Cauvery River in Tamil Nadu, India. They found that point sources, specifically surface runoff from catchment areas, were to blame for the decrease in water quality. To detect the spatial-temporal changes in the water quality of the Taizi River in Northeast China, Bu et al. (2014) divided the river into three clusters based on the wet and dry seasons of mainstem rivers and their tributaries. They then examined 67 sampling locations. In their study, Kumar and Padhy (2014) employed multivariate statistical methods to manage river basins and measure water quality. To categorize the sampling stations and estimate the sources contributing to the decline in water quality of the Hindon River, Rizvi et al. (2015) used PCA and CA. Sharma et al. (2015) used CA and PCA to analyze surface water quality data from the Uttarakhand-based rivers Ganga and Yamuna. It was discovered that the decline in water quality was caused by both anthropogenic (the discharge of home and industrial wastewater, runoff from agricultural land, and corrosion byproducts of abandoned hydroelectricity installations) and natural (surface runoff) reasons. Chaturvedi et al. (2016) used CA, FA, and DA on the surface water of Balipara in the Sonitpur district of Assam, India's North Brahmaputra River basin. While FA assisted in identifying the factors bringing about variation in surface water and DA assisted in determining the relative contribution of each water quality parameter towards the recognized sources, CA assisted in classifying the pollutants and depicting the interrelationships between them. Herojeet et al. (2017) used PCA and CA to analyze surface water quality data gathered in India's Himachal Pradesh region's Nalagarh Valley. The mineral weathering, ion exchange, runoff from agricultural land, and industrial and domestic wastewater discharge caused the variance in surface water quality.

Bonansea et al. (2018) used PCA to identify differences between the sites and applied CA to the reservoir sample sites to classify the sites. Dutta et al. (2018b) used multivariate statistics to examine the geographic variance in the Nag River's water quality and to pinpoint the causes of the river's pollution. Using PCA, fewer latent variables and varifactors were found, each contributing to a hydro-chemical meaning: fecal contamination for varifactor 6, pollution caused by heavy metals for factor 2, pollution caused by organic matter for factor 3, and pollution caused by minerals and nutrients for factor 1. PCA and cluster analysis assisted in identifying and evaluating geographical variations in the types of river pollution. Municipal wastewater dumping into rivers is the main cause of such degraded water quality. However, other elements contributing to declining water quality include livestock activity near the river, solid waste disposal, wastewater discharge from industry, and low river flow rates. Jaiswal et al. (2019) proved the value of multivariate statistical methods for assessing the Yamuna River's water quality in both monsoon and other seasons. The PCA result showed that dissolved salts and minerals had the greatest impact on the river, followed by organic and nutritional materials. The physicochemical characteristics' geographical fluctuation suggested that the river may be divided into four categories (going from upstream to downstream): (a) Group 1, which included Paonta, Kalanaur, Mawi, and Palla, was appropriate for drinking purposes, irrigation purposes, and survival of aquatic life; (b) Group 2, which included Delhi, Mohana, and Mathura, was adversely affected by a higher concentration of organic loads from many drains, including Najafgarh and Shahdara; (c) Group 3, which included Agra and Etawah, was adversely affected by severe pollution load from domestic sewage, runoff from agricultural fields, and pesticide; and (d) group 4, consisting of Auraiya, Hamirpur, and Pratappur, had worked on the betterment on the condition of the water.

Gyimah et al. (2021) used PCA to assess 16 water quality metrics and categorized the various monitoring locations according to the degree of pollution. According to the literature, multivariate statistical techniques assist in developing active management strategies that take advantage of optimal flow and enable water resource management plans to reach their desired levels. The research makes it clear that those nonlinear interactions between the crucial factors and variations in the geographical and temporal scales make categorization a laborious task. Gupta et al. (2020) worked on 17 distinct sampling locations along the Narmada River's stretch between Amarkantak and

Hoshangabad, analyzing the river's physicochemical properties. In addition, PCA described three and two PCs, respectively, for the pre- and post-monsoon seasons. For the pre- and post-monsoon seasons, respectively, HCA generated three and two groups based on comparable water quality parameters. These groups visually depicted the seasonal variation in water quality in space and time and showed that urban pressure is primarily responsible for the change in water quality.

Ali et al. (2021) studied multivariate statistical analysis (FA and FCA), which revealed that seawater incursion is to blame for the occurrence of boron. He has taken into consideration that turbidity generated from the weathering of silicate from the Gangetic plains' alluvium deposits as well as human activities in the eastern Ganga river (flowing through the state of West Bengal).

Maity et al. (2022), by taking into account 24 parameters at 11 monitoring sites based on the six-year projection of the pollutant sources, multivariate statistical techniques (FA, CA, and DA) were used to assess the spatial and temporal variation of Damodar River water quality (2014–2019). Stepwise, DA removes ammonia, DO, potassium, temperature, TC, TFS, and turbidity, the important parameters mainly for seasonal variation in the water quality. FA extracts the most significant seasonal parameters. CA divides sampling locations into three categories, allowing for the identification of water quality's geographical variance.

The interaction between water's various (physicochemical and biological) elements and the environment is complex and cannot be inferred using a straightforward statistical method. The MSTs have become a crucial data analysis tool for investigating data in complex data matrices. The CA produced the best sampling strategy by grouping similar sampling stations into a single cluster. While DA recognizes the specific parameter that brings spatiotemporal variance in various groups, PCA/FA assists in identifying the factors that are responsible for the deterioration of water quality and further helps in the source distribution. The development and creation of appropriate strategies following identifying the elements accountable for water quality decline showed that MSTs are effective in managing water resources.

3.5 Water quality index

WQI was established to inform concerned citizens and policymakers about the general quality of water (including surface and groundwater) (Kamboj and Kamboj, 2019; Kamboj et al., 2020). By converting the water quality characteristics into a dimensionless number, the WQI aids in a better understanding of the water quality of a body of water (Shah and Joshi, 2017; Kamboj et al., 2020; Semy and Singh, 2021). The WQI is used to forecast the water quality for different uses, including drinking water, irrigation water for livestock and agriculture, recreation, and aesthetics (Naubi et al., 2016; Bora and Goswami, 2017; Sener et al., 2017; Iqbal et al., 2019; Khan et al., 2020; Roy et al., 2021; Ali et al., 2021). The WQI assesses any management plan's success or failure to preserve the water quality (Rickwood and Carr, 2009; Naubi et al., 2016; Shah and Joshi, 2017; Bora and Goswami, 2017; Dutta et al., 2018b; Iqbal et al., 2019; Lkr et al., 2020; Roy et al., 2021; Maity et al., 2022). WQI can generally be constructed in four steps, as shown in Figure 3.1.

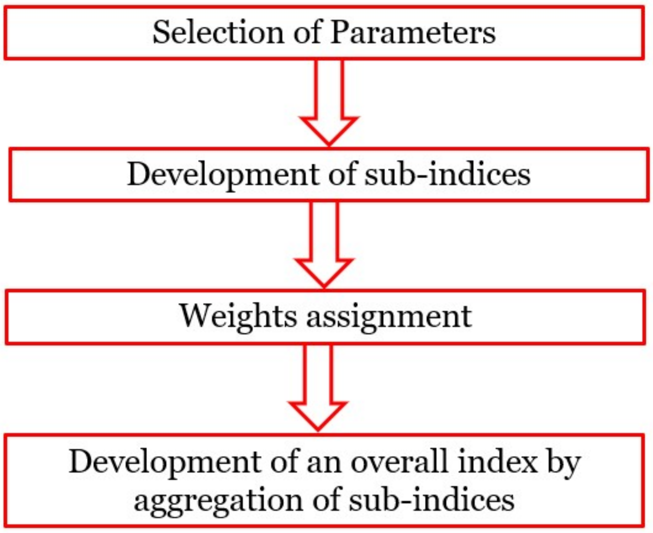


Figure 3.1: Steps for developing WQI

The original WQI, also known as the weighted arithmetic WQI, was created by Horton (1965). This instrument has been used to assess the water quality of rivers, lakes, and groundwater. Numerous WQIs have since been created and used in diverse surface and groundwater habitats across the globe. The creation of Horton's index inspired scholars all over the world to create WQIs to describe water quality. The Munich technique of evaluating water quality was created in Europe in 1969 and was founded on chemical and biological factors.

Liebman (1969) proposed the Munich method of evaluating water quality. Using this technique, color-coded water quality index maps were created for the German state of Bavaria. Although the idea behind this system was similar to Horton's Index, grades and weights were assigned based on subjective judgment. The NSF WQI, which is widely used in many countries, was subsequently developed in 1970 based on the recommendations of experts (Brown et al., 1970; Abrahao et al., 2007; Effendi et al., 2015; Bhutiani et al., 2016; Ewaid, 2017; Misaghi et al., 2017; Gupta et al., 2017; Dewata, 2019). Both additive and multiplicative processes underlie the NSF WQI. One of Horton's index's flaws was the selection of the parameters, which Brown et al. (1972) addressed by using a floating survey built using the Delphi method developed by the Rand Corporation. However, this index cannot address the subjectivity and ambiguity inherent in the challenging environmental concerns (Tyagi et al., 2013; Kamboj et al., 2020).

Prati et al. (1971) started a project in the US to create an index for water pollution. This index was created based on research into the water quality categorization systems already in place in nations like New Zealand, Germany, England, Czechoslovakia, various US states, Poland, and the Soviet Union. This index was primarily created to determine the level of surface water pollution. This index was used to assess the water quality information gathered in the Italian region of Ferrara.

During this time, McDuffie and Haney (1973) proposed an index known as River Pollution Index (RPI). Eight pollution variables, including biodegradable organic matter, coliform count, nonvolatile suspended particles, percent oxygen deficit, average nutritional surplus, dissolved salts, temperature, and refractory organic matter, were used to formulate this index, which is reasonably valid.

At about the same time, Walski and Parker (1974) developed a significant index that was specially created concerning water recreation usage. This index was created using the geometric mean and indicators of water quality. Parameters such as suspended particles, turbidity, nutrients, grease, color, pH, temperature, coliform, etc., were used to formulate this index.

The index created by Brown et al. (1970, 1973) had many serious flaws, including its lack of objectivity. This index was developed using the Delphi approach, in which various expert panels rated the same water quality indicators differently. Harkins (1974) offered an index based on nonparametric multivariate ranking to solve this issue. The fact that this index's value must be computed every time new data is made available is one of its primary limitations because comparisons can only be made when the combined dataset of interest of all values is updated. This index cannot accurately represent the water quality at the regional and national levels regularly.

In 1976, SRDD developed an index known as SRDD WQI (SRDD, 1976). It is frequently referred to as Scottish WQI. The water quality parameters for this index were chosen using the Delphi approach. The SRDD WQI was created expressly for Scotland, although a modified version was later applied to many river basins in many nations (Thailand, Spain, Portugal and Iran). This index's creation was comparable to that of the NSF WQI.

The Ross Index was created by Ross in 1977. BOD, ammonia, DO, and suspended particles were identified as the leading causes of differences in water quality when data for rivers in the Clyde basin in Greater Britain were examined. Making this index into a weighted additive model was further pushed to be utilized in England. The general water quality index, the potable water supply index, the aquatic toxicity index, and the potable sapidity index are the four indices that make up this index. On a worldwide basis, these indicators are not widely used (Abrahao et al., 2007).

The Bascaron index was created in Spain in 1979. This index was initially used to evaluate the general water quality, but a modified version was later used to assess the surface water quality for particular uses, such as aquaculture. The parameters can be removed or chosen with flexibility using the Bascaron index. Twenty-six water quality factors were used to create this index. Scottish WQI is frequently used in conjunction with this index. According to Pesce and Wunderlin (2000) and Debels et al. (2005), the indicator has gained popularity in Latin American nations (Argentina and Chile). Dunnette (1979) subsequently developed OWQI, and later Cude (2001) established the OWQI for the River Oregon utilizing eight water quality parameters. The harmonic averaging notion is essential to the OWQI. However, it was only applicable to the Oregon River. It was only used to assess the water quality for recreational purposes despite the fact that the OWQI assesses changes in water quality and effects on it significantly (Darvishi et al., 2016). Furthermore, the Idaho Department of Environment Quality (IDEQ) uses this index to evaluate the river water quality in Idaho.

Karr (1981) created the Index of Biotic Integrity (IBI) to evaluate the biological health of aquatic bodies. This index may be used alone, in combination with other indices, or as part of an aggregate index. Benthic ecologists frequently use this indicator to evaluate the biological health of surface water (Lunde and Resh, 2012; Mazor et al., 2014).

Smith (1990) significantly contributed to New Zealand's WQI sector. This index represented four applications of water: water supply, fish spawning, bathing, and general purposes. The addition and subtraction of water quality parameters were considerably simpler tasks. Currently, many water organizations are using this index as a planning tool. It is a straightforward method of disseminating data about water quality in New Zealand. A few modifications to the Brown WQI's mathematical foundation were made in 1994 by Dojlido et al. (1994). The Polish Vistula River has shown promise when using the upgraded WQI.

British Columbia Water Quality Index (BCWQI) was created in the middle of the 20th century by the Canadian Ministry of Environment. It compared the measured parameters of the water quality with the allowed limits and assisted in determining the water quality. The WQI's disadvantage is that it does not reveal the water quality trend until it has deviated most from the norm. To analyze water quality and provide data to water quality executives and locals, the CCME created the CCME WQI in 2001 (CCME, 2001). The CCME WQI is simple to calculate, flexible in the parameter choices, and also applicable to legal requirements. Researchers widely utilized CCME WQI to assess water quality (Khan et al., 2003; Sharma and Kansal, 2011; Mostafaei, 2014; Gupta et al., 2017; Jaiswal et al., 2019; Maity et al., 2022). However, this index exaggerates factor F1 (i.e., scope), making it simple to sway the outcome. This is simple to accomplish during index development by focusing on the criteria that are most and least helpful for defining a class of water, and it is something that cannot be applied to every ecosystem (Tyagi et al., 2013).

A measure of stream water quality was created and named the Florida Stream Water Quality Index (FWQI) as part of the Strategic Assessment of Florida's Environment Indicator Project. The three categories for this indicator are good, middling, and poor water quality. Later, the Metal Pollution Index (MPI) was created to assess the level of heavy metal pollution in groundwater and surface water bodies (Mohan et al., 1996). Several researchers have utilized this index to assess the quality of rivers, the sea, and drinking water (Amadi, 2011; Onojake et al., 2017; Ewaid, 2017; Khan et al., 2020; Khan et al., 2021a, c). This method is beneficial for determining the combined impact of all the metals on overall pollution and rates the aggregate impact of specific heavy metals on the entire water quality. Further research by Amadi (2011) revealed that the lowest water quality occurs when metal concentrations exceed their maximum permitted levels. This index uses both standard values as well as ideal values to calculate sub-indices.

Hebert (2005) made another outstanding addition to the field of WQI by creating an index called the Indice de Quallite Bacteriologique et Physicochimique (IQBP). It underwent extensive testing in the Canadian province of Quebec. This index was first

designed to evaluate the water quality for swimming and other recreational activities, as well as the preservation of aquatic life. This index was also used in the 2000s to evaluate the water quality of all the major rivers in Quebec, Canada. The Dalmatian index, created in 1999 for the water bodies in Dalmatia utilizing nine water quality factors, assisted in determining Serbia's overall water quality (Stambuk–Gilianovic, 1999). A new WQI was created by Liou et al. (2004) based on the geometric average of the standardized scores of nine chosen parameters. Based on established evaluation curves, the standardized score was calculated. Kim and Cardone (2005) also developed a scatter score index. This index was initially created to trail changes in water quality near mining sites in the United States, but it was later used in areas that had not been affected. This indicator assesses how the quality of the water has changed over time and space. To calculate this index, any number of parameters may have been utilized.
Standards and recommendations for water quality have no bearing on this index's calculation. With information acquired from 18 distinct streams, Tsegay et al. (2006) suggested a chemical WQI to evaluate the water of the Wheeler Lake Basin (Northern Alabama). After normalizing each observation to the parameter's highest concentration, this index combines the data from the seven different parameters. Boyacioglu (2007) created a basic index, i.e., the Universal Water Quality Index (UWQI). It was developed to evaluate the water's suitability for drinking. Most water quality work done globally is related to the UN Millennium Development Goals (UNEP GEMS, 2007), which calls for providing all people access to clean drinking water by 2015. As a result, Rickwood and Carr (2009) created the Global Drinking Water Quality Index (GDWQI), an index based on the CCME WQI.

A lot of researchers and scholars have adopted the Arithmetic WQI method (Bhutiani et al., 2016; Shah and Joshi, 2017; Ewaid, 2017; Gupta et al., 2017; Lkr et al., 2018; Dutta et al., 2018b; Chaudhary et al., 2019; Iqbal et al., 2019; Sharma et al., 2020; Gupta et al., 2020; Pramanik et al., 2020; Chabuk et al., 2020; Ali et al., 2021; Semy and Singh; 2021; Kumar et al., 2022a). The comprehensive pollution index (CPI) is a key tool for evaluating the water quality of aquatic bodies (Sidabutar et al., 2017; Wang et al., 2018; Matta et al., 2018; Kumar et al., 2020a; Pramanik et al., 2020; Roy et al., 2021; Kumar et al., 2021b). CPI can be used to access the total pollution loads of water bodies. BIS (2012) and WHO (2011) recommendations for drinking water quality were utilized to determine the WQI.

The introduction of MSTs in recent years has marked a significant advancement that helps determine the most crucial aspects of water quality to measure the WQI (Mostafaei, 2014).

Remote sensing has been used in WQIs to assess the caliber of water sources (Katyal et al., 2012; Alsaqqar et al., 2015; Jayalakshmi and Velappan, 2015; Sener et al., 2017; Shil et al., 2019; Chabuk et al., 2020; Ali et al., 2021; Oseke et al., 2021) because it facilitates the creation of raster maps and the distribution of water quality measurements in space.

A hybrid probabilistic WQI has been created to address the general drawbacks of the existing WQIs. By merging the Fuzzy Interference System (FIS), Bayesian Networks (BNs), and Probabilistic Neural Networks (PNNs), Nikoo et al. (2011) developed this index. The PMF of the water body quality is provided by this type of index based on the data on the current water quality.

For the vulnerability evaluation of surface water quality, Sikder et al. (2015) employed the IMWQI. This novel indicator effectively measures both the geographical and temporal aspects of water quality. IMWQI is employed in developing nations to help create pollution prevention plans. The IMWQI is simple for the general public to understand and aids in understanding regional water pollution in general. Despite these benefits, this indicator lacks scientific integrity; consequently, more synoptic tests in the rivers of developing nations have been suggested to achieve a practical characteristic.

Naubi et al. (2016) evaluated the efficacy of employing the Department of Education (DOE) WQI to monitor the water quality of Malaysian rivers. It was discovered that the crucial water quality criteria were missing from the existing WQI (phosphorus, nitrogen, iron, zinc, and E. coli). Therefore, some modifications to the current WQI are advised, such as adding important water quality criteria that aid in a more precise assessment of water quality.

The first water quality index (WQI) was created by Bhargava (1983) for the Ganga River in India to evaluate the water's suitability for human consumption. This index examined the water quality using four categories of characteristics, including the number of coliforms, toxicants, heavy metals, color, odor, turbidity, sulfide, and chloride. To analyze and verify the water quality parameters for various categories of practices based on the standards specified by the CPCB, India, Ved Prakash et al. (1990) modified Brown's NSF WQI to create the River Ganga Index (Abbasi and Abbasi, 2012). Many academics and researchers used this index (Bhutiani et al., 2016; Singh et al., 2018; Kharake and Raut, 2021). An OIP was developed by Sargaonkar and Deshpande (2003) to assess the state of the river. In this index, a number of water quality factors were classified and evaluated, as well as compared to Indian standards and other widely accepted WHO recommendations. Several researchers used this particular index (Katyal et. al., 2012; Kamboj and Kamboj, 2019).

In 2018 (Bhatti et al., 2018), grab sampling was used to gather 29 samples from Nagarparkar, Pakistan. Eighteen physicochemical characteristics were used to evaluate the quality using the WAWQI. According to the study, just 35% of the measures fell within the established WHO criteria, while the remaining 65% were outside of what is considered to be acceptable for water quality.

Pesce and Wunderlin (2000) utilized 13 physicochemical parameters to evaluate the water quality using the WQI and WQI min techniques. The quality was at its highest in the autumn and at its lowest in the winter.

In 2019 (Golbaz et al., 2019), a special swimming pool WQI (SPWQI) based on 13 physicochemical and biological parameters was created to monitor the quality of swimming pools. The SPWQI has modified the WAWQI approach. This index helped control and improve water quality. In some other studies in 2019 (Gupta et al., 2019), creating an international WQI based on WHO guidelines involved using artificial neural networks (ANN). Using five physicochemical parameters, including turbidity, pH, EC, DO, and FC, the study found that ANN based on cascade forward architecture effectively predicted the WQI. Extensive research is necessary to acquire the desired results due to the ANN method's restriction, which can alter as parameters change. In 2019 (Abbasnia et al., 2019), the WAWQI method was used to examine the quality of 654 excavated wells in Sistan and Baluchistan, Iran. The drinking quality of the mined wells was rated as outstanding and good overall.

In 2021, grab sampling was used by Karunanidhi et al. (2021) and gathered 61 samples using the WAWQI method from the Shanmuganadhi River basin in India, containing eight physicochemical parameters like calcium, sodium, sulfate, and fluoride. According to the WQI results, 52% of the samples were deemed unfit for human consumption, while 48% were deemed OK. The researchers recommended treating or recharging the groundwater samples for drinking water using artificial means to lower fluoride levels. In another study in 2020 (Chabuk et al., 2020), using the WAWQI method and GIS software, data for the water of the Tigris River in Iraq was evaluated for the rainy and dry seasons in 2016. The findings showed that potassium, conductivity, TDS, and bicarbonate concentrations were higher in the dry season than in the rainy season. The calculated WQI revealed that the river's water quality was low due to nearby human activities. The study also showed that applying WQI was only effective after the water had been cured because of the high concentrations that could be present in untreated water. In 2020 (Ustaoglu et al., 2020), utilizing information from February 2017 to January 2018 and the WAWQI methodology, the quality of the Turnasuyu Basin in Turkey was assessed. The basin's water quality was rated suitable for usage by the general population. The physicochemical parameters were measured throughout the year and found within acceptable WHO standards. However, human activity may affect the basin's quality downstream. In 2020 (Seifi et al., 2020), the researchers changed the WAWQI index by adding a Monte-Carlo simulation for weight distribution. Iran's Kerman aquifer was studied by taking 1189 samples both during the dry and wet seasons. Based on the calculated WQI, the aquifer's water quality was poor. The results demonstrated that the WQI evaluation could benefit from the Monte-Carlo method.

Ali et al. (2021) used the Water Quality Index (WQI) and Synthetic Pollution Index (SPI). The lower section of the Ganga River that flows through West Bengal was evaluated for its suitability for human consumption. Eleven characteristics were considered for this study over nine years (2011-2019) at ten different locations from Beharampur to Diamond Harbour. In nine years, the eastern Ganga showed variations in WQI from 55 to 416 and SPI from 0.59 to 3.68. A reasonable association between WQI and SPI supported the outcome. The whole river stretches in 2011, 2012, and 2019, and locations close to the coast for nine years were significantly polluted, according to the map interpolated by GIS. SPI was built by Ma et al. (2009), and due to its simplicity, it was later used in several studies to determine how pollutants affect water quality (Solangi et al., 2018, 2020; Hui et al., 2020; Sunar et al., 2020).

Maity et al. (2022) employed the WQI developed by the CCME to assess the water quality of the Damodar River in West Bengal on a temporal and spatial scale. Poor water quality is typical at all sample locations and during all seasons. Due to the input from both point and nonpoint sources, the monsoon season exhibits a greater pollution level. The middle class is increasingly polluted due to dense urban areas and massive industries.

According to a study of prior studies, the CCME-WQI and WAWQI methodologies were primarily employed to gauge water quality. The physical, chemical, and biological water parameters are the most typical inputs utilized to create these indices. However, given that these water quality indices are unpredictable in complicated environmental circumstances, some degree of uncertainty was found in their application (Ahmed et al., 2021). Due to the use of a small number of factors and development for a particular location, these indices are mostly biased. The creation and assessment of the WQIs were accompanied by these uncertainties. For instance, the water quality may differ between two distinct lake points at a certain time of day. Due to the water bodies' dynamic nature, the physicochemical characteristics can alter throughout a single day, from sunrise to nightfall (Ahmed et al., 2021). As a result, the following are some causes for why the majority of these indices misclassify water quality: First and foremost, each standard's sensitivity to the kind of predetermined parameters used for development, followed by the usage of a constrained number of variables or parameters and the weighting of each parameter. The WQI value can be manipulated to change the category of water quality when a single parameter is present in high concentration. There is a need to examine and compare these indices to remove the uncertainties and biases in these standards since all have recognized no index.

Four appropriate water quality indices were used in this investigation based on the available dataset. Statistical modeling was done on all four water quality indices to determine the most accurate indicator to predict the state of water quality and create a water quality management plan.

3.6 GIS application in river water quality

A major problem of the 21st century is guaranteeing everyone access to sufficient clean water for domestic usage. However, despite a steady increase in water demand, anthropogenic activities are degrading the quality of the Earth's unevenly distributed water supplies (Khouni et al., 2021).

Wastewater treatment facilities, excessive fertilizer, and pesticide usage in all anthropogenic activities produce wastewater that comprises physical, chemical, and microbiological pollutants (Ali et al., 2021). These pollutants deteriorate water purity, which could lead to major environmental issues that endanger aquatic communities' general health. In many less developed nations where infrastructure for assessing water quality and sanitation did not expand with population development and industrial advancements, rivers serve as the principal water source for household, industrial, and agricultural outputs (Ahmed et al., 2010). Untreated water is frequently discharged directly into the watershed, causing serious degradation to rivers and the environment. As a result, there has been an increase in public awareness of the value of surface water quality to both public health and the ecosystem. Numerous research studies have focused on evaluating surface water quality and mitigating its consequences from pollution and environmental contamination. Therefore, a fundamental grasp of the physical, chemical, and microbiological features considered the indicators of water quality is necessary to accurately assess the quality of river water (Khouni et al., 2021). However, integrating the massive amounts of data that need to be acquired to regulate a natural resource at such a level is always challenging due to the size and complexity of a watershed's hydrological, geological, and environmental characteristics (Mtetwa et al., 2003).

Additionally, the expense of producing these data has become a problem, which has prevented governments, particularly in developing nations, from implementing comprehensive and trustworthy river management techniques. However, the primary strategy for addressing sustainable management of natural resources in general and water resources, in particular must be integrated management of variables at the watershed scale. The Integrated Water Resources Management principles have made this evident (Usali and Ismail, 2010). Thus, the use of space data is a suitable method to estimate and fulfill the required large computational supplies (Gowri et al., 2008).

The GIS is acknowledged as a potent tool for managing geographic figures holistically without sacrificing the spatiotemporal variability that is frequently essential in determining water quality (Mtetwa et al., 2003; Gowri et al., 2008; Sharma et al., 2021b). This technology combines standard database operations, statistical analyses, and the distinct geographic analysis and visualization advantages provided by maps and spatial databases, allowing us to investigate the cause-and-effect relationship using visual interpretation (Arslan, 2001). It has evolved into a tool for researchers and managers of natural resources because it also can evaluate and model this complicated phenomenon (Sharma et al., 2021b). In addition, GIS techniques and the hydrogeochemical NETPATH software package were frequently used in hydrogeochemical modeling to establish baseline data for surface and groundwater (El Osta et al., 2020).

Spatial interpolation techniques in GIS are used to generate spatially continuous data by forecasting the values of a characteristic at unsampled sites (Sener et al., 2017). These techniques fall into deterministic interpolation methods and geostatistical interpolation methods (Qu et al., 2017). Among the interpolation techniques, inverse distance weighted, kriging, spline, trend, and cokriging interpolations are often employed (Mirzaei and Sakizadeh, 2016).

Additionally, this helps authorities or decision-makers rank zones for mitigation plans in order of importance. The potential technologies for managing water resources are GIS and remote sensing. These technologies can be applied to various issues relating to water resources, including water supply, water quality, and forecasting floods. These methods are useful for comprehending the natural environment at various global, national, and regional scales (Gowri et al., 2008; Ali et al., 2021).

The specific objectives of the study and the characteristics of the research objects must guide the selection of the interpolation models (Qiao et al., 2018). However, it has not always been clear whether one interpolation technique is better than another (Gong et al., 2014). Thus, interpolation techniques like IDW and kriging have been widely applied to water quality evaluation and pollution mapping (Mirzaei and Sakizadeh, 2016; Panhalkar and Jarag, 2015). In reality, kriging and IDW interpolation have been used for various backdrops. Panhalakr and Jarag (2015) stated that the IDW is even more accurate and superior to kriging (El-Zeiny and Elbeih, 2019; Paul et al., 2019). Additionally, a study by Gong et al. (2014) demonstrated that the IDW method had a higher level of accuracy than the Kriging approach in forecasting the levels of various pollutants in groundwater.

The word "inverse" refers to the fact that when compared to sample points that are far away, points that are close have larger weights and more effect in calculating unknown points. This method uses a linear combination of data (Ali et al., 2021). Based on this idea, IDW could improve the monitoring of management systems and its evaluation capabilities to monitor and control pollution (Arslan, 2001; Sener et al., 2017; Chabuk et al., 2020; Ali et al., 2021).

Water quality managers can identify possible sensitive zones for water pollution by using the water quality index in conjunction with GIS (Srivastava et al., 2011; Katyal et al., 2012; Rawat and Singh, 2018; Madhloom and Alansari, 2018; Zhang, 2019). It is acknowledged that GIS can map the spatial allocation of specific water quality metrics and delineate acceptable pollution zones (Rawat and Singh, 2018; Singh et al., 2022). Information on water resources can be easily understood through the maps produced by GIS. The public has become more informed, and authorities are more inclined to use precautionary measures to reduce the pollution of water resources due to the freely accessible information (Usali and Ismail, 2010).

It has been found that integrating GIS with indices is a well-established method for groundwater vulnerability and suitability evaluation (Rawat and Singh, 2018; Hussain and Abed, 2019), but very little research is available for surface water. The work by Srivastava et al. (2011) showed how to use WQI combined with GIS to identify the various pollution zones in river Mahi (Gujarat). The study done by Katyal et al. (2012) on river Yamuna (Delhi) is to determine its vulnerability utilizing a combined strategy of WQI and GIS, which is also mentioned in the literature. Remote sensing has been utilized in WQIs to evaluate the water quality (Alsaqqar et al., 2015; Jayalakshmi and Velappan, 2015; Sener et al., 2017; Chabuk et al., 2020; Ali et al., 2021). It aids in the spatial allocation of the water quality metrics and creates raster map classes that can be used to make suitable managerial action plans by authorities.

3.7 Water quality modeling

In light of major environmental situations like resource depletion, climate change, population boom, and growing public awareness, water pollution control and water quality management measures have become increasingly important (Kumar, 2018). Though researchers worldwide are cooperating with the government, the quality of the world's water is still declining in many regions (Vishnuradhan et al., 2012; Jadeja et al., 2022). According to UNICEF (2008), 3.4 million deaths yearly are caused by unsatisfactory sanitation and hygiene practices, insufficient water supply, and water-related diseases, primarily among children. Water is vital for a country's growth since access to safe water falls under fundamental human rights (Kumar et al., 2022b).

It would be ideal for constructing a WQM to forecast changes in land use, population growth, effluent discharge, and climatic conditions. A WQM helps fill the data gaps that frequently prevent accurate water quality evaluation and management (Parmar and Bhardwaj, 2014, 2015). The WQMs assist us in recognizing the sources of pollution and many biogeochemical phenomena in the water bodies that are otherwise challenging to assess with field monitoring alone (Arya and Zhang, 2015). They also help anticipate potential future events in specific water bodies (Vishnuradhan et al., 2012; Luo et al., 2019).

One of the challenges in evaluating the water quality in developing nations like India is the dearth of data on water quality. Therefore, WQMs are crucial in bridging the data gaps that frequently obstruct the evaluation and water quality management. The WQMs are affordable tools for simulating the fate and movement of pollutants in water bodies (Wang et al., 2013; Luo et al., 2019).

Most stream flow and water quality studies aim to identify the data and knowledge required to manage water resources, including their use, regulation, and development. Through these evaluations, time and money can both be saved, and future water resource development becomes affordable (Taheri Tizro et al., 2014). The primary goals of water quality modeling could be to (i) proceed with a cause-and-effect relationship, (ii) identify the effects of pollutant sources, (iii) assess the level of monitoring that is required, (iv) assess alternative planning and management strategies, (v) concentrate on additional monitoring and management goals, and (vi) evaluate current and expected water quality conditions (Rehana and Mujumdar, 2012; Ghashghaie et al., 2018; Das et al., 2021).

The investigation and forecasting of water quality include a variety of techniques and strategies. Additionally, most water-related software, including SWAT, QUAL2K, MIKE-11, etc. (Rehana and Mujumdar, 2012; Ghashghaie et al., 2018; Santy et al., 2020; Cely-Calixto et al., 2021; Das et al., 2021) benefit from specialized tools to evaluate the stream quality. One of the essential techniques used in water quality modeling and forecasting is time series analysis. Time series studies are now employed in various scientific fields, including physics, economics, and engineering (Huang et al., 2015; Valeriy et al., 2015; Huang et al., 2017). This topic includes water resources engineering since lakes, oceans, streams, and groundwater resources all have various properties that can be characterized using time series data. This approach aids in understanding and simulating the process by which a phenomenon generates previous observations (Parmar and Bhardwaj, 2015; Ghashghaie et al., 2018; Luo et al., 2019).

It helps predict future values based on historical data as well. A time series is a collection of data collected over a period of time with equal gaps between each data point. The interval can be defined as the time steps taken daily, weekly, monthly, and yearly (Ghashghaie et al., 2018). Participation in decision-making across various hydrological processes and operating systems uses time series analysis. Time series analysis in hydrology has two primary purposes: first, it helps to understand and model the stochastic mechanism underlying the phenomenon, and second, it helps to predict future values of the phenomenon (Arya and Zhang, 2015; Ghashghaie et al., 2018; Luo et al., 2019).

Using time series analysis, the modeling of hydrological components has been the subject of numerous publications. It is also possible to use this strategy to forecast water quality. Additionally, a key stage in integrated water resources management might be the assessment of current water resources, which includes figuring out the quantity and quality of discharge, recognizing its volatility on a watershed scale, and predicting these variables (Yurekli and Kurunc, 2005; Kurunc et al., 2005). The stochastic nature of hydrological phenomena also encourages water resource engineers and hydrologists to take advantage of time series modeling and forecasting techniques (Taheri Tizro et al., 2014).

3.7.1 Time-series analysis

ARIMA models could reproduce the main statistical properties of a hydrologic time series. ARIMA models have been put to use to examine both runoff and river discharge (Yurekli and Kurunc, 2005; Kurunc et al., 2005), lake water levels (Sheng and Chen, 2011), sediment yield (Hanh et al., 2010) and quality of water (Papamichail et al., 2000; Ahmad et al., 2001; Hanh et al., 2010; Parmar and Bhardwaj, 2014, 2015; Arya and Zhang, 2015; Ghashghaie et al., 2018; Luo et al., 2019).

The primary statistical features of a hydrologic or environmental time series can be replicated using ARIMA models. In their work on stream analysis, Thomas and Fiering (1962) employed auto-correlated models. Chow and Kareliotis examined the univariate time series of rainfall and temperature in 1970. They found periodic components in time series that were strictly yearly and leniently six months apart. Using Autoregressive Integrated Moving Average, McKerchar and Delleur (1974) defined the fundamental procedure for applying time series in hydrology. They also applied seasonal modeling to examine the seasonal features of stream parameters. Stream pattern identification and forecasting using time series modeling are effective for integrated water resources management. It has been extensively utilized to forecast hydrologic variables, including rainfall, outflow, and flood (Komornık et al., 2006; Damle and Yalcin, 2007).

Zhang (2003) used a hybrid ARIMA/ANN model to benefit from both models' linear and nonlinear modeling advantages. According to the results, the combined model performed better at forecasting actual data sets than ANN or ARIMA when used independently.

Komornık et al. (2006) investigated the Czech hydrological time series, demonstrating the great predicting accuracy of this type of model. In order to predict the flood values in the Mississippi River, Dalme and Yalcin (2007) used time series analysis. The findings of their investigation demonstrated the validity of forecasting as well as the applicability of time series modeling in generating daily discharge.

3.7.2 Applied time series analysis of groundwater quality

Time series analysis has been used to model groundwater quality in many places. To match the water loss series using a stochastic process, Chang (1988) devised a modeling method that includes the homogeneity test of the data and the best model selection.
Using a time series study of well water quality data for 1964 and 1965, Wilson et al. (1992) identified variations in groundwater quality brought on by anthropogenic activities. Loftis (1996) included a few glimpses of national assessments of different waste investigations in evaluating international studies on regional and localized groundwater quality. In an industrial area in Seoul, Korea, Lee and Lee (2003) assessed and calculated the possibility of groundwater naturally being reduced. The time series of water temperature has been the subject of various investigations. Time series analysis was utilized by Kim et al. (2005) in a study that looked at the impact of the tide on groundwater quality in a coastal area in Korea. Additionally, the lower Mekong River's temporal variations in turbidity, dissolved oxygen, conductivity, temperature, and fluorescence were examined using time series analysis (Irvine et al., 2011). Water quality modeling is crucial to maintaining and conserving water quality (Singh et al., 2004; Su et al., 2011; Seth et al., 2013; Prasad et al., 2014; Parmar and Bhardwaj, 2014).

3.7.3 Applied time series analysis of surface water quality

Hirsch et al. (1982) employed new techniques to look for monotonic trends in monthly water quality data. Additionally, utilizing data sets from Niagara, it has been researched how water quality indicators such as pH, alkalinity, total phosphorus, and nitrate concentrations change over time (El-Shaarawi et al., 1983). Yu et al. (1993) used four different nonparametric techniques. Surface water quality data from the Arkansas, Verdigris, Neosho, and Walnut River basins were studied to study trends in 17 key elements.
The seasonal Kendall test was used to analyze the trend of water quality data from Plynlimon, mid-Wales (Robson and Neal, 1996), which studied the time series of the Strymon River's discharge and water quality indicators in Greece from 1980 to 1997. Using the turning point test and Kendall's rank correlation test, Gangyan et al. (2002) examined the temporal sediment load features of the Yangtze River. In Lake Tahoe,

USA, Jassby et al. (2003) created a time series model for Secchi depth. Panda et al. (2011) investigated the trends in the sediment load of an Indian tropical river basin.

Hirsch et al. (1982) presented methods for looking for monotonic trends in monthly data on water quality. For seasonal time series, the first approach is a nonparametric test to identify the trend. The second seasonal Kendall estimator method calculates trend magnitude. The third approach provides a tool to examine temporal variations in the association between constituent concentration and stream flow. Additionally, El-Shaarawi et al. (1983), employing a 5-year data set of Niagara, researchers examined temporal variations in water quality indicators (on Ontario Lake). The findings showed that pH and alkalinity were falling while nitrate was rising. Yu et al. (1993) studied trends in 17 key elements using four distinct nonparametric approaches by examining surface water quality data from the Arkansas, Verdigris, and Neosho basins, as well as the Walnut River basin. Robson and Neal (1996), through a seasonal Kendall test and analysis of 10 years' worth of upland stream and bulk deposition water quality data from Plynlimon, mid-wales, discovered that the dissolved organic carbon in the stream water had been rising over time. However, there was no evidence of a pH increase. It was suggested that multi-decade long-term monitoring programs could be used. In work done by Turner et al. (1996), The results of simulations over extended periods of Lake Bosumtwi (Ghana) demonstrated that stochastic climatic variations that were quite comparable to those seen this century could cause the whole range of lake levels seen in terrace deposits. The low salinity of only 1% shows that Lake Overflow eliminated dissolved solutes recently in the geological past.

Data on river water quality have been analyzed for trends and specific time changes, mostly using graphical and statistical time series techniques. The information gathered may be connected to some socio-economic factors, such as urbanization, agricultural or industrial expansion, and wastewater discharge in the vicinity or upstream of the measurement site. Such a study can be extended to more rural sites to analyze water quality development and assess the seasonal effect on annual patterns (Cun and Vilagines, 1997).

Papamichail et al. (2000), to lessen the negative effects sustained by interests exploiting the river, stochastic models were studied to improve our grasp of monthly flow and some aspects of water quality metrics and the ability to forecast them of the Strymon River (Greek section). Specifically, they used a time series of monthly flow measurements and a few water quality metrics to create seasonal and nonseasonal

ARIMA models for the Strymon River. Forecasting monthly values for one or more periods in the future can be done using the models that were chosen for each parameter data collection.

Antonopoulos et al. (2001) analyzed Greece's Strymon River discharge and water quality parameters time series data from 1980 to 1997. Trends in the following variables were found using the nonparametric Spearman's criterion: discharge, EC_W, DO, SO_4^{2-}, Na^+, K, and NO_3^{3-}. The Kolmogorov-Smirnov and two tests were used to verify the best-fitted models. Investigations were also conducted to examine the connections between constituent concentration, load, and discharge. Although loads and discharge have a positive association ($r>0.9$), concentrations and discharge have a poor correlation ($r<0.59$). Ahmad et al. (2001) completed a study to evaluate information on water quality gathered from the Ganges River in India. Three stochastic modeling techniques were used to model the observed time series of water quality: multiplicative ARIMA model, deseasonalized model, and Thomas-Fiering model. We identified the multiplicative ARIMA model with nonseasonal and seasonal components as a practical model. It was advised to forecast the river's water quality indicators using deseasonalized modeling.

With the help of a water quality monitoring program in New Zealand, Stansfield (2001) used the nonparametric seasonal Kendall test and Sen Slope test to analyze trends in water quality time series. It was possible to demonstrate the significance of considering the detection limits of variables and sample frequencies. The results showed less trend detection occurred when the sampling frequency increased from monthly to quarterly. Results also revealed that, compared to monthly data, the quarterly data come with a distinct magnitude in terms of a slope. Gangyan et al. (2002) examined through the turning point test, Kendall's rank correlation test, and Anderson correlogram test to analyze the temporal sediment load characteristics of the Yangtze River to establish randomness and identify the trend. They used the monthly sediment load data from 1950 to 1969 as well as the annual sediment load data for the years 1950 to 1990. An autoregressive model was used to model the stochastic component. One hundred years of monthly sediment data were produced and well-matched with observed data.

Jassby et al. (2003) created a time series model for Lake Tahoe (USA), considering interannual variability. Although the mean annual Secchi disc depth has decreased by roughly 10 m since 1967, the Secchi depth was occasionally found to be over 40 m, which prompted a massive restoration effort. High annual fluctuation obscured restoration efforts and compliance with water quality regulations. The model suggested a tool to assess compliance with water quality criteria in cases when precipitation abnormalities may last for years. Additionally, other research has concentrated on time series of water temperature, such as Webb et al. (2003), who demonstrated a strong association between air and water temperature when discharge is below the yearly median. Kurunc et al. (2005) performed a time series analysis of the Yesxilirmak River's stream flow and water quality elements at the monitoring station of Durucasu. In this work, the ARIMA and Thomas-Fiering modeling techniques were compared. The best models of each component of water quality and stream flow with both modeling methodologies were obtained using a 13-year monthly time series of records. The study's findings indicated that, of the two techniques, the Thomas-Fiering model provides more accurate predictions of the components of water quality and stream flow for the Yesxilirmak River than the ARIMA model.

Panda et al. (2011) examined changes in the tropical river basin's (India) sediment load and investigated how climate and human forcing processes affect the land ocean fluvial system. Analysis was done on sediment time series collected from 133 gauging stations during 1986–1987 and 2005–2006 on various timescales. The results demonstrated that the sediment load has significantly decreased. It was discovered that most river basins' reduced sediment loads because of non-significant declining trends in rainfall and numerous years of drought. Additionally, among tropical rivers, the Narmada River demonstrated the greatest reduction in sediment loads (2.07×10^6 t/yr) due to the dam's construction. Furthermore, Irvine et al. (2011) completed a study on the lower Mekong River's temporal variations in selected parameters. The findings indicated that a substantially developed vertical variation in turbidity, DO, and conductivity in inundated forest fringe may be attributed to a number of variables, counting dissolved material release from bed silt and a floating organic-rich particle layer near the lake's bottom.

Halliday et al. (2012) examined two hydrochemical time series that were created from stream samples collected in Wales' Upper Hafren catchment. Determinants were selected in a nonstationary time-series analysis framework to find determinant trends, seasonality, and short-term dynamics. The findings show that long-term and frequent monitoring can better understand a catchment's hydrochemistry. This ongoing research shows the necessity of long-term and high-frequency monitoring to comprehend hydrochemical catchment dynamics completely.

Parmar and Bhardwaj (2014) studied water quality management through a time-series prediction model and statistical analysis. The statistical mean, median, mode, standard deviation, kurtosis, skewness, and coefficient of variation of Yamuna River have been compared using the monthly variance of water quality standards. R-squared, root mean square error, mean absolute error, maximum absolute error, normalized Bayesian information criteria, Ljung-Box analysis, projected value, and confidence intervals were used to validate the model. Future values for water quality parameters have been predicted using an auto-regressive integrated moving average model. The pH, free ammonia, total Kjeldahl nitrogen, dissolved oxygen, and WT curves are platykurtic and leptokurtic, respectively. It is noted that the predictive model is useful at 95% confidence limits.

Arya and Zhang (2015) worked on the four water quality measurement stations along the Stillaguamish River (Washington). They used the time series analytic approach to model and predict univariate DO and temperature. The normality assumption for modeling the univariate time series was satisfied using the order series method. The Auto-Regressive Fractionally Integrated Moving Average model was then employed to examine the time series with a long memory, while the ARIMA models were used to research stationary and nonstationary time series.

Parmar and Bhardwaj (2015) analyzed the trend and predicted the water quality through regression, correlation coefficient, ARIMA, box-Jenkins, ACF, PACF, lag, fractal, Hurst exponent, and predictability index. The predictive model is useful at 95% confidence levels, and all WT show a platykurtic curve. Different locations for BOD, AMM, and TKN exhibit Brownian motion (true random walk) behavior. Water quality along the Yamuna River is good in Hathnikund, deteriorates in Nizamuddin, Mazawali, and Agra D/S, and then improves again in Juhikha.

Ghashghaie et al. (2018) utilized time series analysis to examine Madian Rood River's quality at Baraftab station. Nine water quality metrics were investigated. A review of the observed time series reveals that, except Na+ and SAR, all parameters have a consistent upward tendency. Using the ACF and PACF of time series, the order of models for each parameter was established. The quality of stream flows was generated and anticipated using the ARIMA model. To assess the generation and validation outcomes, the Akaike Information Criterion (AIC), Determination Coefficient (R^2), Root Mean Square Error (RMSE), and Volume Error in Percent (VE%) criteria were used.

Luo et al. (2019) used the time series method in the Guidu Fu section of the Qingyi River to create the ARMA model for concentrations of DO, BOD_5, COD, Cr, NH_3-N, and TN. The projected concentrations were examined and verified using the measured values.

The promising techniques for forecasting and simulating water quality variables are WQMs. As said above, there is plenty of literature on using WQM to forecast pollutants in rivers around the world. Since the river system is extremely large, it is necessary to predict how pollutants would behave. This study has developed an economic river management plan for river Gomti to help decision-makers.

3.8 Assimilative capacity

Several years ago, there was an increase in the relevance of the water quality issue, mainly because water pollution in lakes and rivers is becoming increasingly problematic (Yuceer and Coskun, 2016). About 80% of all wastewater, as per the wastewater report (2018) from the IWA, is released into rivers throughout the world, where it poses threats to human health, the environment, and climate and can alter the waterways' assimilative capacity (AC) (Torres-Bejarano et al., 2022). For water resources to be managed effectively, it is crucial to understand the effects of wastewater discharges on them. Hydrodynamics and WQM are crucial tools for understanding these consequences, often based on water sources' absorption capacity (Villota-Lopez et al., 2021). The term "assimilative capacity" describes a water body's innate capability to self-cleanse and/or self-repair through the dilution and/or dispersion of waste and pollution without endangering the aquatic environment. Additionally, it can show the maximum amount of pollutants that can accumulate, be destroyed, changed, and transmitted outside of the ecosystem's volume without interfering with its regular activity or the amount of controllable pollutants that can be added to each water flow in a river (Kulikova et al., 2018). The loss of an aquatic ecosystem's natural potential for self-purification and self-restoration, which translates into a reduction in assimilative capacity because this capacity enables the natural treatment of wastewater in rivers, is a detrimental effect of polluting activities (Lee et al., 2017).

The 1972 Stockholm conference introduced the first representation of the environment's ability for assimilation. The term "assimilative capacity" has been appropriated in the context of marine pollution to describe the inherent power of waterways to dilute and distribute pollutants and pollution without harming the aquatic environment. The idea behind using the concept of assimilative capacity in different environmental management processes was typically founded on creating a necessary framework for the later design of suitable environmental standards and regulations (Torres-Bejarano et al., 2022).

Assimilative capacity is defined differently worldwide, with the United States' total maximum daily load (TMDL) being the most often used definition for regulatory purposes. The maximum pollutant that can exist in a water system is impaired, independent of the source of the pollutants (Landis, 2008). It is a division of the object-oriented methodology created to analyze river basin point-source pollution reduction. Additionally, assimilative capacity, a byproduct of the stressor-based monitoring strategy, has been employed in numerous projects to demonstrate how biomonitoring approaches can be used to measure biological states across time (Maruya et al., 2014). It is significant to remember that the same notion has been employed in numerous research in addition to these various definitions. Numerous governments have used multiple techniques to lessen the negative impact of non-point source pollution entry, including nutrient loads in the Xiangxi watershed in China. The eco-hydrological model and the water evaluation tool are two options that can be used to combat these detrimental impacts and to lessen the risks in earlier research (Strehmel et al., 2016).

Additionally, assimilative capacity must guarantee a reference minimum flow condition linked to a specific danger level (Abbasi and Abbasi, 2012). Investigated is a probabilistic assessment of the harm to human health from the danger of metal pollution entering a river (Saha et al., 2017). When dealing with dangerous compounds, the assimilative ability is often relatively constrained, meaning that toxic substances have a considerably lower assimilation capacity (Abbasi and Abbasi, 2012). Two studies conducted in 1994 demonstrated the ability of paper mills to generate effluents by utilizing chlorine dioxide in their bleaching process, after being diluted realistically in the receiving water, either had no adverse effects on the aquatic ecosystem or had only minor ones (Landner et al., 1994). The effective method of inspection in pioneer mills, avoiding excessive chemical dosage, unstable production conditions, and unintentional spills are likely the main causes of this minimal impact (Landner et al., 1994). Additionally, when dealing with dangerous resistant substances that tend to condense in the environment and assemble in aquatic biota, the assimilative capacity is typically quite constrained (Hashemi Monfared et al., 2017). Many researchers have decided on a strategy for managing water quality experimentally because of the significant function that absorption capacity plays as a water quality metric (Hashemi Monfared et al., 2017).

A practical element of water quality indices is adjusting water flow to lessen the harm caused by unpermitted pollutant entrances. This is a corrective step in pollution crisis management in actual circumstances. To identify proper effluent ranges for a promotion to the Brockville Water Pollution Control Center (WPCC), which releases treated effluent into the St. Lawrence River, an examination of the St. Lawrence River's assimilative capability was conducted (Brockville Water Pollution Control Center, 2004). Additionally, two useful ideas are applied in various water quality management contexts: absorption capacity and dilution flow. Regarding pollution, an inexpensive drainage design aims to balance the impacts of continuous and irregular discharges against the water's capacity for assimilation (Loucks and Van beek, 2005). The San Joaquin Basin (SJR) used real-time water quality management to evaluate the safe discharge of pollutant loads (Nigel and Quinn, 2005). The Nottawasaga Valley and the area around Lake Simcoe have been protected through the funding provided by the Province of Ontario through the Ministry of the Environment for Assimilative Capacity Studies (ACS). As defined by oceanographers, assimilative capacity is the potential of natural waters to dilute, disseminate, and absorb industrial pollutants without endangering lucrative commercial fish species (Keeling, 2007).

Various studies have been developed to simulate the assimilation capacity, which needs the solution of the pollutant transport equation. The extension and evaluation of an analytical framework for a model of pollution transfer in the convective region of rivers (Schmalle and Rehmann, 2014). Additionally, numerous analytical and numerical research looked for the most practical way to describe how dissolved and suspended particles are transported and transformed by the advection-dispersion formulas that are used to calculate water quality indicators (assimilative capacity and dilution flow) (Hashemi Monfared and Dehghani Darmian, 2016; Hashemi Monfared et al., 2017).

Given that different rivers have varied capacities for assimilation (Abbasi and Abbasi, 2012), researchers attempted to propose a practical model to establish water quality management tools, as the significance of a credible simulation model (Assimilative capacity and dilution flow) was noted. Wen and Lee (1998) devised a multi-objective neural network optimization method for controlling river water quality. The model was then used in Taiwan's Tou-Chen basin. A sequential dynamic genetic algorithm was used as an optimization model to regulate the water quality of the Karoon River (Iran)

(Karamouz et al., 2003). De Smedt et al. (2005) explored modeling and optimization methods to assess temporal and geographical pollution utilizing an injected tracer. Chile's Chilla'n River was the first place where the process was effectively used. Their findings showed that the observed data and the modeling conclusions were in good accord. Gillibrand's report (2006) detailed steps to build modeling methods that will enhance estimates of the water bodies' capacity for assimilation, which is used in marine aquaculture. Yandamuri et al. (2006) studied the reasons as follows: (1) the overall treatment cost, (2) the equality of those who release pollutants, and (3) the DO content for a multi-objective optimization framework was presented to determine the ideal pollution load in rivers. Monitoring and controlling strategies are used to evaluate the efficiency of the quality management of water networks. The ability of an ecosystem to ingest and absorb pollutants is determined by its hydrodynamic and biological properties, which reduce the danger of pollution and maintain the quality of the environment and water. Chen et al. (2012) worked on Northeast China's Heilongjiang River's water network to implement their strategy, which recognized monitoring networks and data on water quality as crucial components in pollution management methods.

A method was expanded using a volume-equivalent equation to identify aluminum dilution, find sources of aluminum in surface water, groundwater, and wastewater from filter backwash, as well as losses brought on by spill discharge, sedimentation, and water discharge from the reservoir. The technique was applied to 13 reservoirs, and information on the concentrations of aluminum and Dissolved organic carbon (DOC) in the reservoirs' influent water was examined (Colman et al., 2011). De Andrade et al. (2013) framed the Simulated Annealing (SA) method and the Raised Flow Water Quality Simulation Model (QUAL2E) to present a model for river pollution reduction. This method was used in the Brazilian Santa Maria da Vitoria River basin to calculate the necessary oxygen content for biological activity. The CE-QUAL-W2 simulation model completed drinking and agricultural water allocation for the Karaj Dam in Iran. The findings demonstrated that the established quality-quantity model was better suited for abrupt pollution scenarios, including water allocation (Haddad et al., 2014; Mahmoudi et al., 2016).

Assimilation capacity was calculated using a nonlinear programming model (NLP) in one of the most recent modeling studies (Farhadian et al., 2014), Although this model encountered two challenges in determining assimilation capacity: (1) High runtime; (2)

In some instances, the challenge was insurmountable. Additionally, in their research, when the pollutant input concentration exceeds the assimilative capacity, it was handled by enhancing the dilution flow using defined goal functions, mean unallowable concentration, and length of contact (T).

Dehghani et al. (2020) used a one-dimensional pollutant transport model to determine a river's ability to absorb pollutants. Hashemi Monfared et al. (2017) found the assimilative capacity and dilution flux using a one-dimensional model with two objective functions (pollutant concentrations and the pollutant's distance from the river water). It was discovered that the river flow variation during different seasons could change the assimilative capacity by 97%. Obin et al. (2021) used the WASP (Water Quality Analysis Simulation Program) model to calculate the water environmental capacity of the Lushui River (China) in all atmospheric conditions. Cely-Calixto et al. (2021) worked on the Magdalena River (Colombia water) quality parameters, simulated using the mathematical model QUAL2K, demonstrating the river's propensity to purify due to its high flow. Establishing monitoring programs in water bodies where river and outflow volumes are statistically analyzed along with water quality metrics is one of the most popular techniques for assimilative capacity assessments. Configuring a simulation model for concentration and water quality to determine assimilative capacity is a popular technique (Gurjar and Tare, 2019; Quinn et al., 2021). The simulation of scenarios where specified water quality restrictions are violated is another popular technique (Novo, 2017; Villota-Lopez et al., 2021). This approach, which involves using a two-dimensional hydrodynamic and WQM, was primarily taken into account in this study since it can serve as a springboard for the creation of robust water quality objectives that are essential to the management of water resources.

Using hydrodynamic and water quality modeling, Feria Diaz et al. (2017) examined a segment of the Sin River in Colombia to identify its deoxygenation and reaeration rates. This analysis evaluated the Sin River's capability to assimilate wastewater discharges. The most significant human water resources are rivers and surface water. Unfortunately, pollutants from untreated domestic, agricultural, and industrial wastewater disposal decrease the quality of these vital human resources' water and can cause the environment to suffer permanent harm (Hashemi Monfared et al., 2017). In these situations, meeting the minimum acceptable quality standards for drinking water and other uses is frequently impossible due to the high water treatment expenses. Considering the water flow modification, pollution can be reduced through one of the most affordable methods. Assimilative capacity and dilution flow are crucial for controlling water pollution in a river (Farhadian et al., 2014). For each water flow in the river, assimilative capacity is defined as the entrance of controllable pollution, and dilution flow is considered for uncontrollable entering pollution, which is larger than assimilative capacity. However, a practical and cost-effective method of managing water quality is to estimate the amount of allowable pollutant concentration entering a river while considering water flow (Farhadian et al., 2014).

Zainudin et al. (2015) evaluated the possible risk of pollution in the rivers, specifically the Terumpah, Che Minah, Semangar, Beluntu, Penawar Besar, and Mertang Besar Rivers, which are situated in the center of the development region. Water quality and hydraulic data were taken at these rivers to create a numerical model. BOD_5 and NH_3-N levels in the Semangar River declined by up to 4.0 mg/dm^3 and 0.34 mg/dm^3, respectively, according to the model results. With 14.0 mg/dm^3 of BOD_5 and 0.8 mg/dm^3 of NH_3-N, the Beluntu River underwent the greatest degradation. The class III BOD_5 limits for the Matang Besar, Che Minah, and Beluntu Rivers' waste assimilative capacity (WAC) were 15, 43, and 10 kg/day, respectively. In contrast, the Terumpah River cannot receive any BOD load without exceeding the same limit.

Munfarida et al. (2020) evaluated the water quality in accordance with government regulations and computed the pollution load-carrying capacity of the Cibatarua River in the Pamulihan district following regulatory requirements of the environmental agency. The water quality indicators are the TDS, BOD_5, COD, pH, oil and grease, and DO. Based on the findings, Government Law No. 82/2001's standards for BOD_5 and oil and grease were exceeded.

Nurseitova et al. (2021) demonstrated the usefulness of using the Nelder-Mead method and the gradient approach in a detailed comparative analysis of optimization methods for addressing the defined inverse issue. The assimilation potential of the Kazakhstani portion of the Ili River basin might be evaluated. Since the BOD calculations were done at k = 0:23/day, the resulting estimate establishes the upper limit of the basin's assimilation capacity (the greatest seasonal value of the maximum permitted load). This figure translates to a 20°C water temperature often seen during the summertime low water period. The predicted value of the maximum permitted load would drop in the winter when the rate of breakdown of pollutants is substantially lower. Additionally, the results can be used to forecast changes in pollutant concentration if river inflow into Kazakhstan's territory declines.

Chapra et al. (2021) determined the greatest or "critical" DO deficit that can be computed analytically as a function of the BOD concentration at the mixing point, DO saturation, and the self-purification rate using the traditional Streeter-Phelps model. According to the findings, high-velocity streams will be particularly vulnerable to temperature increases. This is important because such systems generally develop in hilly areas, where they are more vulnerable to lower oxygen saturation due to lower oxygen partial pressure. Such systems often display high self-purification constants because of their fast reaeration rates, which leads to higher absorption capacities than slower-moving lowland rivers. Saturation decreases mostly determine the overall sustainable mixing-point concentration for CBOD in slow-moving rivers. For faster-moving streams, the temperature-regulated reductions in saturation and self-purification have an equal impact on the total sustainable load.

Torres-Bejarano et al. (2022) discovered that the changes in discharge flows have a more significant impact on a Sin River's sensitivity than discharge concentration changes; the river was primarily affected by a halving of its flow and a 400% increase in current point source flows. This idea can affect the river's planning and prevention programs in terms of the wastewater flows that the river can support without exhausting its assimilative capacity; this aspect is not yet considered for the river's planning and prevention programs. Sin River water quality modeling provides the competent environmental authorities with a starting point for assessing the river's capacity for self-purification under the present condition of discharge and predicting which conditions will affect this natural process.

According to the literature review, assimilative capacity and dilution flow are two crucial tools for controlling water pollution in a river. Assessment of assimilative capacity is helpful for policymakers and stakeholders as a cost-effective solution for water quality management.

3.9 Impact of rising temperatures on water quality

One of the most critical environmental problems is climate change, which results from global warming. Freshwater ecosystems and the world's water resources are now being impacted by it (Das et al., 2021; Santy et al., 2022). Some of the reasons contributing to the increase in temperature include an increase in the rate of CO_2 emissions and GHGs, including CH_4, nitrous oxide, and Chlorofluorocarbons (CFCs) (Abeysingha et al., 2020; Santy et al., 2022). As per the National Oceanic and Atmospheric

Administration (NOAA, 2019), almost 414.7 ppm of carbon dioxide is present in the world's atmosphere. The global temperature has risen by 0.85°C between 1880 and 2012 (IPCC, 2013) and is considered as frequently the main element changing precipitation's amount, kind, and intensity. This impacts the hydrological cycle (Islam et al., 2012). The extent of this influence is impacted by both anthropogenic activities and industrial growth (Santy et al., 2022).

According to the various Representative Concentration Pathways (RCPs), warming of 1.5-4.3^{0}C has been predicted for India for the 2080s (2071-2100) compared to the 1961-1990 baseline period (Krishnan et al., 2020; Das et al., 2021; Santy et al., 2022). Similar to this, with the exception of a few locations, short-term estimates indicate that precipitation will increase across India by the 2030s. According to various RCPs, from the baseline of 1961–1990, the 2080s are expected to see a rise in annual precipitation of 6–14% across India (Abeysingha et al., 2020; Krishnan et al., 2020). Such a shift in temperature and precipitation would majorly affect water availability for several industries, especially agriculture, and threaten the security of livelihoods. Thus, it is essential to quantify the effects of climate change on the geographical and temporal variability of water resource availability in various river basins to comprehend possible water resource issues and create basin-specific adaptation plans (Unger-Shayesteh et al., 2013).

Since regional hydrological circumstances differ, so will the effects of climate change on the availability of regional water resources in each river basin. Therefore, it is crucial to comprehend how a river basin will respond hydrologically to climate change in order to prepare local adaptation plans (Bisht et al., 2018; Abeysingha et al., 2020).

WT and DO in the water serve as crucial indicators of the ecosystem's health in a river water body (Chapra et al., 2021). Various climatological defining variables, most notably AT, have negatively impacted WT in warming climates (Webb et al., 2003; Van Vliet et al., 2013). When WT is intensified, river DO saturation levels will decline, which will have a negative effect because most river water quality is predicted on such saturation levels (Van Vliet et al., 2013). In particular, saturation DO is a notable marker of river water quality and is considered as a standard pollution indicator (CWC, 2019). Water quality degradation and ecological distortion may result from the impact of climate change on DO with WT (El-Jabi et al., 2014; Svendsen et al., 2016; Danladi Bello et al., 2017). Since WT and DO concentration are inversely connected, changes in WT impact the river's capacity to self-purify by reducing the quantity of oxygen used for biodegradation (Khan et al., 2017; Kauffman, 2018). It is important to comprehend future river water quality and potential changes in quality standards under climate change warming signals and its impacts on WT and DO concentration (Rajesh and Rehana, 2022).

DO depletion was projected by water quality modeling studies for several basins across the world under changing streamflow, WT, and land use (Rehana and Mujumdar, 2011, 2012; Ficklin et al., 2013; Danladi Bello et al., 2017; Du et al., 2019; Santy et al., 2020; Chapra et al., 2021). Regression models were used in these investigations to model WT (Rehana and Mujumdar, 2011) and process-based stream temperature models (Ficklin et al., 2013; Du et al., 2019) and the quality of river water models such as QUAL2K (Rehana and Mujumdar, 2012; Santy et al., 2020). Such studies, however, focus on simulating DO levels with streamflow, WT, and land use, which limits their applicability to data-scarce and ungauged sites (Rehana and Mujumdar, 2011, 2012; Ficklin et al., 2013; Danladi Bello et al., 2017; Du et al., 2019; Santy et al., 2020). However, the DO saturation level, which establishes a baseline for evaluating the oxygen content of water based on salinity, oxygen partial pressure, and WT, determines the oxygen concentration of unpolluted water (Chapra et al., 2021). Therefore, this is significant in establishing the upper limits and minimum requirements for diverse river usage (CPCB, 2019). Still, it has not been evaluated concerning climate change (Rajesh and Rehana, 2022).

The link between WT and DO concentrations in tropical rivers is impacted by climate change (Danladi Bello et al., 2017). Tropical rivers have higher WTs and are prone to more solar radiation (Taniwaki et al., 2017). For instance, Indian tropical river systems experience low flow during the non-monsoon and summer seasons, having the highest WTs (Santy et al., 2020).

Some studies (Ficklin et al., 2013; Javadinejad et al., 2021) projected that poor water quality in terms of DO, EC, and silt concentration could result from a rise in stream temperature and a decrease in stream flow during the dry season due to climate change. Land use and cover changes, particularly the growth of agricultural land, which might result in an increased nutrient concentration, have an impact on the water quality estimates as well (Gyawali et al., 2013; Ostad-Ali-Askari et al., 2017; Santy et al., 2020). The increasing water quality and sewage damage could be because of the increased growth of population and industrial activities (Khattiyavong and Lee, 2019; Ostad-Ali-Askari, 2022) and as a consequence, the degradation of the quality of water

(Khan et al., 2017).

Such investigations used regression models to model WT (Jain and Singh, 2020; Saha and Ghosh, 2020). In a prior study (Santy et al., 2020), a standalone WQM revealed that DO and microbiological pollution decreased due to warming and a reduction in low flows, whereas organic and nutrient pollution increased in the Ganga River. Eutrophication and fish kills are possible outcomes of growing nutrient pollution and declining DO. In contrast, several Ganga River studies have revealed increased monsoon flows and improved water quality for sustainable socio-economic situations with climate change (Jin et al., 2015). El-Jabi et al. (2014) evaluated the surface water quality of 15 rivers in New Brunswick, Canada, based on nine factors under climate change. The weighted method and the CCME method were applied to evaluate the water quality for all rivers individually under the current and projected climatic conditions. The information collected from this study will help engineers and managers of water resources better understand the thermal regimes of rivers and the effects of climate change on water quality in relation to drinking surface water.

The literature review reveals that the impact of climate change on river WT is highly dependent on AT and other parameters. Since AT is the characteristic that is anticipated to alter the most due to climate change, river WT is also a crucial component. So, assessing the impact of rising temperatures on water quality is an important prospect to consider by stakeholders and policymakers for formulating a water quality management plan.

3.10 Conclusions and research gaps

According to a literature review, the Gomti River is considered one of India's most polluted rivers. The use of solely primary monitoring was one of the key limitations noted in the earlier research (Srivastava et al., 2011; Malik et al., 2011; Shah et al., 2015; Tangri et al., 2018; Singh et al., 2018; Kumar et al., 2022a). Additionally, most of these investigations conclude by comparing the observed data to the requirements for water quality. This has proven insufficient to identify the causes of water quality decline, understand spatiotemporal variation in various segments of the river Gomti, and develop a strategy and plan for managing water quality. The usage of MSTs has recently been documented in various research investigations conducted on the River Gomti of Lucknow, Uttar Pradesh, India (Singh et al., 2005; Dutta et al., 2018a; Goel et al., 2018; Iqbal et al., 2019; Kumar et al., 2020b; Khan et al., 2020; Kumar et al., 2021c; Khan et al., 2022; Kumar et al., 2022a). Additionally, no studies have used SPI or CPI as water quality indicators.

The current work uses an integrated method to analyze the surface water quality of the Gomti River, which flows through Lucknow (UP), India, employing MSTs, WQIs, GIS, statistical modeling, assimilative capacity, and climate change (effect of rising temperature). The combined use of these technologies is anticipated to provide a first thorough assessment of the current settings of the water quality in the Gomti River in Lucknow (UP). Academics and policymakers are anticipated to benefit significantly from the study's findings.

CHAPTER - 4

MATERIALS AND METHODS

4.1 General

The research work embodied in this thesis has been carried out with the aim of water quality management with reference to assimilative capacity and climate change (impact of rising temperature) by identifying, quantifying, and characterizing selected pollutants of an important river Gomti which is the lifeline of Lucknow. The methodology adopted to achieve objectives includes various steps, as depicted in Figure 4.1.

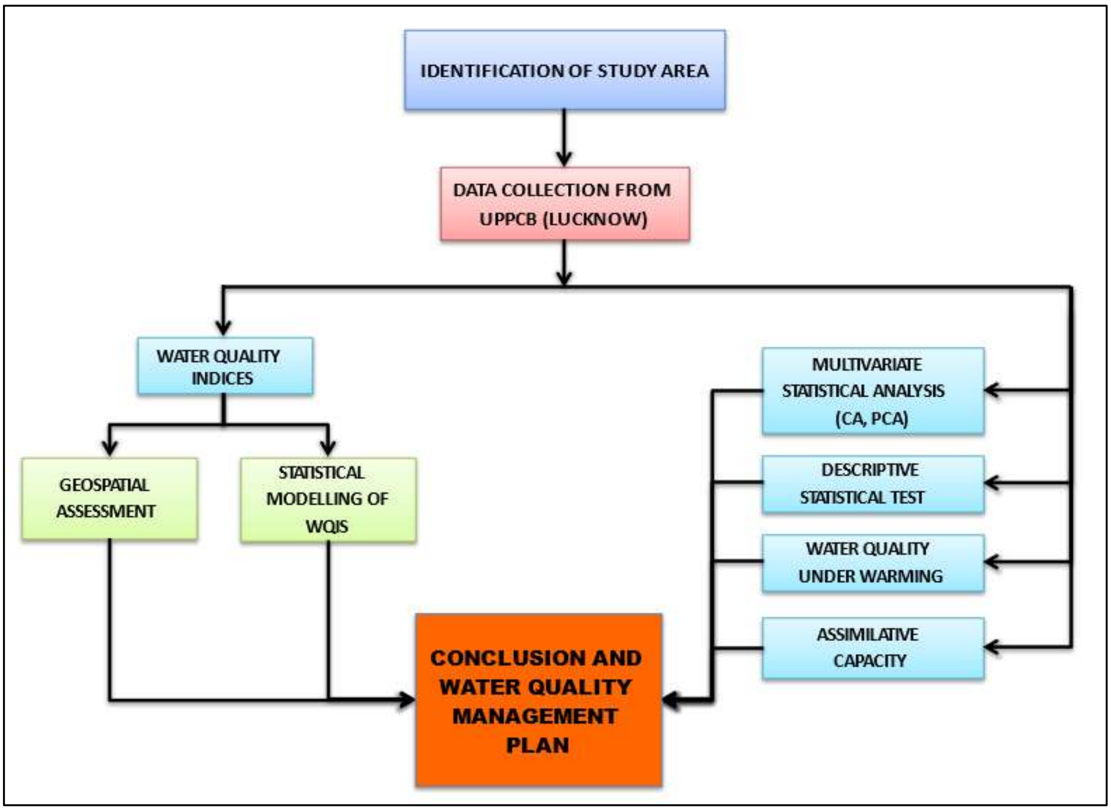


Figure 4.1: Flow diagram for the detailed methodology of the research plan

This study is based on the data collected by the Uttar Pradesh Pollution Control Board (UPPCB), Lucknow (UP), which monitors the water quality along the Gomti River in Lucknow. First, the monitored data for physicochemical and biological parameters from 2013 to 2017 was acquired from the UPPCB database. Descriptive statistics and multivariate statistical approaches were used to investigate further the multifarious nature of the data sets gathered from the UPPCB database. Seasonal and spatial variation in the dataset was analyzed using one-way Analysis of Variance (ANOVA). Simultaneously, an extensive literature review was carried out to finalize the four most suitable WQIs based on the data received. These indices were used to assess the water quality of river Gomti, followed by its integration with GIS to mark out different zones based on the magnitude of pollution. Statistical modeling was used to forecast or to predict these four indices for river Gomti, which would facilitate future predictions of WQIs and assessment of the Assimilative capacity of water quality variables in the river.

4.2 Data collection and sampling stations

Based on the possible sources of pollution, sampling stations are chosen by UPPCB (Lucknow). The majority of the locations are located near industrial or urban regions. All seven sampling stations' data from 2013 to 2017 were collected monthly. The changes in water quality are assessed using 14 water quality analysis measures. Table 4.1 lists the measured water quality parameters.

Table 4.1: Measured water quality parameters, abbreviations and units

S. No.	Parameter	Abbreviation	Unit
1	Water Temperature	WT	^{O}C
2	pH	pH	Units
3	Electrical conductivity	EC	µS/cm
4	Total dissolved solids	TDS	mg/l
5	Total alkalinity (as $CaCO_3$)	TA	mg/l
6	Total hardness (as $CaCO_3$)	TH	mg/l
7	Calcium	Ca	mg/l
8	Magnesium	Mg	mg/l
9	Chloride	Cl	mg/l
10	Dissolved oxygen	DO	mg/l
11	Biochemical oxygen demand	BOD	mg/l
12	Chemical oxygen demand	COD	mg/l
13	Total Coliform	TC	MPN/100 ml
14	Fecal Coliform	FC	MPN/100 ml

The UPPCB, Lucknow, collected monthly data on all the aforementioned water quality parameters at seven sampling stations, namely S1 - Manjhi Ghat, S2 - Up Stream water intake, S3 - Kuriyaghat, S4 - Downstream Mohan Meakins, S5 - Nishat Ganj Bridge, S6 - Upstream Barrage, and S7 - Downstream STP Nala Bharwara junction (ANNEXURE – I). The first sampling station (S1) is located in a low-pollution area on the upstream side of Lucknow city. The remaining five stations (S2, S3, S4, S5, and S6) are located in the middle of the route, with high pollution levels. The last sample station (S7) is situated in the moderately polluted downstream zone. Table 4.2 and Figure 4.2 give the specifics of the sampling stations. By taking into account the contributions from diverse pollution sources that affect the water quality, the sampling strategy used by the UPPCB, Lucknow, was created to comprehend the broad pollution causes at significant sites that characterize the river water quality (Dutta et al., 2018a).

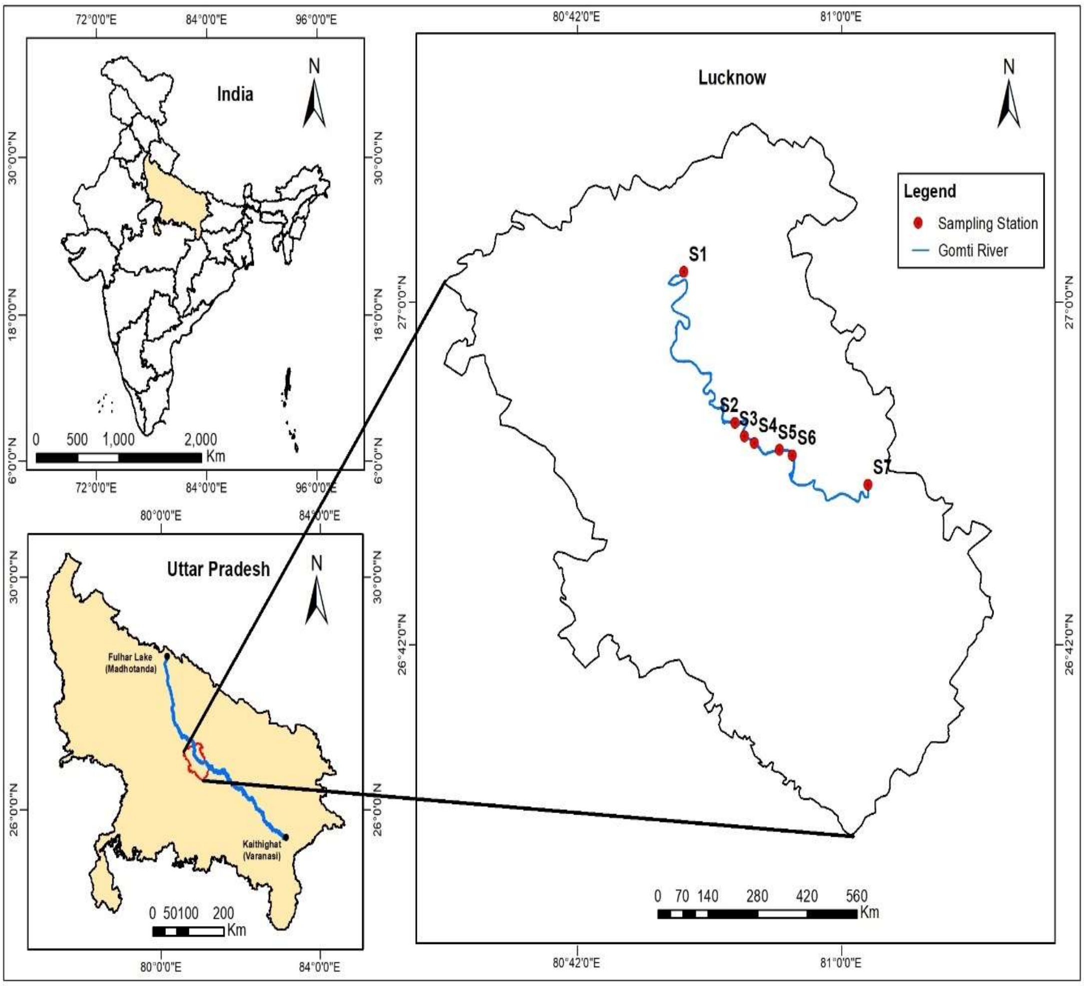


Figure 4.2: Map showing sampling stations in the river Gomti at Lucknow

Table 4.2: Location of the sampling stations and their geo-coordinates of the Gomti River at Lucknow

Sampling station	Station code	Landmark of sampling location	Latitude	Longitude	Elevation	Distance between sampling stations
Station 1	S 1	Manjhi Ghat	27°01'37.10"N	80°50'19.20"E	111 m	0
Station 2	S 2	U/S water intake	26°53'14.58"N	80°53'59.86"E	111 m	32.5 Km
Station 3	S 3	Kuriyaghat	26°52'29.30"N	80°54'42.14"E	102 m	3.2 Km
Station 4	S 4	Downstream Mohan Meakins	26°52'07.67"N	80°55'25.46"E	109 m	1.4 Km
Station 5	S 5	Nishat Ganj Bridge	26°51'44.19"N	80°57'11.94"E	112 m	3.5 Km
Station 6	S 6	U/S Barrage	26°51'25.22"N	80°58'07.32"E	110 m	1.8 Km
Station 7	S 7	D/S of STP Nala Bharwara junction	26°49'47.34"N	81° 3'35.56"E	108 m	16.0 Km

4.3 Statistical analysis of water quality data

When biological and physicochemical analysis of surface water resources is conducted, the resulting data sets are frequently found complex or multifarious due to fluctuations in the observed values over time and space. On the other hand, water quality data sets exhibit some characteristics that are particular to them. Such data sets also frequently contain “outliers," or observations that are much higher or much lower than most of the other observations in the whole data set. As a result, the distribution of most data sets on water quality on both temporal and spatial scales is skewed. It is vital to keep in mind that the presence of outliers could indicate measurement, instrument, or recording error, but most often, outliers could indicate significant data points that need additional research. Therefore, outliers cannot be entirely excluded while evaluating the water quality. When analyzing such data sets, statistical approaches, also known as non-parametric methods, that are resistant to these “strange values," such as employing the mode -the value that appears in the data set the most frequently, instead of the mean should be used. Since the data sets for water quality generated for this research were not normally distributed, the transformation was required before parametric tests. The modification helped to normalize the distribution of the data. Microsoft Excel 2016 and IBM SPSS Statics 26 software were used for all statistical analysis.

4.3.1 Descriptive statistics

For each water quality measure, statistical data analysis was performed to determine the mean, median, mode, standard deviation, kurtosis, skewness, coefficient of variation, and correlation coefficient. The statistical measures mean, median, and mode, respectively, describe the average value, the midway values of an ordered sequence, and the value that occurs the most frequently. The standard deviation is a measure that explains the sample’s dispersion or variability. Kurtosis describes the amount of flatness or peaking in the area surrounding a frequency curve’s mode. The term “skewness” refers to data symmetry. The coefficient of variation (CV) provides the sample's relative measurement (Parmar and Bhardwaj, 2013; Rawat et al., 2017).

4.3.2 Analysis of variance

Analysis of variance (ANOVA) is a statistical technique that uses the F test to look at how the means of a set of variables or data differ from one another (Eq. 4.1).

$$F = \frac{Variation\ within\ the\ sample\ mean}{Variation\ between\ the\ samples} \quad 4.1$$

The population means are assumed to be equal for the F-test null hypothesis. Low F values indicate no substantial difference between the sample means and that the null hypothesis is correct. Contrarily, a high value of F indicates statistically significant variation among the sample means and rejects the null hypothesis. In the current study, a one-way ANOVA was conducted to find differences for each of the water quality metrics between the seasons, the seven sampling sites, and the years of sampling. The identification of water quality characteristics that caused appreciable differences in river water quality was made easier by the resulting ANOVA values. Statistics were deemed to be significant at a probability level of ($p \leq 0.05$), where p is the chance that the test statistics would have been more extreme by chance if the null hypothesis were true. To lessen the likelihood of a false positive, sometimes referred to as a type I error, a low alpha value of 0.001 was employed (incorrect rejection of a true null hypothesis) (Rizvi et al., 2016; Pujar et al., 2020; Kumar et al., 2022a).

4.3.3 Coefficient of correlation

The correlation coefficient (r) calculates the strength of association between two relevant variables. It shows how one variable's value varies when another's value increases or decreases. Dimension lessness and a scaled range of -1< or < 1 are two properties of correlation measures. The correlation becomes a test for temporal or spatial trends when one variable is a measure of time or location. Pearson's r is the most often used correlation metric. Because ‘r’ quantifies the linear relationship between two variables, it is also known as the linear correlation coefficient. r = 1 if the data are perfectly linear and have a positive slope (Roy et al., 2021). Eq. 4.2 provides the correlation coefficient ‘r’ between the variables X and Y if X and Y are two variables.

$$r = \frac{n\Sigma^{(xy)} - \Sigma^{(x)}\Sigma^{(y)}}{\sqrt{(n\Sigma^{x^2} - \Sigma^{x^2}}\sqrt{(n\Sigma^{y^2} - (\Sigma^{y^2})}} \quad 4.2$$

Where n is the number of data, and the sample means are denoted by x and y. If the value of the correlation coefficient r between two variables, X and Y, is relatively high, this indicates that the two variables are significantly connected.

4.3.4 Regression analysis

Regression analysis (RA) is a mathematical technique for separating variables without a significant statistical relationship between the dependent and independent variables (Rawat et al., 2017). The formula for defining the regression line of the dependent variable Y on the independent variable X is as follows:

$$Y = mX + C \qquad 4.3$$

Where, m = slope

C = intercept

Equation 4.4 illustrates a linear regression, which describes a linear line and the linear relationship between X and Y. It has been determined using the equation of the regression coefficient.

$$m = r \times \frac{SD_y}{SD_x} \qquad 4.4$$

Where, m = regression coefficient

r = correlation coefficient

SDy = standard deviation of Y series

SDx = standard deviation of X series

This demonstrates that the regression line's slope for the standardized data points is r, and this line passes through the origin. Sometimes, it is helpful to independently compute r_{xy} from the data using equation 4.5.

$$r_{xy} = \frac{E(XY) - E(X)E(Y)}{\sqrt{(E(X^2) - E(X^2)(E(Y^2) - E(Y)^2)}} \qquad 4.5$$

Where, $r_{x,y}$ = correlation coefficient

E (XY), E(Y), E(X) = expected value of variables XY, Y, and X, respectively.

4.3.5 Multivariate statistical techniques

A statistical technique known as multivariate analysis allows for the simultaneous examination of observational data pertaining to two or more variables (Singh et al., 2005; Pati et al., 2014; Arora and Keshari, 2021). Finding patterns among complex components in an environmental system is a useful strategy for simplifying complicated phenomena and extracting crucial information for assessing test findings (Chakravarty and Gupta, 2021). The information gathered can be utilized to suggest management and control strategies that are efficient and flexible (Saha and Paul, 2019; Ali et al., 2021). Therefore, the river water quality data was submitted to two multivariate approaches, namely Principal Component Analysis (PCA) and Cluster Analysis (CA) to identify the most likely sources of pollution and to isolate the factors that caused a significant variation in the water quality (Kumarasamy et al., 2014; Pandey and Dikshit, 2016; Gyimah et al., 2021; Arora and Keshari, 2021; Maity et al., 2022).

4.3.5.1 Principal component analysis

Principal component analysis (PCA) aims to create new, uncorrelated variables called principal components (PCs) from the original ones. The original variables are combined linearly to form the principal components (Herojeet et al., 2017; Ali et al., 2021). The standardized linear combination makes it possible to compare different linear combinations meaningfully (Dutta et al., 2018b; Gupta et al., 2020). PCA isolates the collection of linear combinations, or PCs that together account for all variance in the initial data set. In order to describe the entire data set into defined variables with large data reduction and little loss of original information, PCA gives information on the most important parameters (Chaturvedi et al., 2016; Pramanik et al., 2020). It is a successful pattern recognition technique that aims to reduce a vast range of highly correlated variables into a more manageable number of independent (uncorrelated) variables (PCs) (Singh et al., 2005; Sharma et al., 2015; Maity et al., 2022).

The normalized variables in the current study were subjected to PCA to extract significant PCs and minimize the contribution of variables of low importance. These PCs underwent varimax rotation, producing Varifactors (VFs) (Love et al., 2004; Shil et al., 2019). The Varimax rotation was carried out to alter the PCA coordinates. Given that all the coefficients will be either big or near zero, with few intermediate values, it maximized the sum of the variances of the squared loadings. Because of this, a smaller set of variables typically explains roughly the same amount of information as a larger set of initial observations (Kaur and Dua, 2012; Hema et al., 2014).

Kaiser-Mayer-Olkin (KMO) and Barlett's test of sphericity were used to evaluate appropriateness of the data for use in PCA. KMO calculates sample adequacy and identifies the percentage of variables with common variation (Maity et al., 2022). KMO values greater than 0.5 are often regarded as satisfactory for PCA. The KMO score of 0.809 in the current investigation suggested that the data set was suitable for PCA. The correlation matrix was an identity matrix, indicating that the variables were unrelated and it was determined by Bartlett's test of sphericity. This study's significance level of 0.000 (Table 4.3) (less than 0.05) revealed that the variables had substantial associations and could be grouped together.

Table 4.3: Kaiser-Meyer-Olkin measures and Barlett's test of sphericity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.809
Bartlett's Test of Sphericity	Approx. Chi-Square	9123.19
	df*	91
	Sig.*	0.000

*df - degrees of freedom; Sig. - significance

4.3.5.2 Cluster analysis

The fundamental goal of Cluster analysis (CA), a technique, is to group items according to a given selection criterion, producing high levels of internal homogeneity (inside clusters) and exterior heterogeneity (between clusters) (Li et al., 2014; Barakat et al., 2016). The hierarchical agglomerative clustering technique shows relationships of similarity between any of the samples and the complete data set. Typically, a dendrogram (tree diagram) is used to illustrate it (Gupta et al., 2020). The Euclidean distance often indicates how similar two samples are, and a distance can be represented by the variance between the samples' analytical values (Jaiswal et al., 2019).

Using squared Euclidean distances as a similarity measure, Hierarchical Agglomerative CA was carried out on the normalized data set in this work using Ward's approach. Ward's method evaluated the distances between clusters using an analysis of variance approach to reduce the Sum of Squares (SS) of any two clusters that could develop at each phase (Arora and Keshari, 2021; Maity et al., 2022).

4.4 Water quality indices

The tools known as "Water Quality Indices" (WQIs) were developed to offer concise data on water quality (Kamboj and Kamboj, 2019; Kamboj et al., 2020). It is a method for displaying a numerical expression that defines a specific level of water quality and is obtained cumulatively (Shah and Joshi, 2017; Semy and Singh, 2021). In other words, WQIs condense a lot of data about water quality into manageable chunks (such as excellent, good, bad, etc.) for consistent reporting to management authorities and the general public (Lkr et al., 2020; Roy et al., 2021; Maity et al., 2022). Chapter 3 discusses the applicability, flexibility, and growth of WQIs internationally.

Four WQIs that best capture the water quality of the river Gomti were chosen based on the thorough literature review and the available data. Generally, the most used and accepted approach of WQIs, the Arithmetic water quality index (Arithmetic WQI) and the Ved Prakash water quality index (CPCB-WQI), were taken into consideration for this study due to the extensive literature on their applicability worldwide for the assessment of water resources. On the other hand, the Synthetic Pollution Index (SPI) and Comprehensive Pollution Index (CPI) were used, which had never been applied to the river Gomti.

4.4.1 Arithmetic water quality index

The Arithmetic water quality index (Arithmetic WQI) approach was developed by Brown et al. in 1970 and later by Cude (2001). It was introduced by Horton in 1965 and used in the current study to evaluate water quality. The Gomti River's water quality can be assessed using the weighted arithmetic WQI for irrigation, drinking, and other uses. These three formulae were used to determine the arithmetic WQI:

$$Q = \frac{(Vo - Vi)}{(Vs - Vi)} \times 100 \qquad 4.6$$

Where Qi, Vo, Vi, and Vs are the subindex, actual value, ideal value, and standard value for the ith parameter, respectively. pH and DO were set to their ideal levels of 7 and 14.6 mg/l, respectively, while all other parameters had Vi set to zero.

$$Wi = \frac{K}{Vs} \qquad 4.7$$

Where Wi is the unit weightage for the ith parameter, which was determined by inversely relating each observed physicochemical parameter's value to the BIS (2012)/WHO (2011) standard value (Vs), however, K is a constant taken as unity for all of the reported physicochemical parameters. Then, using Eq. (4.8), an arithmetic WQI based on a simple arithmetic average was calculated:

$$\text{Arithmetic } WQI = \sum_{i=1}^{n} \frac{WiQi}{\sum_{i=1}^{n} Wi} \qquad 4.8$$

The computations of unit weightage (Wi) based on the constant (K) and standard values (Vs) are summarised in Table 4.4. Based on the calculated arithmetic WQI, Table 4.5 (Brown et al., 1972) summarizes the water quality grading.

Table 4.4: Unit weightage (Wi) of different parameters and their standards used for Arithmetic WQI, SPI, and CPI determination

S. No.	Parameter	Standard value (Vs)	Unit weightage (Wi)
1	WT	40	0.034435
2	pH	6.5-8.5	0.183655
3	EC	300	0.004591
4	TDS	500	0.002755
5	TA	120	0.011478
6	TH	300	0.004591
7	Ca	75	0.018365
8	Ma	30	0.045914
9	Cl	250	0.005510
10	DO	5	0.275482
11	BOD	5	0.275482
12	COD	10	0.137741

Table 4.5: Arithmetic WQI range, category, status, and possible usage of the water sample

Value of WQI	Category of Water	Water Quality Status (WQS)	Possible Usage
0 – 25	A	Excellent	Drinking, irrigation, and industrial
26 – 50	B	Good	Drinking, irrigation, and industrial
51 – 75	C	Poor	Irrigation and Industrial
76 – 100	D	Very poor	Irrigation
Above 100	E	Unsuitable for drinking and fish culture	Proper treatment is required before use

4.4.2 Synthetic pollution index (SPI)

The suitability of the water quality in the Gomti River was assessed using the SPI. The index was built using the next three relationships. In the first phase, the proportionality constant (K) was calculated using the strategy described below:

$$K = \frac{1}{\left(\sum_{i=1}^{n} \frac{1}{Si}\right)} \qquad 4.9$$

The number of parameters is n, and the standard value of the ith parameter is Si. The weight coefficient (Wi) was calculated in the second stage using the method listed below.

$$Wi = \frac{K}{Si} \qquad 4.10$$

Finally, the SPI was computed using the following approach:

$$SPI = \sum_{i=1}^{n} \frac{Ci}{Si} \times Wi \qquad 4.11$$

Where Ci stands for the concentration measured for each identified physicochemical water quality parameter, according to the SPI (Gautam et al., 2015; Solangi et al., 2018) calculated levels, water quality is categorized into five groups, as illustrated in Table 4.6.

Table 4.6: SPI range, status, and possible usage of water sample

SPI Range	**Water classification**	**Water Quality Status (WQS)**	**Probable usage**
<0.2	Suitable for drinking	Excellent	Drinking, irrigation, and industrial purpose
0.2-0.5	Slightly polluted	Good	Drinking, irrigation, and industrial purpose
0.5-1.0	Moderately polluted	Poor	Irrigation and industrial purpose
1.0-3.0	Severally polluted	Very Poor	For irrigation purpose
>3.0	Unsuitable for human consumption	Worst	Proper treatment is required for any kind of usage

4.4.3 Comprehensive pollution index (CPI)

Water bodies' overall pollution loads are evaluated using CPI. The calculation is performed using the following equation (Wang et al., 2018; Matta et al., 2018; Pramanik et al., 2020):

$$CPI = \frac{1}{N}\sum_{I=1}^{n} PIi \tag{4.12}$$

$$PIi = \frac{Ci}{Si} \tag{4.13}$$

Where, PIi = pollution index of the ith parameter,

Ci = measured concentration of the ith parameter

Si = standard concentration of the ith parameter

Table 4.7: CPI, water quality classification, and uses

CPI Range	Status	Use
0.0-0.20	Clean	Very good and can be used for drinking purposes
0.21-0.40	Sub clean	Good and can be used for domestic purposes
0.41-0.8	Qualified	Some pollutants are detected, but their concentrations accord with the standard and can be used in Irrigation and Industrial purpose
0.81-1.0	Basically Qualified	Concentrations of some pollutants exceed the standard, i.e., poor quality, and can be used for irrigation purposes only
1.01-2.0	Polluted	Concentrations of some pollutants exceed the standard, i.e., very poor quality (polluted) can be used restrictedly for irrigation
≥2.01	Seriously Polluted	Concentrations of some pollutants exceed the standard, i.e., very polluted quality and proper treatment required before use

4.4.4 Ved Prakash water quality index (CPCB-WQI)

The index was created to assess the river Ganga's overall water quality profile and to pinpoint the sections where the difference between the desired and actual water quality is great enough to call for immediate pollution control actions (Bhutiani et al., 2016). The index had the weighted multiplication form:

$$CPCB - WQI = \sum_{I=1}^{P} WiIi \qquad 4.14$$

Ii stands for the ith water quality parameter's subindex, Wi stands for the ith water quality parameter's weight, and p stands for the total water quality parameters.

The index was created using the NSF-WQI (Brown et al., 1970), with a few weighting adjustments to match the Central Pollution Control Board (CPCB) of India's water-quality standards for various types of usage (Sarkar and Abbasi, 2006; Abbasi and Abbasi, 2012). Through Delphi, a set of parameters was chosen. As stated in Table 4.8, the subindex equation was used to calculate the subindex values.

Table 4.8: Subindex equation of the index (Ved Prakash et al., 1990)

Parameter	Range Applicable	Equation
DO (Percent Saturation)	0-40 % saturation 40-100 % saturation 100-140 % saturation	IDO = 0.18+0.66 (sat %) IDO = -13.5+1.17 x (sat %) IDO = 263.34-0.62 x (sat %)
BOD (mg/l)	0-10 10-30 >30	IBOD = 96.67-7 (BOD) IBOD = 38.9-1(BOD) IBOD = 2
pH	2-5 5-7.3 7.3-10 10-12 <2, >12	IpH =16.1+7.35 x (pH) IpH = 142.67+33.5 x (pH) IpH = 316.96-29.85 x (pH) IpH = 96.17-8.0 x (pH) IpH = 0
Fecal coliform (FC) (counts/100 ml)	$1\text{-}10^3$ $10^3\text{-}10^5$ 10^5	Icoli = 97.2-26.60 X log (FC) Icoli = 42.33- 7.75 X log (FC) Icoli = 2

All of the chosen parameters received significance ratings to assign weights. The parameter with the greatest relevance rating earned a temporary weight of 1. All additional temporary weights were calculated by dividing each individual mean rating by the highest. The ultimate weights were then calculated by dividing each temporary weight by the total of all weights. These weights were adjusted to meet the requirements for different kinds of users' water quality. Table 4.9 illustrates the process for acquiring weights and modified weights. Table 4.10 lists the water classification in relation to the final index values.

Table 4.9: Method of obtaining weights and modified weights

Parameters	Mean of all significance rating	Temporary weights	Final weights	Modified Weights
DO	1.4	1.0	0.17	0.31
FC	1.5	0.9	0.15	0.28
pH	2.1	0.7	0.12	0.22
BOD	2.3	0.6	0.1	0.19
Total			0.54	1.00

Table 4.10: Classification of water quality according to CPCB-WQI

S. No.	CPCB-WQI Range	Category	Class by CPCB
1	63-100	Good to excellent	A
2	50-63	Medium to good	B
3	38-50	Bad	C
4	<38	Bad to very bad	D & E

4.5 Geographical information system (GIS) integration

All geographic and spatial aspects of the development and management of water resources require using GIS with remote sensing and mapping (Rawat and Singh, 2018; Hussain and Abed, 2019). These methods offer strong analytical and visualization tools that can be used to describe, examine, and simulate the processes and functions of natural systems. Additionally, experimenting with satellite image processing and cross-referencing with field data can produce a different and precise parameter detection method. The benefit of merging satellite image analysis with field data concerning evaluating the precision of water quality detection has been highlighted by several authors (Bouaziz et al., 2011; Morshed et al., 2016). The development of interpolate techniques and spatial analysis modeling has been the subject of substantial research. These techniques span from analytical to semi-empirical ways of calculating and creating quantitative or qualitative water maps (Chabuk et al., 2020). Water quality Indices (WQIs) in conjunction with GIS can overcome most of the problems mentioned above. They can be used to specify the status of the water, even though mathematical modeling of river water quality needs more hydraulics and hydrodynamics data and wide validation (i.e., excellent, good, bad, etc.) (Rawat and Singh, 2018; Madhloom and Alansari, 2018; Zhang, 2019). Other mathematical models can be connected with this application to provide significant outputs relevant to many scientific and environmental domains. The GIS has geographical analytic tools to handle vast data (Madhloom and Alansari, 2018).

4.5.1 GIS maps using the interpolation method

The river Gomti's water quality index maps were made using ArcGIS 10.4 software. The interpolation map for each water quality metric for 2013 through 2017 for the river Gomti was created using the inverse distance weighted (IDW) interpolation method.

The interpolation in GIS software was carried out based on the maps of the river Gomti in the shapefiles. The IDW is a method that primarily applies Waldo Tobler's first law of geography (El-Zeiny and Elbeih, 2019; Paul et al., 2019, Chabuk et al., 2020). The accurate local deterministic interpolation approach is the foundation of the IDW method. The interpolation method (IDW) calculates the average distance from known sites to those near the unknown points to estimate the unknown values at a given place (Ali et al., 2021). In the IDW, the projected values will be affected more by the points closer to the forecasted site than by the points farthest from it (Panhalkar and Jarag, 2015). This study used this process to construct interpolation between the chosen points or locations within the range of the minimum and maximum values for each parameter. IDW is thought to be more appropriate than other approaches (such as kriging and Topo to raster), which produce an interpolation for the chosen points with more variance, according to Panhalkar and Jarag (2015), El-Zeiny and Elbeih (2019) and Paul et al. (2019). The weighted distance between measured and unknown sites is used in ArcGIS 10.4 IDW's interpolation method to project the values of each. The weights have an inverse relationship with the measurement's distance from the power value, p. The default value for the ArcGIS platform is 2, which is the parameter p set in this study. The following is the mathematical formula used by IDW to forecast an unknowable value (Chabuk et al., 2020; Ali et al., 2021):

$$Zp = \frac{\sum_{i=0}^{n} \frac{z_i}{d_i^p}}{\sum_{i=0}^{n} \frac{1}{d_i^p}} \tag{4.15}$$

Zi is the value of the measured site, Zp is the value of an unknown point, di is the distance from the known position, and p is the chosen exponent.

4.6 Assimilative capacity

About 80% of all wastewater, according to the 2018 wastewater report from the International Water Association (IWA), is released into rivers throughout the world, where it poses threats to human health, the environment, and the climate and can alter the waterways' Assimilative Capacity (AC). For water resources to be managed effectively, it is crucial to understand the effects of wastewater discharges on them.

Hydrodynamic and WQMs are crucial tools for studying these impacts, typically based on water sources' assimilation capacity (Villota-Lopez et al., 2021). The term "Assimilative Capacity" describes a water body's innate capability to self-cleanse and/or self-repair, either through the dilution and/or dispersion of waste and pollution without endangering the aquatic environment. Additionally, it can show the maximum amount of pollutants that can accumulate, be destroyed, changed, and transmitted outside of the ecosystem's volume without interfering with its regular activity or the amount of controllable pollutants that can be added to each water flow in a river (Kulikova et al., 2018). Through this research, it is crucial to comprehend how the discharges' volumes and concentrations affect the river Gomti assimilative capacity and under what circumstances because this ability enables a natural treatment of wastewater in rivers (Egbe et al., 2018). In particular, saturation DO and BOD are well-known indicators of river water quality and are regarded as standard indicators of assimilative capacity (Rajesh and Rehana, 2022).

Water quality research and modeling have been utilized for assimilative capacity analysis in various water bodies. The creation of monitoring programs in water bodies incorporates statistical analysis of river and discharge flows with concentrations of water quality parameters. Water quality forecasting is the most widely used technique to estimate assimilative capacity (Gurjar and Tare, 2019; Quinn et al., 2021). Another popular technique is simulating scenarios where certain water quality thresholds are violated (Novo, 2017; Villota-Lopez et al., 2021). This research mostly predicted the DO and BOD values for 2018 to 2027 using the time series prediction approach. These values have also been compared to the specified designated best use (Source IS 2296:1992) of water quality for managing the river Gomti's water quality.

Primary water quality criteria are a few chemical traits that the CPCB has defined as the minimum standards for water quality in India. Additionally, the standard IS 2296:1992 from the Bureau of Indian Standards includes recommendations for water quality parameters for various uses (Table 4.11).

Table 4.11: Water quality standards in India (Source IS 2296:1992)

Characteristics	**Designated best use**				
	A	**B**	**C**	**D**	**E**
Dissolved Oxygen (DO) mg/l, min.	6	5	4	4	-
Biochemical Oxygen demand (BOD) mg/l, max.	2	3	3	-	-

4.7 Statistical modeling (Water quality)

WQMs can be used to achieve effective and efficient river system management. WQMs help validate pollutant load estimates, establish cause-and-effect relationships between various polluting sources and water quality, and evaluate how the river system would respond to multiple management scenarios (Wang et al., 2021).

To keep the pollution levels within acceptable ranges, the prediction of river water quality is essential for effective basin management. The water quality can be modeled utilizing hydrochemical data, linear regression and structural equations, predictability, trend, and time-series analysis (Seth et al., 2013; Parmar and Bhardwaj, 2014, 2015). Water quality managers employ analytical techniques like regression equations to compare present water quality levels with predetermined requirements (Ravikumar et al., 2013; Parmar and Bhardwaj, 2014, 2015). The time series prediction method is used in the study for the forecasting of all four assessed WQIs. It has two main advantages:

- It is the simplest method available, and it is based on historical trends in water quality change that have followed the same course without structural modifications;
- Predicts water quality without considering variables that affect how it will change (Parmar and Bhardwaj, 2014; Ghashghaie et al., 2018).

R-Squared and Stationary R-Square, Root Mean Square Error, Mean Absolute Percentage Error, Mean Absolute Error, Maximum Absolute Percentage Error, Maximum Absolute Error, Normalized Bayesian Information Criterion, Ljung-Box Q(18), and using Statistical analysis, Time series analysis, Auto-Regressive Integrated Moving Average, Autocorrelation Function and Partial Autocorrelation Function has been estimated to analyze trend and prediction of water quality.

4.7.1 R-Squared and Stationary R-Squared

R-squared is the proportion of the variance for a dependent variable that measures how much the model can describe the total variance in a series when it is stationary. When a pattern follows a trend or a seasonal cycle, the stationary R-squared is favored over the ordinary R-squared. This is because the stationary section of the model is compared to a basic mean model using the stationary R-squared. Positive, negative, or zero stationary R-squared values are possible. Positive values mean the present model outperforms the baseline model. In the current model, positive numbers indicate better than the baseline model (Box et al., 2008; Parmar and Bhardwaj, 2014, 2015).

4.7.2 Root Mean Square Error

The Root Mean Square Error (RMSE) is a commonly used measure of value differences. It determines how far a dependent series differs from the predicted level (Box et al., 2008; Parmar and Bhardwaj, 2014, 2015). The RMSE of an estimator in terms of the estimator parameter is calculated using equation 4.16.

$$RMSE\ (\theta) = \sqrt{E[(\theta - \theta)^2]} \qquad 4.16$$

4.7.3 Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) is a metric for how far a dependent series deviates from its modeled level. It does not matter what units are used; therefore, it may be used to relate series with different units (Box et al., 2008; Parmar and Bhardwaj, 2014, 2015). Accuracy is given as a percentage;

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} | \frac{Ai - Fi}{Ai} | \qquad 4.17$$

Where, Ai - actual value and

Fi - predicted value.

MAPE = zero (for perfect fit), but it has no restrictions at the upper level.

4.7.4 Mean Absolute Error

The Mean Absolute Error (MAE) is a metric that measures how far a series differs from the level that its model anticipated. It is expressed in the same units as the original series. In addition, the MAE is a metric for determining how far forecasts or projections differ from the final result. It is provided by;

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} |\mathrm{F_i} - \mathrm{A_i}| = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} |\mathrm{e_i}| \qquad 4.18$$

The absolute error is e_i, the prediction is F_i, and the determined value is A_i. In time-series analysis, it is a typical measure of forecast error (Box et al., 2008; Parmar and Bhardwaj, 2014, 2015).

4.7.5 Maximum Absolute Percentage Error

The Maximum Absolute Percentage Error (MaxAPE) measures the highest anticipated error. It imagines a forecasted worst-case scenario (Box et al., 2008; Parmar and Bhardwaj, 2014, 2015).

4.7.6 Maximum Absolute Error

The Maximum Absolute Error (MaxAE) is a metric that estimates the biggest anticipated error in the same units as the series it relies on. It is possible to imagine the worst-case scenario while making forecasts. MaxAE and MaxAPE may occur at separate times throughout the series. When a large series value's absolute error is marginally higher than a small series value's absolute error, the maximum absolute error and maximum absolute percentage error occur at the smaller series value (Box et al., 2008; Parmar and Bhardwaj, 2014, 2015).

4.7.7 Normalized Bayesian Information Criterion

Normalized Bayesian Information Criterion (Normalized BIC) is an overall measure of a model's fit that accounts for its complexity. It's a score based on the mean square error that considers the model's number of parameters and the length of the series (Box et al., 2008; Parmar and Bhardwaj, 2014, 2015).

$$\mathrm{BIC} = \chi^2 + \mathrm{k}.\ln(\mathrm{n}) \qquad 4.19$$

It is used to assess the constant (k). It considers the performance of a parameterized model in terms of its ability to forecast data and penalizes the model's complexity, which is defined as the total number of parameters it contains.

4.7.8 Time series analysis

It collects data points taken at regular intervals and often at successive times. Future projection methods are based on known previous events to predict data points before they are observed and included in the realm of time-series analysis. The time-series model considers that observations closer in time to one another are more tightly connected than those further apart in Time-series models. On the other hand, they are typically defined by a natural one-way ordering of time, which means that the values for a current period are derived from prior values instead of future values (Lu et al., 2014; Parmar and Bhardwaj, 2014, 2015; Luo et al., 2019).

4.7.8.1 Auto-Regressive Integrated Moving Average

Three terms characterize the Auto-Regressive Integrated Moving Average (ARIMA) model of a time series (p, d, q). The technique of detecting integer, generally extremely small values as 0, 1, or 2 of model patterns p, d, and q in data is known as time series identification. When the value is 0, the element in the model is no longer necessary. The middle element, d, is studied before p and q. Before settling on the values of p and q, the objective is to ascertain whether the process is stationary and, if not, to make it stationary. A stationary process has a consistent mean and variation across the research period. AR (p) represents the time series of an autoregressive model (Box et al., 2008; Parmar and Bhardwaj, 2014, 2015; Luo et al., 2019), and is defined as;

$$\mathrm{Yt} = \propto_0 + \propto_1 \mathrm{Y}_{t-1} + \propto_2 \mathrm{Y}_{t-2} + \cdots + \propto_p \mathrm{Y}_{t-p} + \varepsilon_t \qquad 4.20$$

Where the term ε_t is a source of randomness referred to as white noise, αi denotes constants. It is supposed that it possesses the following characteristics:

$$\mathrm{E} = [\epsilon_t] = 0,$$
$$\mathrm{E} = [\varepsilon_t^2] = \sigma^2,$$
$$\mathrm{E}[\varepsilon_t \varepsilon_s] = 0 \text{ for all } t \neq s$$

Because autoregressive and moving average components might coexist in a series, both forms of correlations are necessary to model the patterns. To understand this, if both elements are present only at lag 1, consider the linear equation;

$$y_t = x_t \beta + \varepsilon_t \qquad 4.21$$
$$\varepsilon_t = \rho \varepsilon_{t-1} + v_t \qquad 4.22$$

Where -1< p < 1 and v_t is dependent and identically distributed (iid) and from expectation values;

$$E(v_t, v_{t-1}) = 0 \quad 4.23$$

In this approach, the disturbance follows a first-order autoregressive model (AR1) process. As a result, the present error mixes the previous error plus some shock. As a result, the equation may be rewritten as follows:

$$y_t = x_t\, \beta + \rho\varepsilon_{t-1} + v_t \quad 4.24$$

Also, we know that

$$y_{t-1} = x_{t-1}\beta + \varepsilon_{t-1} \quad 4.25$$

$$\varepsilon_{t-1} = y_{t-1} - x_{t-1}\beta \quad 4.26$$

From Eq. (4.24) $y_t = x_t\beta + \rho(y_{t-1} - x_{t-1}\beta) + v_t$

$$y_t = x_t\beta + \rho y_{t-1} - \rho x_{t-1}\beta + v_t \quad 4.27$$

4.7.8.2 Auto Correlation Functions and Partial Auto Correlation Functions

Auto Correlation Functions (ACF) and Partial Auto Correlation Functions (PACF) analysis are necessary to find an appropriate model for a given time series data. The link between the data in a time series is reflected in these statistical metrics. Plotting the ACF and PACF across consecutive time lags is typically beneficial for modeling and forecasting (Parmar and Bhardwaj, 2015; Ghashghaie et al., 2018). The sequence of AR and MA phrases can be determined using these plots. This may be represented as:

For a time series {x(t), t=0,1,2, ….} at lag k the autocovariance is defined as;

$$\gamma k = Cov(xt, xt+k) = E[(xt - \mu)(xt+k - \mu)] \quad 4.28$$

at lag k, the autocorrelation coefficient is defined as;

$$\rho_k = \frac{\gamma_k}{\gamma_0} \quad 4.29$$

The mean of the time series is μ equal to E [x t]. The time-series variance is the autocovariance at lag zero, i.e., γ0. The autocorrelation coefficient k is dimensionless;

hence it is unaffected by the measurement scale, -1≤ ρk ≤ 1. Statistics Box and Jenkins referred to yk as the theoretical autocovariance function (ACVF), and ρ_k was called the theoretical autocorrelation function (ACF).

After allowing for data at intermediate delays, the partial autocorrelation function (PACF) is used to assess the correlation between an observation k periods ago and the current observation (i.e., at lags k). PACF (1) and ACF (1) are similar at lag 1.

The real or theoretical ACF and PACF values cannot be established since the stochastic process underlying a time series is unknown. Instead, these values should be derived from the training data, the most recent time series available. The sample ACF and PACF values are the estimated values of the ACF and PACF, respectively, based on the training data. At lag k, the most credible sample estimate for the ACVF is;

$$c_k = \frac{1}{n}\sum_{t=1}^{n-k}(x_t - \mu)(x_{t+k} - \mu) \qquad 4.30$$

Then the estimate for the sample ACF at lag k is given by;

$$r_k = \frac{c_k}{c_0} \qquad 4.31$$

Here, {x(t), t=0,1,2, ….} is the training series of size n with mean μ.

4.8 Effect of temperature change on river water quality

River water quality indicators like DO and WT serve as crucial signals for determining the ecosystem's health in a river water body (Chapra et al., 2021). Climates that are warming up have a negative effect on WT when different defining climatological variables, primarily AT, are intensified (Van Vliet et al., 2013). Since most river water quality standards depend on such saturation levels, intensifying WT will have negative effects in terms of a decline in river DO saturation levels (Van Vliet et al., 2013). In particular, saturation DO is a notable indicator of river water quality and is regarded as a standard indicator of pollution (Rajesh and Rehana, 2022). Deterioration of water quality and ecological distortion may result from the impact of climate change on DO in relation to WT (Svendsen et al., 2016; Danladi Bello et al., 2017). Every change in WT reduces the river's capacity to self-purify by reducing the quantity of oxygen that can be dissolved and used for biodegradation because WT is inversely related to DO concentration (Khani and Rajaee, 2017; Kauffman, 2018). Therefore, knowing the expected river water quality and potential changes in quality standards under climate change warming signals heavily relies on understanding climate change influences on WT and saturation oxygen concentration.

The climate model employed in the study was the projections by the climate model of the Coupled Model Intercomparison Project Phase 5 (CMIP5), which is based on several uniform forcing scenarios known as Representative Concentration Pathways (RCPs). Each scenario represents a time series of emissions and concentrations of the full range of GHGs, aerosols, and chemically active gases throughout the twenty-first century, along with changes in Land Use Land Cover (LULC), and is characterized by the Radiative Forcing (A measure of an imbalance in the Earth's energy budget brought on by natural (such as volcanic eruptions) or human-induced (such as GHG from fossil fuel combustion) changes) in the year 2100 (IPCC, 2013). The two most often considered scenarios in this study are "RCP 4.5" (an intermediate stabilization route that produces a Radiative Forcing of 4.5 W/m^2 in 2100) and "RCP 8.5" (a high concentration pathway that produces a Radiative Forcing of 8.5 W/m^2 in 2100).

Assessment of climate change over the Indian region (Krishnan et al., 2020) provided the simulated daily minimum, mean, and maximum AT for 1970–2100. The averaged worldwide and over India temperature and precipitation forecasts from the CMIP5 models are summarised in Table 4.12.

Table 4.12: Change in surface air temperature (TAS, °C) for the Indian region for the historical (1951-2014), near future (2040-2069), and far future (2070-2099) periods for the RCP 4.5 and RCP 8.5 scenarios from the CMIP5 models

Variables	**Estimates from CMIP5 (base period 1850-1900)**				
	Indian region estimates				
	Historical	**RCP 4.5**		**RCP 8.5**	
Period	**1951-2014**	**2040-2069**	**2070-2099**	**2040-2069**	**2070-2099**
TAS (^{0}C)	0.72 (0.47 to 1.28	2.67 (1.72 to 3.70)	3.27 (2.25 to 4.27)	3.37 (2.32 to 4.68)	5.33 (3.70 to 6.11)

4.8.1 Relating air temperature, water temperature, and water quality index

A relationship between AT, WT, and water quality index is developed to obtain WT and water quality index for RCP 4.5 and RCP 8.5 scenarios. Linear regression analysis of the past time series data is carried out to relate AT to WT and WT to WQI. Mean monthly WT data for 1998-2017 along the Gomti River was obtained from CWC (Lucknow) of the sampling station at Lucknow. Based on the latitude and longitude information of the CWC (Lucknow) sampling station (Hanuman Setu), the corresponding mean monthly AT data for the corresponding years 1998-2017 were obtained from the NASA POWER (Prediction of Worldwide Energy Resources) AT data (https://power.larc.nasa.gov/). The AT data used for the present study was obtained from the Climate of Lucknow-IMD (https://mausam.imd.gov.in/lucknow/mcdata/climatology_lucknow.pdf), i.e., $40^{O}C$ (Highest mean temperature over Lucknow). Linear regression analysis is carried out by fitting the data into different regression models available in Microsoft Excel-2016 and IBM SPSS Statistics 26 to determine the most reliable relationships of the above data.

4.8.2 Bascaron WQI (BWQI)

The water quality index is anticipated to alter as river WT rises due to climate change, and these changes must be measured (El-Jabi et al., 2014). Bascaron WQI (BWQI) originated in Spain (Bascaron, 1979) and is now widely used throughout the world (Pesce and Wunderlin, 2000; Debels et al., 2005; Kannel et al., 2007; Massoud, 2012; Ismail and Robescu, 2019). The overall index is estimated to be a subjective water quality index (Eq. 4.32).

$$\mathrm{BWQI} = \mathrm{k}\frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{CiPi}}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{Pi}} \qquad 4.32$$

Where, n = the total number of variables,

Ci = after normalization value given to the variable i,

Pi = relative weight given to each parameter (value ranged between 1 and 4 according to its importance and influence on the water quality (4 for highest impact and 1 for less impact),

k = subjective constant, which represents the visual impression of river pollution. k could have a value of 0.25, 0.5, 0.75, or 1.

Pesce and Wunderlin (2000) provide the fundamental standards by which one of these values should be chosen. But in this study, k was set to 1 to only take into consideration differences caused by measured factors (Kannel et al., 2007; Pesce and Wunderlin, 2000; Ismail and Robescu, 2019), (Eq. 4.33):

$$\mathrm{BWQI} = \frac{\sum_{i=1}^{n} \mathrm{CiPi}}{\sum_{i=1}^{n} \mathrm{Pi}} \qquad 4.33$$

Pesce and Wunderlin (2000) utilized DO, turbidity, and conductivity to determine the water quality using the minimum possible parameters and derived the minimum water quality index (Kannel et al., 2007; Massoud, 2012). Three water quality parameters – WT (P= 4), DO (P= 1), and BOD (P= 1) were included in the evaluation process in the current study because of their significance on the impact of rising temperatures on water quality. DO is a key factor for aquatic life and plants and is a barometer for river health. WT affects the availability of oxygen concentration in the water, besides its effects on rates of chemical and biological processes. BOD include a wide variety of material such as decaying plant and animal matter, industrial waste, and sewage, which, after decomposition by bacteria, results in oxygen demand.

The final BWQI was created using the normalization factors and their relative weights adopted from various literature for the selected parameters: Pesce and Wunderlin (2000), Cude (2001), Debels et al. (2005), Sanchez et al. (2007), Kannel et al. (2007), Massoud (2012) and Ismail and Robescu (2019). The classification system used to categorize the water quality was proposed by Dojlido et al. (1994) and Pesce and Wunderlin (2000). As per this classification system, BWQI is in the range of 0-25 (very bad), 26-50 (bad), 51-70 (medium), 71-90 (good) and 91-100 (excellent).

CHAPTER - 5

RESULTS AND DISCUSSION

5.1 General

Water comprises the main factor governing the processes, functions, and attributes of the river ecosystem. Water quality characteristics of rivers arise from a massive amount of physical, chemical, and biological interactions. Deterioration in the water quality of the river Gomti is attributed to the increasing human pressures for agricultural, domestic, and industrial needs. A lot of importance has been given to monitoring the water quality of rivers in the country to determine the causative factors responsible for their deterioration, as well as identifying the most polluted river stretches in the country. The focus of the present study is to formulate a water quality management plan in reference to assimilative capacity and climate change (impact of rising temperature) by identification, quantification, and characterization of selected pollutants of the river Gomti, which passes through Lucknow (UP). Descriptive and multivariate statistical approaches were used to investigate further the multifarious nature of the water quality data sets. Seasonal and spatial variation in the dataset was analyzed using one-way ANOVA. Simultaneously, the four most suitable WQIs based on data received were used to assess the water quality of river Gomti, followed by its integration with GIS to mark out different zones based on the magnitude of pollution. Statistical modeling was used to predict these four indices for river Gomti, which would facilitate future predictions of WQIs and assessment of the assimilative capacity of water quality variables in the river.

5.2 Water quality assessment (Biological and physicochemical parameters)

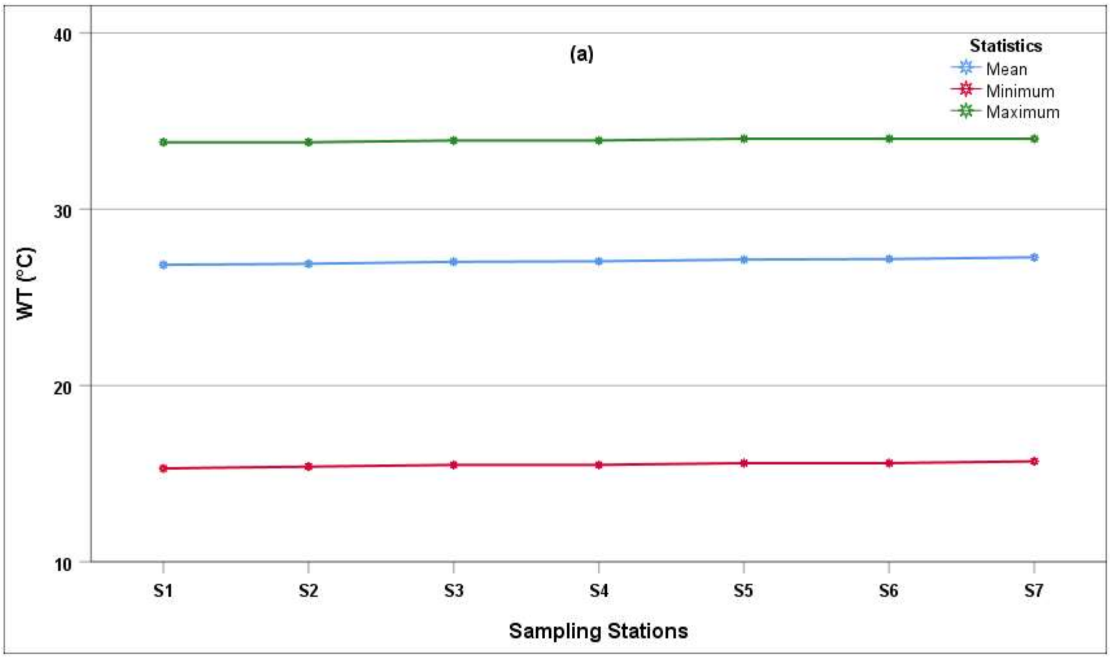
Assessment of the water quality of the river Gomti in the selected study stretch is done monthly for five consecutive years (2013-2017) in terms of its biological and physicochemical parameters. The term “water quality” is an extensively used expression with an enormously wide spectrum of meanings. From the user's perspective, this phrase refers to those chemical, physical, and biological qualities we use to assess the appropriateness of water. A freshwater body's physical and chemical characteristics indicate the climatic, geochemical, geomorphological, and pollution conditions (largely), mainly in the drainage basin and the primary aquifer. Therefore, assessing the physical, chemical, and biological parameters of the river water quality is essential. Sampling stations wise descriptive statistics of biological and physicochemical parameters of the river Gomti during 2013-2017 are presented in Table 5.1.

5.2.1 Water temperature (WT)

It is a measurement of the average kinetic energy of water molecules. WT is one of the fundamental physical parameters of water quality assessment because it influences the chemical, biochemical, and biological characteristics of the water body (Singh et al., 2018; Kumar et al., 2022b). It affects the rate of chemical as well as biochemical reactions, DO concentrations, and other dissolved gas levels in the water and EC. As WT increases, EC and the rate of chemical reactions increase, and the amount of dissolved gases decreases (Kumar et al., 2021b). Higher WT increases the solubility of harmful substances in water and affects aquatic organisms' tolerance limits. It also affects the photosynthesis of aquatic plants. Sunlight, air temperature, runoff, thermal pollution, and human activities (dams, weirs) are some factors that affect WT (Singh et al., 2018).

In the present study, the WT was found to be vary from 15.3ºC to 33.8ºC with a mean of 26.9ºC at S1, 15.4ºC to 33.8ºC with a mean of 26.9ºC at S2, 15.5ºC to 33.9ºC with a mean of 27.0ºC at S3, 15.5ºC to 33.9ºC with a mean of 27.1ºC at S4, 15.6º C to 34.0ºC with a mean of 27.2ºC at S5, 15.6ºC to 34.0ºC with a mean of 27.2ºC at S6 and from 15.7ºC to 34.0ºC with recorded mean value as 27.3ºC at S7 during 2013-2017 which lies within the WHO's range (40ºC) (Figure 5.1). No permissible limit of WT has been acknowledged by the IS: 2296:1992 and IS: 10500:2012.

The WT observations revealed minimal spatial variance ($p>0.05$) between the monitoring stations. The limited range of latitude along the Gomti River may have contributed to this outcome (Jaiswal et al., 2019). During the study period, June and January had the highest and lowest WTs, respectively. Sharma et al. (2020) observed a comparable value and trend in the Yamuna River, and Kumar et al. (2021c) and Kumar et al. (2022a) in the Gomti River. WT typically varies daily and seasonally with AT. Although surface water bodies can function as a temperature buffer, the restricted temperature tolerance of aquatic organisms means that even slight changes in WT can greatly influence river ecosystems. River WT is significantly affected by high sewage flows and religious ceremonies near the riverbed (Singh et al., 2018).



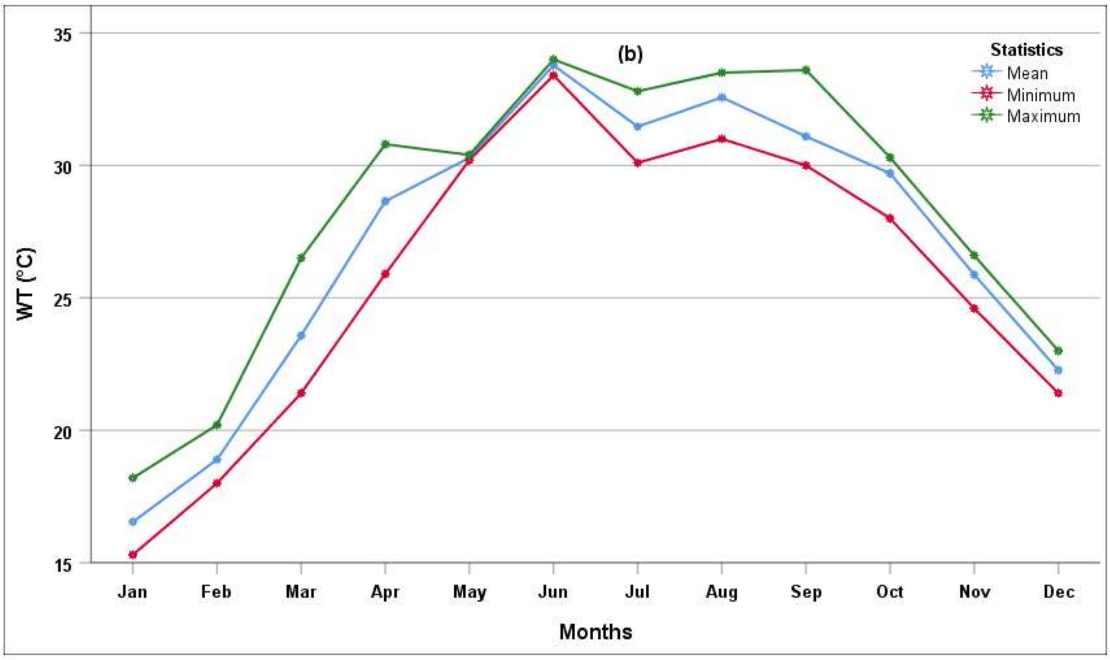


Figure 5.1: Variation of WT for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

5.2.2 pH

The pH of the solution is the negative logarithm of hydrogen ion activity at any given temperature. It is the indicator of the acidic and alkaline nature of the water (Sallam and Elsayed, 2018; Jaiswal et al., 2019). pH of an aquatic body is a significant indicator of the water quality as it influences the biological as well as chemical processes.

Table 5.1: Location-wise descriptive statistics of biological and physicochemical parameters

	WT	pH	EC	TDS	TA	TH	Ca	Mg	Cl	DO	BOD	COD	TC	FC
S1														
Mean	26.85	8.22	384.47	231.37	216.20	196.77	40.17	23.17	13.05	6.81	4.19	14.89	2618	1468
Median	30.00	8.29	388.40	233.00	228.00	206.00	40.80	23.52	13.00	6.90	3.00	14.80	2600	1400
Mode	30.00	8.29	336.00	184.00	228.00	228.00	38.40	25.92	13.00	2.80	2.90	15.20	2800	1100
Minimum	15.30	7.20	172.00	112.00	142.00	120.00	24.80	12.48	8.00	2.80	2.30	12.40	1400	700
Maximum	33.80	8.89	560.20	332.00	252.00	236.00	49.60	29.28	17.00	11.40	11.00	18.40	4000	2700
Range	18.50	1.69	388.20	220.00	110.00	116.00	24.80	16.80	9.00	8.60	8.70	6.00	2600	2000
SD*	5.52	0.36	93.80	47.21	30.07	30.16	6.23	3.89	1.73	2.57	2.57	1.14	587	459
Kurtosis	-0.83	0.86	-0.69	0.11	-0.07	-0.13	-0.47	0.45	0.45	-0.80	2.06	0.50	-0.11	0.79
Skewness	-0.64	-0.77	-0.17	-0.10	-0.90	-0.79	-0.53	-0.74	-0.10	-0.13	1.89	0.48	0.45	0.99
CoV*	0.21	0.04	0.24	0.20	0.14	0.15	0.16	0.17	0.13	0.38	0.61	0.08	0.22	0.31
S2														
Mean	26.91	8.12	397.10	240.83	224.20	202.70	41.49	23.97	14.53	7.26	3.41	18.99	4015	2595
Median	30.00	8.21	413.80	240.00	236.00	212.00	41.60	24.24	14.00	6.70	3.30	18.80	3950	2400
Mode	30.20	8.54	348.00	192.00	236.00	232.00	49.60	25.92	14.00	6.50	3.30	17.60	3500	2200

	WT	pH	EC	TDS	TA	TH	Ca	Mg	Cl	DO	BOD	COD	TC	FC
Minimum	15.40	7.17	180.80	118.00	148.00	128.00	25.60	13.44	11.00	2.90	3.10	13.60	2400	1300
Maximum	33.80	8.58	582.40	346.00	264.00	244.00	49.60	30.24	19.00	10.90	4.20	24.80	7000	4900
Range	18.40	1.41	401.60	228.00	116.00	116.00	24.00	16.80	8.00	8.00	1.10	11.20	4600	3600
SD*	5.51	0.32	98.92	49.84	29.34	31.70	6.24	3.98	1.86	2.13	0.24	2.19	1047	804
Kurtosis	-0.83	1.08	-0.43	0.03	0.36	-0.21	-0.53	0.17	-0.54	-0.77	1.51	0.25	1.42	1.51
Skewness	-0.64	-1.05	-0.26	-0.08	-1.01	-0.80	-0.55	-0.62	0.31	0.23	1.23	0.45	0.92	1.00
CoV*	0.20	0.04	0.25	0.21	0.13	0.16	0.15	0.17	0.13	0.29	0.07	0.12	0.26	0.31
S3														
Mean	27.02	7.87	450.83	274.23	233.47	211.97	43.23	25.11	16.72	5.02	5.19	28.14	15953	11710
Median	30.10	7.83	440.40	255.00	244.00	220.00	44.00	25.68	16.00	5.05	4.60	27.40	9400	4900
Mode	30.30	7.82	364.00	270.00	258.00	236.00	49.60	26.88	15.00	3.50	4.00	28.80	7000	4900
Minimum	15.50	7.11	201.00	128.00	156.00	134.00	27.20	14.40	12.00	0.70	3.60	18.80	4900	2600
Maximum	33.90	8.38	772.50	482.00	272.00	256.00	53.60	32.16	22.00	9.50	9.00	44.80	40000	34000
Range	18.40	1.27	571.50	354.00	116.00	122.00	26.40	17.76	10.00	8.80	5.40	26.00	35100	31400
SD*	5.53	0.29	147.98	84.81	30.57	31.90	6.22	4.21	2.39	2.41	1.49	5.94	11643	10009
Kurtosis	-0.84	0.35	-0.20	0.56	0.16	-0.27	-0.33	0.11	-0.59	-0.50	-0.32	0.78	-0.63	-0.41

	WT	pH	EC	TDS	TA	TH	Ca	Mg	Cl	DO	BOD	COD	TC	FC
Skewness	-0.64	-0.23	0.69	1.08	-0.95	-0.72	-0.64	-0.49	0.25	0.19	0.96	0.96	0.93	1.03
CoV*	0.20	0.04	0.33	0.31	0.13	0.15	0.14	0.17	0.14	0.48	0.29	0.21	0.73	0.85
S4														
Mean	27.05	7.80	469.44	286.53	240.33	218.80	44.75	25.82	18.42	4.36	6.39	34.49	30583	22655
Median	30.10	7.77	454.45	266.00	252.00	228.00	46.40	25.92	18.00	4.20	6.00	35.20	32000	22000
Mode	30.30	7.71	388.00	232.00	252.00	244.00	50.40	28.32	20.00	4.20	6.00	35.20	22000	22000
Minimum	15.50	7.04	212.00	136.00	162.00	140.00	28.80	15.36	13.00	1.30	4.50	24.40	13000	7900
Maximum	33.90	8.26	795.60	496.00	278.00	262.00	55.20	32.64	24.00	8.40	10.00	47.60	58000	43000
Range	18.40	1.22	583.60	360.00	116.00	122.00	26.40	17.28	11.00	7.10	5.50	23.20	45000	35100
SD*	5.50	0.25	148.77	85.77	30.75	32.14	6.56	4.14	2.59	1.74	1.48	5.49	10489	9382
Kurtosis	-0.81	1.43	-0.22	0.51	0.32	-0.23	-0.43	0.07	-0.73	-0.03	-0.18	0.37	0.07	-0.71
Skewness	-0.65	-0.53	0.60	1.03	-1.00	-0.78	-0.56	-0.45	0.12	0.55	0.92	0.58	0.62	0.44
CoV*	0.20	0.03	0.32	0.30	0.13	0.15	0.15	0.16	0.14	0.40	0.23	0.16	0.34	0.41
S5														
Mean	27.15	7.70	496.19	304.77	250.03	228.47	46.55	27.03	21.33	3.02	8.37	43.74	74933	48983
Median	30.20	7.70	474.60	282.00	260.00	238.00	47.20	27.36	21.00	2.80	8.50	44.80	70000	49000

	WT	pH	EC	TDS	TA	TH	Ca	Mg	Cl	DO	BOD	COD	TC	FC
Mode	30.30	7.69	426.00	274.00	268.00	254.00	53.60	28.32	24.00	3.20	8.50	44.80	70000	49000
Minimum	15.60	7.00	224.60	152.00	168.00	148.00	30.40	16.32	14.00	1.10	6.00	31.20	32000	22000
Maximum	34.00	8.15	858.50	538.00	286.00	274.00	56.00	33.60	27.00	6.00	11.50	56.40	110000	79000
Range	18.40	1.15	633.90	386.00	118.00	126.00	25.60	17.28	13.00	4.90	5.50	25.20	78000	57000
SD*	5.53	0.22	155.84	88.70	30.88	32.25	6.62	4.16	2.93	1.19	1.49	6.22	15050	13834
Kurtosis	-0.82	1.78	-0.19	0.61	0.45	-0.18	-0.47	0.18	-0.48	0.75	-0.86	-0.81	0.61	-0.22
Skewness	-0.64	-0.80	0.57	1.05	-1.04	-0.80	-0.55	-0.53	-0.16	1.07	0.25	-0.09	-0.09	0.26
CoV*	0.20	0.03	0.31	0.29	0.12	0.14	0.14	0.15	0.14	0.39	0.18	0.14	0.20	0.28
S6														
Mean	27.18	7.64	512.50	316.47	256.70	235.87	48.26	27.76	23.33	2.45	9.77	50.12	99450	67800
Median	30.20	7.64	489.10	293.00	266.00	244.00	48.80	28.32	23.00	2.10	10.00	49.60	94000	70000
Mode	30.30	7.62	456.00	290.00	282.00	258.00	56.00	28.32	25.00	3.00	10.00	51.60	94000	79000
Minimum	15.60	6.95	221.60	160.00	172.00	156.00	31.20	16.80	15.00	0.60	6.50	35.60	70000	33000
Maximum	34.00	8.09	882.60	554.00	298.00	282.00	59.20	34.56	29.00	5.10	12.50	60.80	130000	79000
Range	18.40	1.14	661.00	394.00	126.00	126.00	28.00	17.76	14.00	4.50	6.00	25.20	60000	46000
SD*	5.54	0.22	158.38	89.24	31.59	32.24	6.92	4.14	3.23	1.12	1.53	6.10	16377	13577

	WT	pH	EC	TDS	TA	TH	Ca	Mg	Cl	DO	BOD	COD	TC	FC
Kurtosis	-0.82	2.15	-0.24	0.58	0.46	-0.18	-0.58	0.30	-0.41	0.07	-0.80	-0.91	-0.42	-0.19
Skewness	-0.64	-0.94	0.47	0.97	-1.00	-0.80	-0.43	-0.48	-0.39	0.83	-0.16	-0.18	0.02	-1.04
CoV*	0.20	0.03	0.31	0.28	0.12	0.14	0.14	0.15	0.14	0.46	0.16	0.12	0.16	0.20
S7														
Mean	27.27	7.48	559.40	343.73	270.30	248.23	50.53	29.40	27.18	1.52	12.48	61.79	151033	108083
Median	30.30	7.50	513.50	314.00	278.00	258.00	52.00	29.04	28.00	1.20	13.00	63.60	150000	110000
Mode	30.80	7.43	489.00	342.00	296.00	258.00	56.00	30.24	29.00	1.00	13.00	63.60	170000	110000
Minimum	15.70	6.89	240.60	172.00	186.00	170.00	34.40	18.72	18.00	0.30	8.50	48.40	94000	49000
Maximum	34.00	7.82	984.20	616.00	316.00	294.00	64.00	36.00	33.00	3.80	18.60	70.80	240000	170000
Range	18.30	0.93	743.60	444.00	130.00	124.00	29.60	17.28	15.00	3.50	10.10	22.40	146000	121000
SD*	5.52	0.19	179.19	99.63	32.15	32.94	6.85	4.33	3.44	0.86	1.69	6.18	30930	28333
Kurtosis	-0.81	1.60	0.02	0.89	0.24	-0.29	-0.42	-0.22	-0.17	0.73	2.47	-0.33	0.47	-0.31
Skewness	-0.64	-0.92	0.59	1.03	-0.85	-0.75	-0.36	-0.40	-0.62	1.11	-0.07	-0.78	0.39	0.40
CoV*	0.20	0.03	0.32	0.29	0.12	0.13	0.14	0.15	0.13	0.57	0.14	0.10	0.20	0.26

*SD - Standard Deviation; CoV - Coefficient of variation

The photosynthesis activities in water affect the pH due to the assimilation of carbon dioxide and bicarbonates, which are eventually responsible for pH variation (Bhateria and Jain, 2016). Most aquatic organisms are extremely sensitive to pH because they have a narrow pH range (6.5-8.5) to survive and grow. Low pH (lower than 5) may cause the death of aquatic organisms, while a very high pH (greater than 9.5) can cause physical damage to the gills, exoskeleton, and fins of fish due to the conversion of nontoxic ammonia to toxic ammonia at high pH. Heavy metal (Pb, Cu, Cd etc.) solubility increases at low pH, causing more water toxicity. Variations in the pH of water within a certain range do not directly impact human consumption but are known to control other physicochemical characteristics of water that are attributed to altering the biotic composition of the system (Iqbal et al., 2019).

The pH of water depends on the water's source, soil types, bedrock, types of pollutions the water encounters in its path, etc. Water can dissolve geological formations (Limestone, calcium silicate, and feldspars), eventually affecting the pH (Jaiswal et al., 2019). The pH of the river water can be changed due to human activities like effluent pollutant discharge from industry, wastewater treatment plants, and mining quarries. The pH varies slightly daily due to photosynthetic activity (consumption of CO_2) in the daytime and respiratory activity at night (Omer, 2019).

All the sampling stations (S1–S7) recorded pH values ranging from 6.89-8.59, 6.89-8.86, 7.11-8.59, 7.23-8.59, and 7.23-8.89 for 2013, 2014, 2015, 2016, and 2017 respectively. The pH of the Gomti River water ranged from 6.89 to 8.89, indicating that it is either mildly acidic or alkaline. The pH levels of the Gomti River were reported to vary within the range of 6.22 to 8.6, as documented by Iqbal et al. in 2019. During the study period, the pH value decreased from S1 to S7. In the whole study period, the maximum pH value was recorded in the months of May and June at sampling station S1, and a minimum pH value was found in August at S7 (Figure 5.2). The slightly lower pH at this site can be attributed to inputs from wastewater in the adjacent areas. According to IS: 10500:2012 and WHO (2011), the permissible pH range is 6.5-8.5. Additionally, according to Class-C standards (IS: 2296:1992), the pH levels showed that the Gomti River water could be used for drinking after disinfection. A similar trend for pH was also reported by Kumar et al. (2021c) and Kumar et al. (2022a) while studying the Gomti River and by Suthar et al. (2010) while studying the Hindon River.

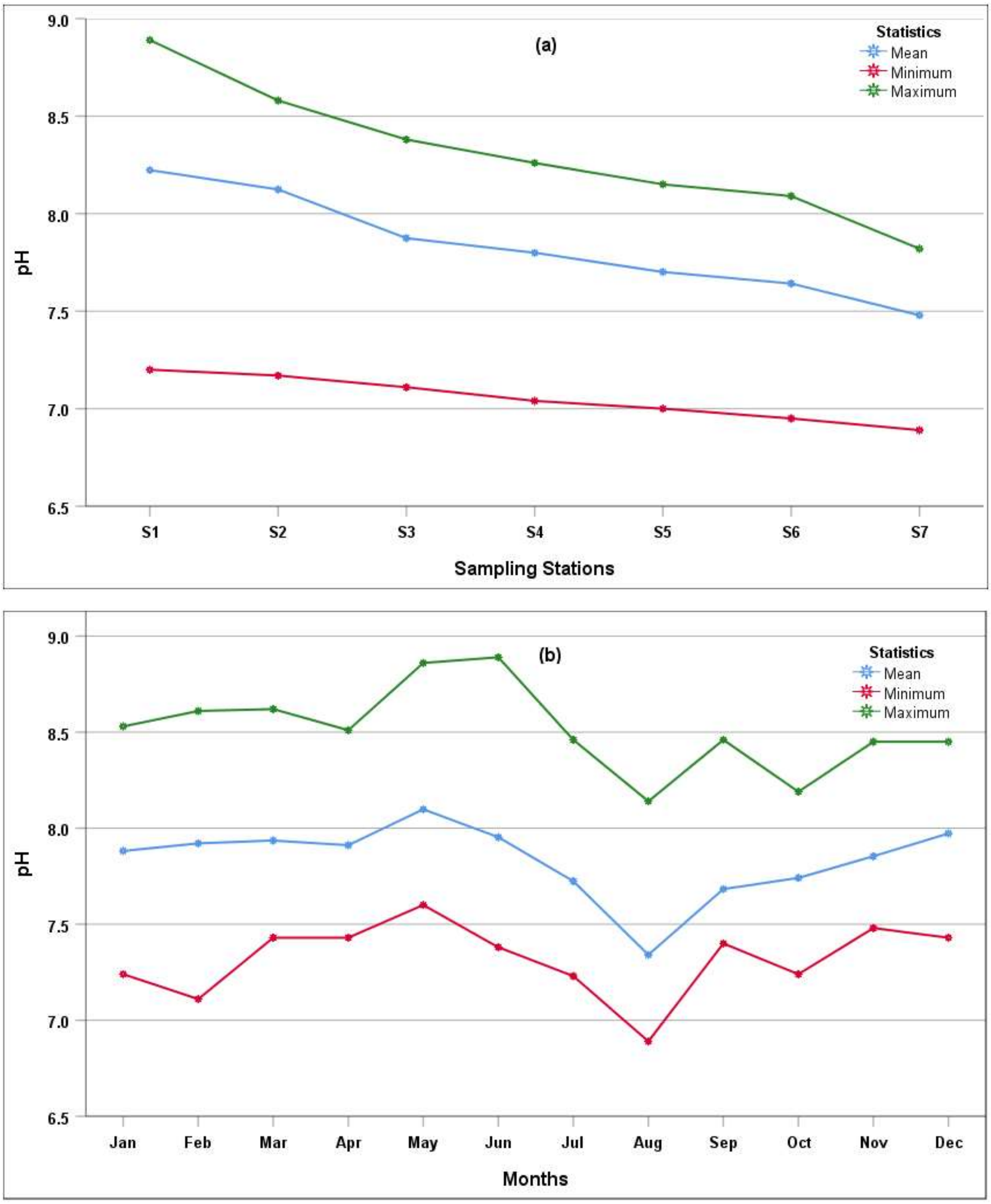
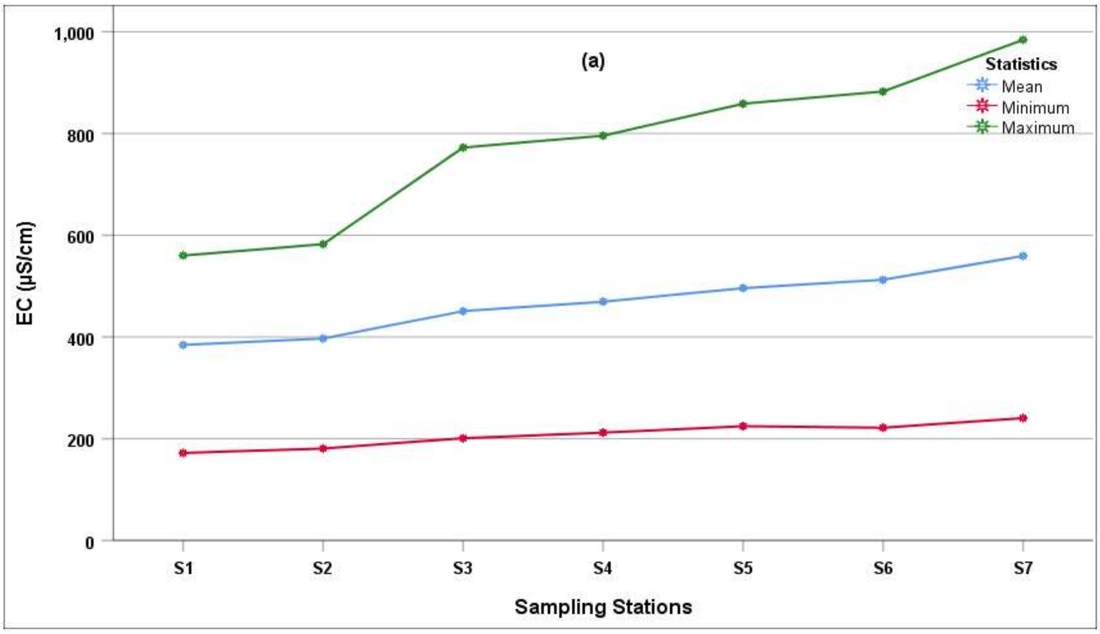


Figure 5.2: Variation of pH for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

5.2.3 Electrical conductivity (EC)

The EC of the water sample is a measurement of the ability of water to conduct an electrical current. It depends on the charged particles' concentration, and more charged particles increase the EC of water (Kamboj and Kamboj, 2019; Hamid et al., 2020). The EC in the water is determined by the presence of principal cations (Na^{+}, Ca^{+2}, K^{+}, and Mg^{+2}) and anions (Cl^{-}, SO_4^{-}, CO_3^{-2}, and HCO_3^{-}) (Jaiswal et al., 2019). Pure or distilled water has a low concentration and, thus, very low conductivity (Kumar et al., 2022b). The conductivity is prominently affected by the different types of dissolved substances in water, temperature, and the concentration of ions. EC is an essential indicator of water quality assessment because it directly influences the water used for drinking and irrigation purposes (Shah and Joshi, 2017). Water lacking the quality of irrigation might impede the growth of plants and may pollutes soil, making it less suitable for agriculture. High-conductivity water causes an unpleasant mineral taste and adversely impacts human health. Heavy metal ions released from pollutants also increase the conductivity of water. However, they make up a small portion of the conductivity. Nitrates (NO_3^{-2}) and phosphates (PO_4^{-3}) are extremely important for biological activity (Kamboj and Kamboj, 2019). EC is the measure that accounts for dissolved solids in the stream. A higher level of conductivity in the stream indicates the possible source of dissolved ions in nearby areas. It is thus considered an important parameter for locating areas exhibiting water quality problems (Hamid et al., 2020).

In this study at S1, S2, S3, S4, S5, S6, and S7, the EC was found in the range of 172.0-560.2 µS/cm, 180.8-582.4 µS/cm, 201.0-772.5 µS/cm, 212.0-795.6 µS/cm, 224.6-858.5 µS/cm, 221.6-882.6 µS/cm, and 240.6-984.2 µS/cm respectively, while the IS:10500:2012 standard is 300 µS/cm. Additionally, all sites that contained permissible limits of EC according to Class E (≤ 2250 µS/cm) were applicable for industrial cooling and irrigation (IS: 2296:1992). The EC values at station S1 are relatively low in this study. This could be owing to the land cover pattern here, which is semi-green, resulting in reduced topsoil erosion (Shah and Joshi, 2017). In the summer season, the EC values were highest at stations S6 and S7. This could be attributed to sewage discharges and anthropogenic activities near these stations' riverbanks. The sampling stations in the downstream region have greater EC values than those in the upstream. Iqbal et al. (2019), Kumar et al. (2021c), and Kumar et al. (2022a) found that the river Gomti has a similar value and trend. River Gomti noted low EC at the first two sampling stations (S1 and S2); this trend was maintained for all five consecutive years (2013-2017). A gradual increase in the EC concentration was observed in subsequent sampling stations and reached the maximum at S7 (Figure 5.3). This could be attributed to the mixing of sewage water into the stream as a number of drains, such as Kukrail Drain, G. H. Canal, Gomti Nagar Drain, Ghasiyari Mandi Drain, Wazirganj Drain, Nagaria Drain, and Sarkata Drain, were observed to fall into the river Gomti in this particular stretch. The Maximum value of EC was observed at S7 for the whole study period.



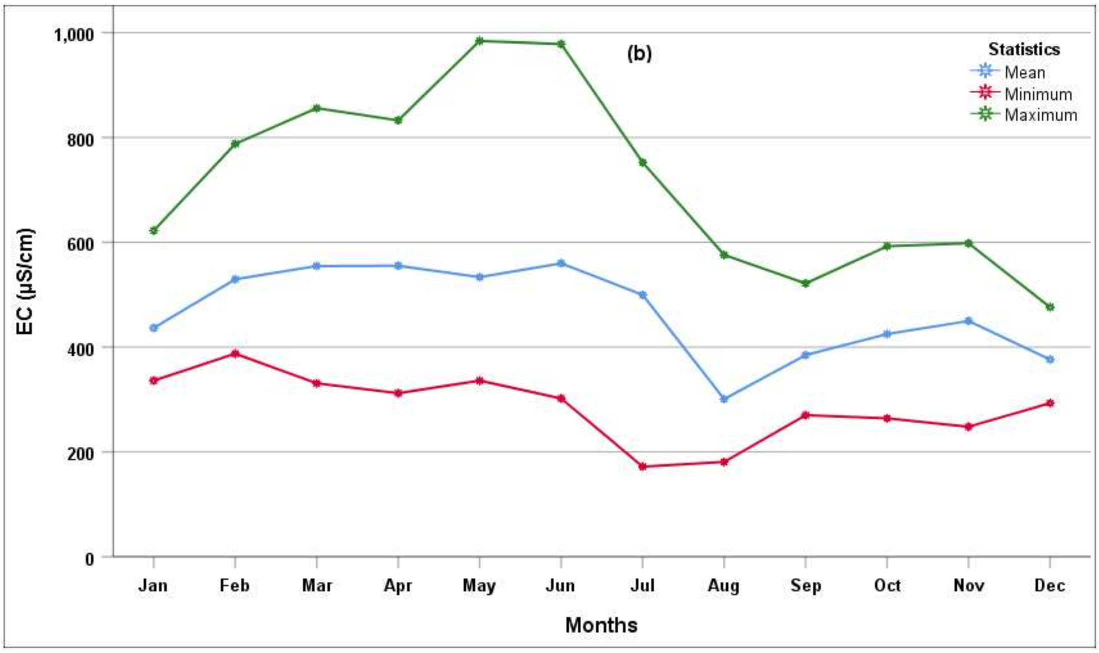


Figure 5.3: Variation of EC for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

5.2.4 Total dissolved solids (TDS)

TDS is a water quality parameter determining the concentration of solid dissolved material (organic and inorganic) in water. The values of EC and TDS are correlated. EC indirectly indicates the changes in TDS (Lkr et al., 2020). The primary components of TDS are carbonates, bicarbonates, chlorides, sulfates, phosphate, and nitrates of calcium, magnesium, sodium, potassium, iron, etc. (Kumar et al., 2021b). TDS consists of oxygen-demanding waste and disease-causing agents that can cause immense harm to public health as gastrointestinal irritation and the central nervous system, provoking paralysis, prickliness, and giddiness, even making it unsuitable for irrigation, mining, aquatic life, and industrial purposes (Gupta et al., 2017; Shah and Joshi, 2017). The source of TDS in river water can be natural (geological condition, surface runoff, and seawater) and anthropogenic (irrigation, wastewater discharge from domestic and industry, and sewage treatment plants) (Sallam and Elsayed, 2018). The high content of TDS in the water source increases the water density. It influences the osmoregulation of aquatic organisms and the BOD and COD, which deplete the DO levels in the aquatic ecosystem. Some dissolved inorganic elements such as nitrogen, phosphorus, and sulfur are also present in the river as essential nutrients for life. Because of nutritional shortages, aquatic organisms may not grow as much under low total solids concentrations (Kumar et al., 2022b).

During the study period from 2013 to 2017, TDS concentrations ranged from 112-332 mg/l, 118-346 mg/l, 128-482 mg/l, 136-496 mg/l, 152-538 mg/l, 160-554 mg/l, and 172-616 mg/l at S1, S2, S3, S4, S5, S6 and S7 respectively. TDS concentrations were under the desired range of 500 mg/l at S1, S2, S3, and S4 but exceeded at S5, S6, and S7, according to the IS: 10500:2012. The lowest TDS was found at S1, while the highest at S7. Downstream sites noted a higher level of TDS than the upstream sites (Figure 5.4). Continual increases from S1 to S7 are caused by the release of large volumes of solid waste, residential wastewater discharge, encroachment, and sewage in areas with high population density (Goel et al., 2018; Iqbal et al., 2019). Variation in TDS concentration was observed to be comparable with variation in EC. The Gomti River receives a lot of precipitation during the monsoon, possibly more than it can handle. This pattern supports the dilution effect and lowers the river's TDS concentration (Singh et al., 2004; Jaiswal et al., 2019). On the other hand, during the non-monsoon season, the river flow decreases, and certain short rivers dry up. As a result, non-monsoon had higher TDS than monsoon. The TDS measurements indicated that the river might be fit for drinking with disinfection (TDS≤500 mg/l; Class A) (IS: 2296:1992). But in non-monsoon conditions, the water at some sites, like S5, S6, and S7, with TDS levels over 500 mg/l, might be safe to consume following conventional treatment. All sites observed acceptable TDS levels ≤1500 mg/l for Class C and ≤2100 mg/l for Class E (IS: 2296:1992).

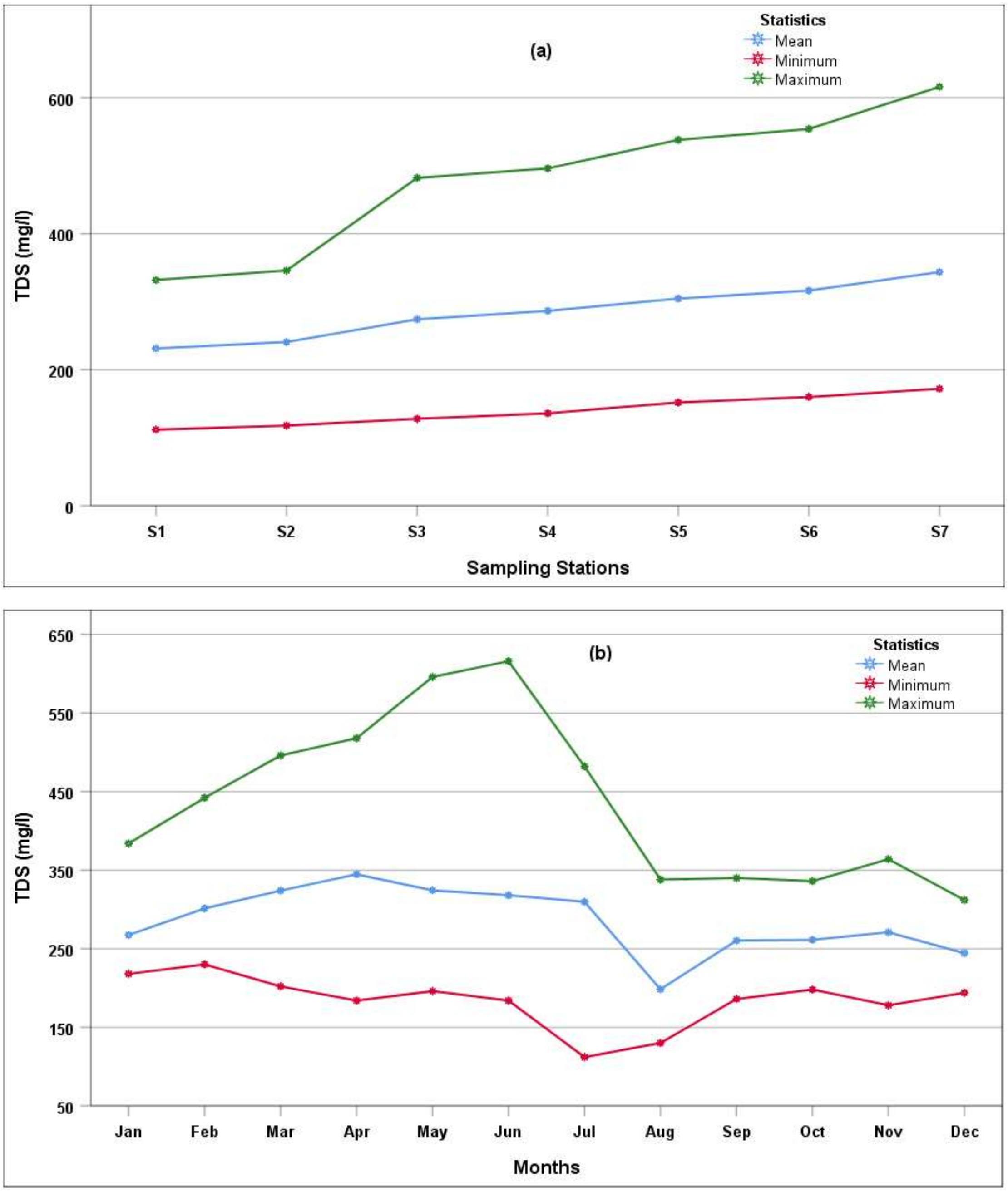


Figure 5.4: Variation of TDS for the period 2013-2017 (a) Spatial (b) Temporal along river Gomti

The Gomti River could be utilized for irrigation and industrial purposes, and it was suitable for drinking following conventional treatment and disinfection, as per the TDS data. Unfortunately, even though it has been shown to be a large load there, the rivers are seen to be the greatest area to dump trash even though this leads to increased TDS in the water, filthy conditions, and health problems in the form of waterborne communicable diseases (Kharake and Raut, 2021).

5.2.5 Total alkalinity (TA)

Because of the different hydroxides, bicarbonates, and carbonates present in water, TA measures an aqueous solution's capacity to neutralize acids (Egleston et al., 2010). The alkalinity of the water must be determined (for example, for corrosion control in conditioning the boiler feed water) to determine the amount of lime and soda required for water softening (Omer, 2019).

TA values for the all-selected sampling stations S1, S2, S3, S4, S5, S6, S7, ranged between 142-252 mg/l with an average of 216 mg/l, 148-264 mg/l with an average of 224.2 mg/l, 156-272 mg/l with an average of 233.5 mg/l, 162-278 mg/l with an average of 240.3 mg/l, 168-286 mg/l with an average of 250.0 mg/l, 172-298 mg/l with an average of 256.7 mg/l, 186-316 mg/l with an average of 270.3 mg/l respectively for the whole study period. For 2013, 2014, 2015, 2016, and 2017, the maximum values of TA is appeared in May, June, and July, whereas the minimum in August and September. The average value of TA was found to be greater than 200 mg/l as per IS: 10500:2012 standards at all sampling stations during the study period. The acceptable and desirable amounts of TA in water bodies are 600 and 200 mg/l, respectively, according to IS: 10500:2012. TA was found to be highest at S7 (316 mg/l) during the summer and lowest during the rainy season at S1 (142 mg/l) (Figure 5.5). This can be caused by dilution brought on by freshwater entering the river system during the monsoon season (Kamboj and Kamboj, 2019). Iqbal et al. (2019), Kumar et al. (2021c), and Kumar et al. (2022a) found a similar value and trend in the Gomti River.

High levels of TA in water could indicate chemical or industrial pollution and be unsuitable for plant irrigation (Jaiswal et al., 2019). Natural waters' alkalinity is a buffer, shielding fish and other aquatic species from abrupt pH shifts. For instance, if an acidic chemical pollutants a lake that is naturally alkaline, the acid and alkaline compounds react to neutralize each other, leaving the pH of the lake water unaffected. The buffering capability should be at least 20 mg/l of calcium carbonate to protect aquatic life (Omer, 2019). However, it can be seen that TA showed an increasing trend from upstream to downstream (S1 to S7), which could be attributed to the mixing of wastewater in the stream as several drains join it along its course. Results of TA in the river Gomti were in close agreement with the study of Khadse et al. (2008), where a high range of TA was reported in the Kanhan River, which carried a considerable amount of sewage water.

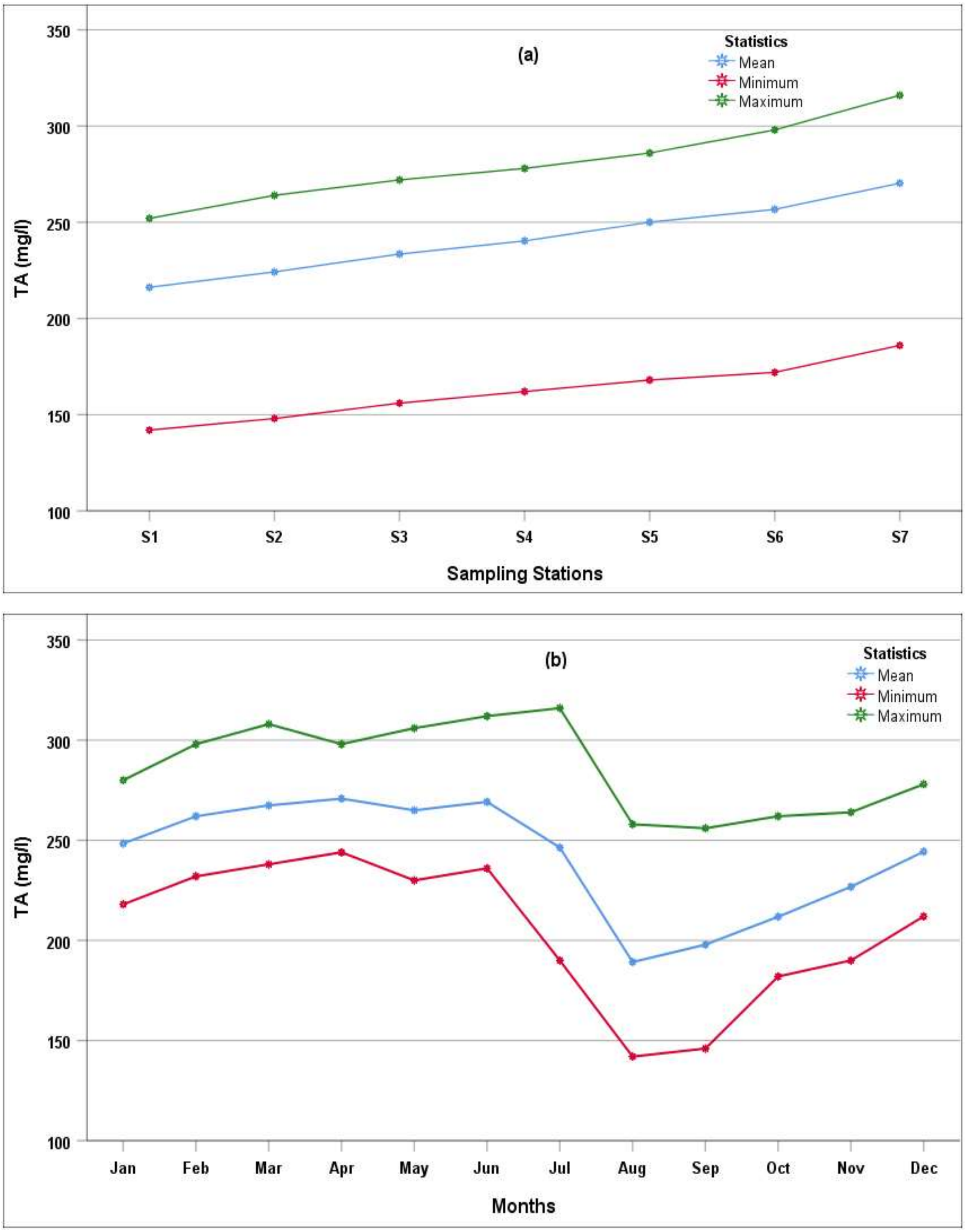


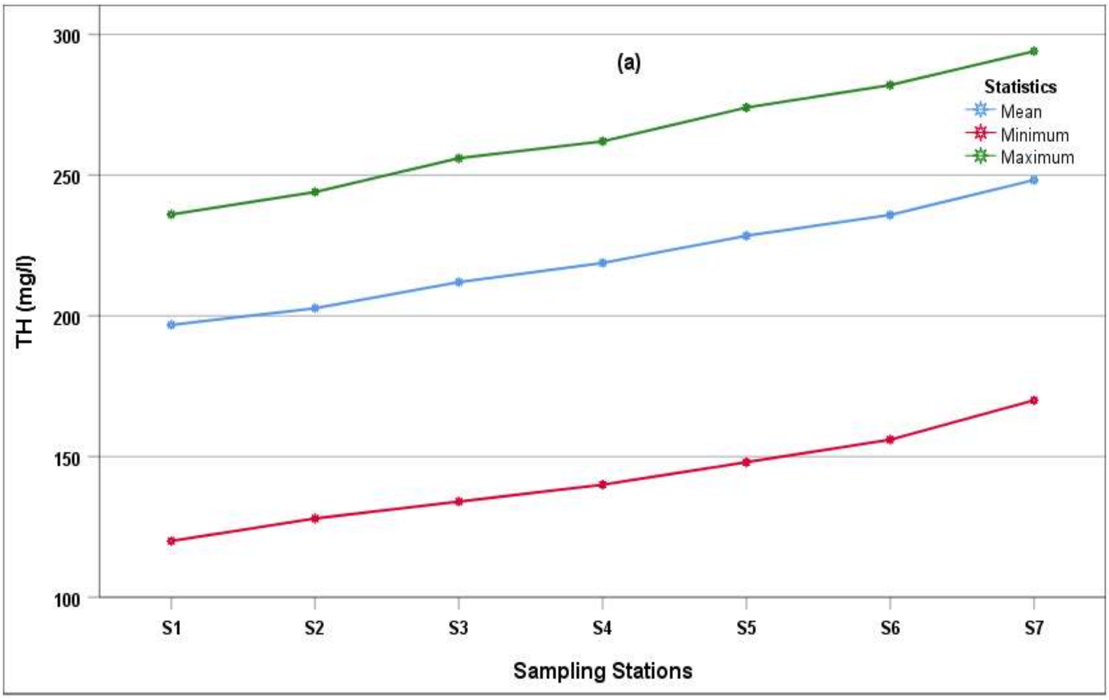
Figure 5.5: Variation of TA for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

5.2.6 Total hardness (TH)

The concentration of TH and other divalent cations in river water is influenced largely by dissolved calcium and magnesium ions in terms of mg/l as $CaCO_3$; however, other cation (aluminum, barium, iron, manganese, strontium, and zinc) also contributes sulfate. The surrounding rocks of the water bodies give the majority of their source (Lkr et al., 2020). The other sources are domestic effluent (sewage and domestic used water) and ineffective treatment of industrial and other waste material (Singh et al., 2005).

The TH of river water has been an essential factor because it affects water's industrial and domestic use. In industries, water is used to manufacture high-quality products, water supply facilities, boilers, cooling towers, membrane clogging, and efficiency of heat exchangers. Hard water is not suitable for many kitchen appliances and domestic purposes such as washing, cleaning, and laundry because it forms scale. Scaling causes problems with pipe blockages as well as producing a characteristic 'watermark' or 'scum line' in baths and sinks when soaps are used. Hard water is also not preferable for drinking (Malakootian et al., 2010).

TH values in present study ranged between 120 mg/l to 236 mg/l, 128 mg/l to 244 mg/l, 134 mg/l to 256 mg/l, 140 mg/l to 262 mg/l, 148 mg/l to 274 mg/l, 156 mg/l to 282 mg/l, 170 mg/l to 294 mg/l with mean values of 196.8 mg/l, 202.7 mg/l, 212.0 mg/l, 218.8 mg/l, 228.5 mg/l, 235.9 mg/l, 248.2 mg/l for sampling stations S1, S2, S3, S4, S5, S6, S7 respectively. In the entire study period, the value of TH seemed to be increasing from S1 to S7, and the lowest range of TH was found in August and September for the whole study period (Figure 5.6).



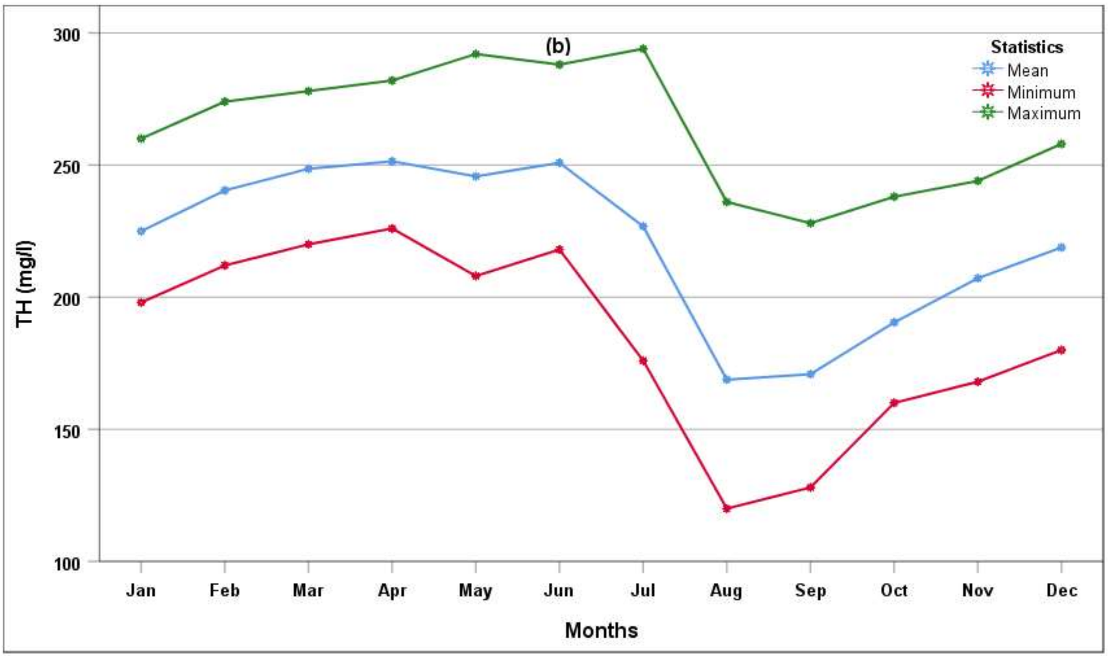


Figure 5.6: Variation of TH for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

Mixing of domestic effluents and enhanced anthropogenic activities were the probable reasons for the high value of TH at this site, which could be supported by the study of Kumar et al. (2021c) and Kumar et al. (2022a) on Gomti River and by Kumar et al. (2015) on Varuna River where the cause of elevated range of TH was attributed to the amalgamation of urban runoff. The levels of TH were far below the 300 mg/l recommended limit (IS: 10500:2012) that could be applied for drinking purposes, but during non-monsoon, it exceeded the allowable level of 200 mg/l for Class A (IS: 2296:1992) at all sampling stations. Based on the TH readings, the Gomti River water is categorized as hard (121-180 mg/l) to very hard water (>180 mg/l) (Bora and Goswami, 2017).

5.2.7 Calcium (Ca) and Magnesium (Mg)

Most of the cationic content in freshwater ecosystems is made up of the major cations, which include Ca and Mg, and have slightly varied seasonal trends in their behavior. Because natural and human-made inputs vary widely, the concentrations of different cations fluctuate significantly on a spatial basis (Jaiswal et al., 2019). Ca reduces chemical toxicity to fish and other aquatic organisms in natural water bodies (Jaiswal et al., 2019). Ca is frequently found in calcium salts ($CaCl_2$ or $CaCO_3$). Ion exchange or calcite precipitation removes calcium. When CO_2 is low, chemical reactions reverse and precipitate calcite. During the study, Ca concentrations varied between 24.7-49.6 mg/l, 25.5-49.6 mg/l, 27.1-53.6 mg/l, 28.5-55.2 mg/l, 30.3-56 mg/l, 31.1-59.2 mg/l, and 34.2-64 mg/l at S1, S2, S3, S4, S5, S6, and S7 respectively, with the maximum and minimum values of 64 mg/l at S7 and 24.7 mg/l at S1 in the river Gomti (Figure 5.7).

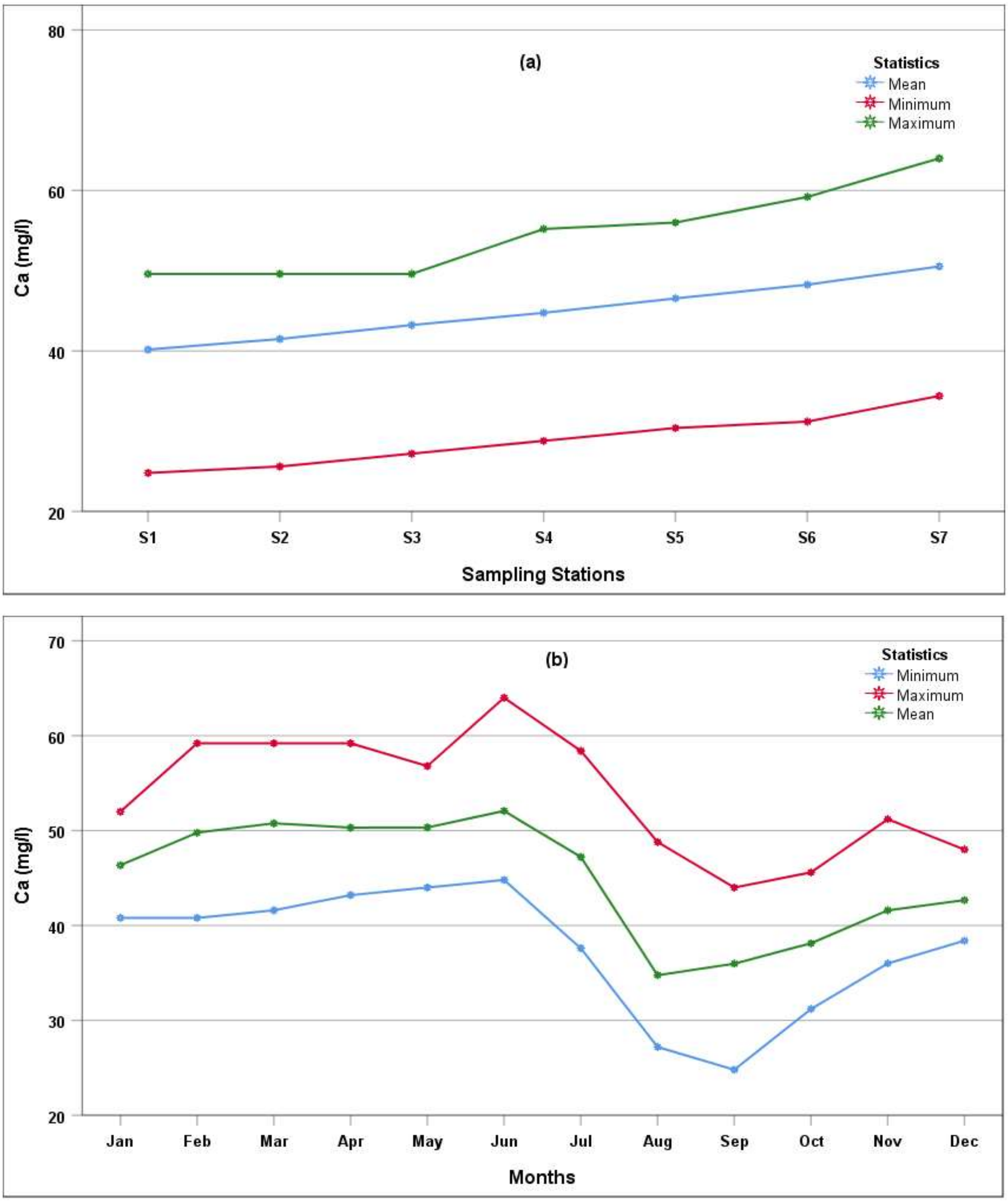
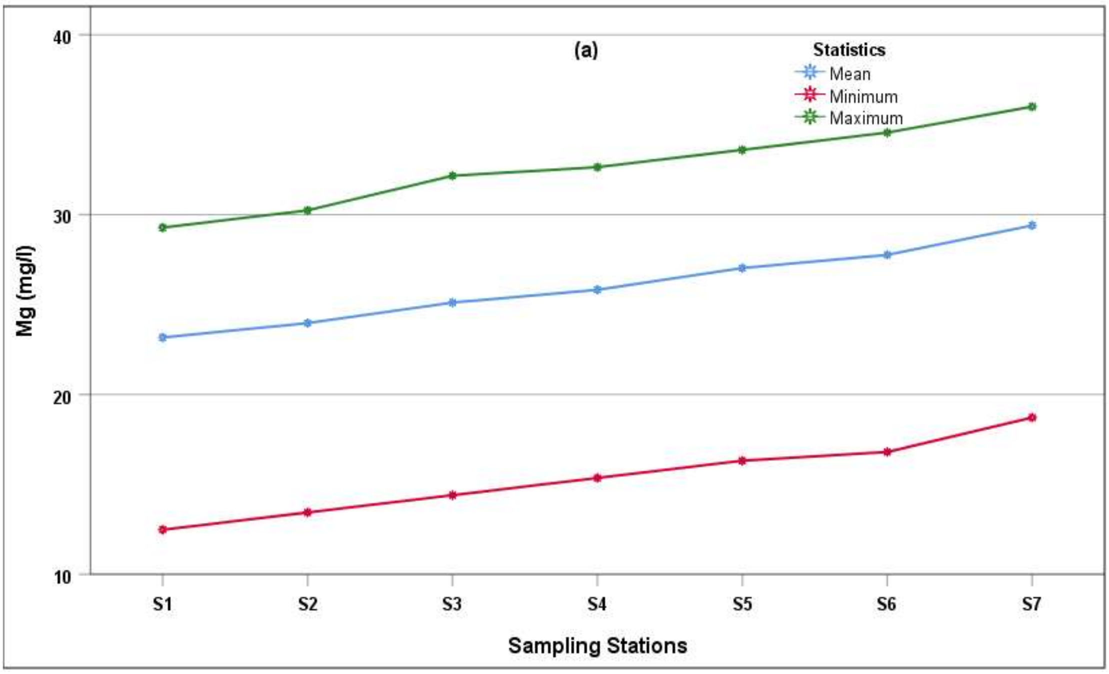


Figure 5.7: Variation of Ca for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

Its greater concentration may be due to temperature rise, water level drop, and household waste accumulation (Lkr et al., 2020). Ca values were substantially within the 75 mg/l limits (IS: 10500:2012) at all sampling points, increasing from sampling stations S1 to S7. These findings are supported by the study of Singh et al. (2005), Singh and Singh (2007), and Kumar et al. (2022a).

Dolomite, marl, and other rocks undergo chemical weathering and breakdown, resulting in Mg formation. This is because of the highest solubility of Mg and the least biological activity of all the elements. Minerals with high Mg content dissolve slowly (Lkr et al., 2020). At sampling stations, Mg concentrations were 12.9-35.5 mg/l in 2013, 12.9-36.0 mg/l in 2014, 19.9-32.1 mg/l in 2015, 16.8-35.5 mg/l in 2016, and 16.7-36.0 mg/l in 2017. The maximum Mg concentration was 36.0 mg/l at S7, while the minimum was 12.48 mg/l at S1. The Mg concentrations were significantly over the permissible limit of 30 mg/l (IS: 10500:2012) at all sampling stations except S1. The measured values of Mg increased from S1 to S7 during the study period (Figure 5.8). This finding can be supported by the study of Rajesh et al. (2015), where the distribution of Mg was recorded in the case of the Ganga river and also supported by Singh et al. (2005), Singh and Singh (2007) and Kumar et al. (2022a) where the distribution of Mg was recorded in case of Gomti River.



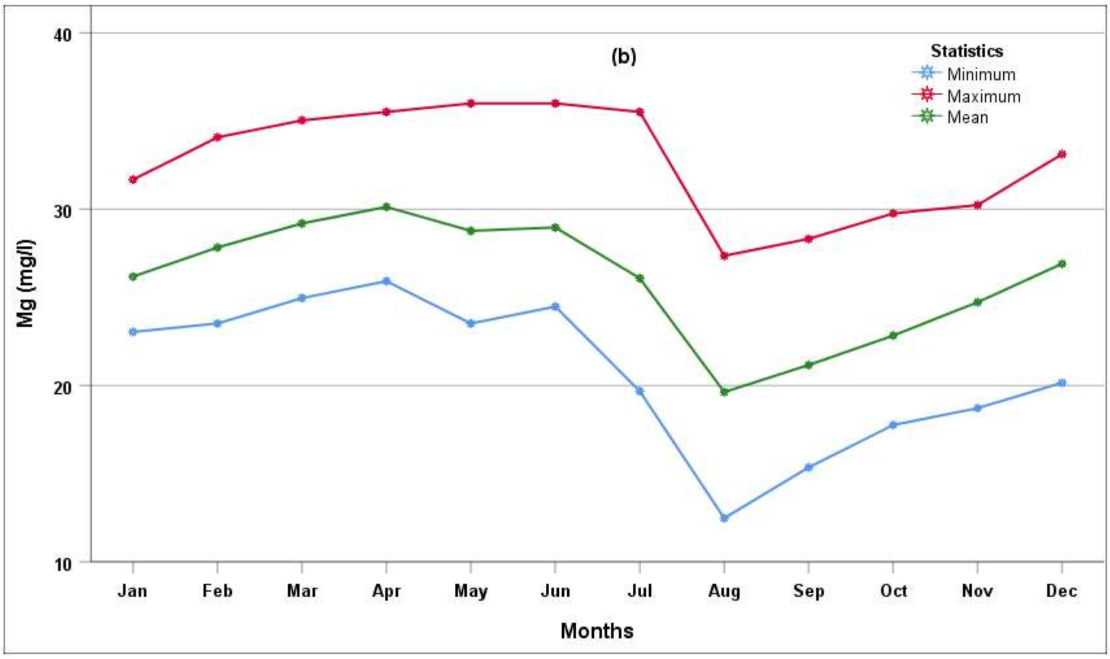


Figure 5.8: Variation of Mg for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

In waters with medium-to-high water mineralization, the Ca: Mg ratio decreases. The most frequent source of Ca and Mg is the erosion of rocks (such as limestone and dolomite) and minerals (such as calcite and magnesite). Ca and Mg can also be impacted by sewage pollution, industrial waste, and soil erosion (Jaiswal et al., 2019).

5.2.8 Chloride (Cl)

Chloride (Cl) is a key indicator of water quality and is present naturally as NaCl, KCl, and $CaCl_2$. There are numerous sources of Cl, including the weathering process that causes different rocks to leach Cl, irrigation runoff, animal feed, and surface runoff from inorganically treated agricultural areas (Bora and Goswami, 2017). Freshwater pollution may be indicated by high chloride concentrations (more than 250 mg/l) (Omer, 2019). Despite the fact that Cl alone is innocuous to humans, its elevated levels can be seen as an "advance warning" of the presence of other harmful pollutants in the water. Water with a high concentration of Cl is unfit for irrigation and is detrimental to aquatic plants and animals (Venkatesharaju et al., 2010). Cl is very mobile, and it usually moves from the soil-water contact to the roots of plants before building up in the leaves (Jaiswal et al., 2019). Although chloride in drinking water does not negatively affect public health, large quantities can give most people a salty taste.

Normally, chlorides are not hazardous to people; however, the sodium in table salt has been linked to renal and cardiac problems (Omer, 2019). Small chloride levels are necessary for typical cell processes in animal and plant life.

The average Cl concentration for the selected water samples was 13.1 mg/l, 14.5 mg/l, 16.7 mg/l, 18.4 mg/l, 21.3 mg/l, 23.3 mg/l, and 27.2 mg/l at sampling stations S1, S2, S3, S4, S5, S6, and S7 respectively (Figure 5.9).

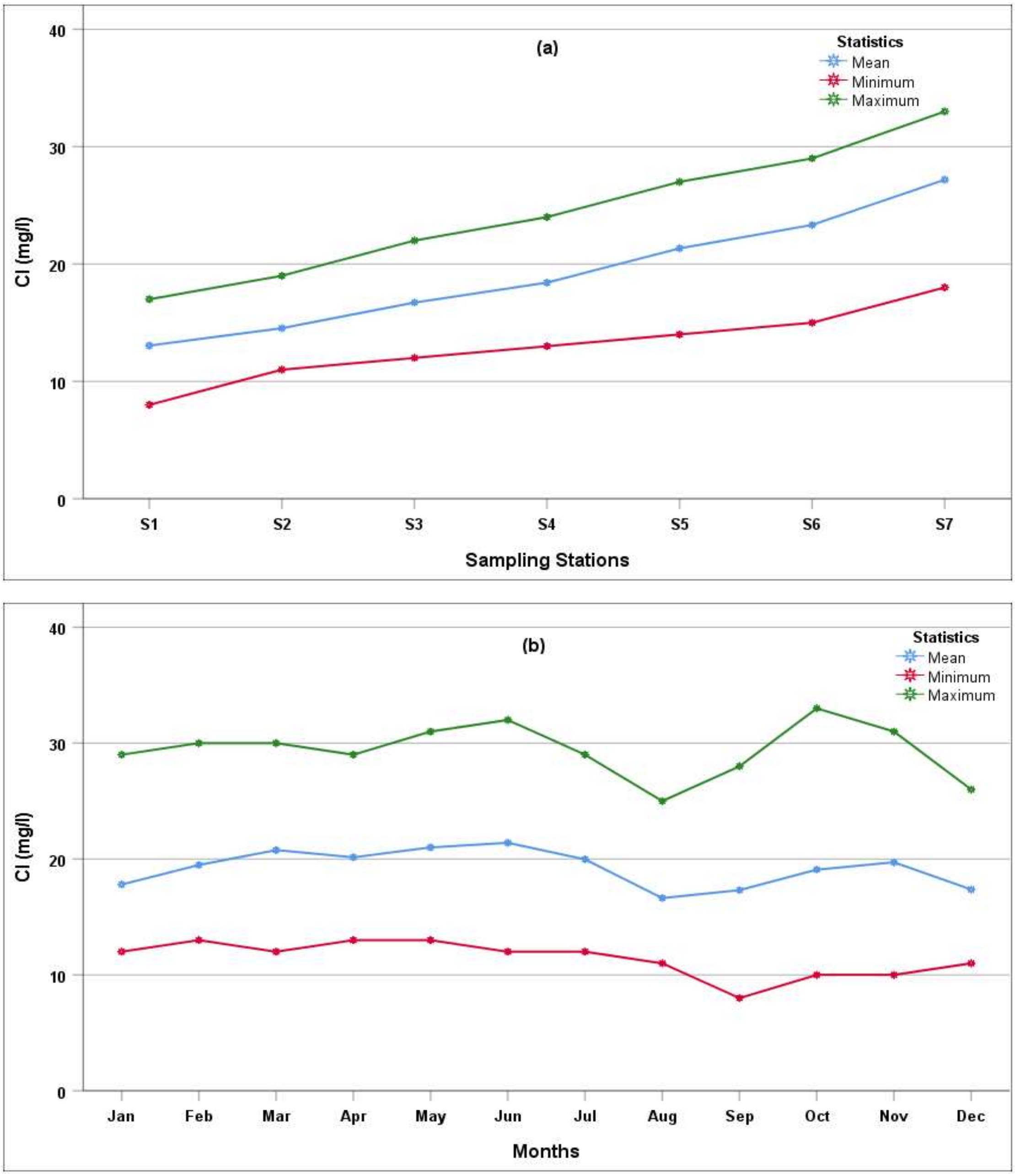


Figure 5.9: Variation of Cl for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

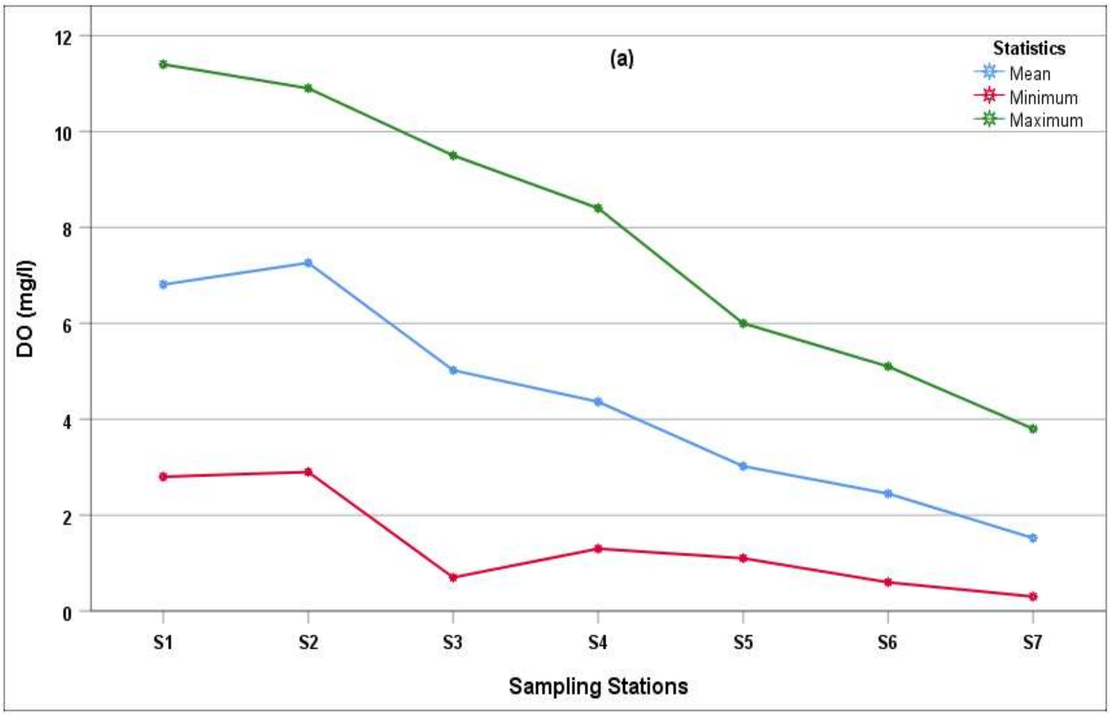
It was found that all sampling stations during the study period contained allowable Cl concentrations according to Class A (≤ 250 mg/l) (IS: 2296:1992), and they followed the desirable limit of IS: 10500:2012. During the study period, the minimum and maximum Cl concentrations were 8 and 33 mg/l at S1 and S7, respectively, demonstrating that the measured Cl values increased from S1 to S7 over the study period. A similar finding was reported by Singh et al. (2005), Singh and Singh (2007), Kumar et al. (2022a), and Edokpayi et al. (2015) while studying the Gomti River and Mvudi River, respectively. This result demonstrated no Cl toxicity along the Gomti River's longitudinal profile.

5.2.9 Dissolved oxygen (DO)

Water bodies have varying concentrations of DO, which is the total amount of oxygen present. The physical, chemical, and biological activity of the water body determines the DO content (Wang et al., 2013; Bora and Goswami, 2017). In water pollution control, DO estimation is crucial. The main factors that help in regulating the DO level in an aquatic environment are atmosphere-water surface exchange, photosynthesis, respiration, and mineralization (Wang et al., 2013). Generally, water sources are in equilibrium with the atmosphere so that oxygen can diffuse across the air-water interface. The amount of DO present in water reflects atmospheric dissolution. For the river, oxygen diffusion across the air-water interface plays an important role in regulating oxygen concentration because of having a high surface area (Hamid et al., 2020). The wind and wave action also helps to regulate the DO level of the river. The amount of DO depends on photosynthesis by plants, respiration by aquatic organisms, decomposition of organic matter/waste, chemical oxidation of minerals, and turbulence (Sanchez et al., 2007; Ravikumar et al., 2013).

The partial pressure of gases varies with altitude, so the amount of DO also varies with altitude. Apart from all this, DO content in water depends on the time of day, rate of flow, depth, altitude, and season (Sallam and Elsayed, 2018). Typically, relatively healthy waters indicate a fluctuation of DO around saturation and diurnal change caused by temperature and metabolism. On the other hand, a significant decline in DO below saturation denotes the presence of untreated wastewater or an excessive amount of nutrients from nonpoint sources of pollution in the stream. The impact of municipal and industrial effluents on the waters was also estimated using the DO concentration to measure water quality (Sanchez et al., 2007). The DO is a significant parameter for water quality assessment because it provides information about the water quality, ecological status, productivity, and health of water bodies (Wang et al., 2013). The DO shows the variation in biological parameters due to aerobic or anaerobic phenomena and reflects the state of river water for aquatic and human life (Gupta et al., 2017). In normal conditions, the running water contains a high amount of DO tending toward saturation compared to stagnant water. Microorganisms require DO to decay organic matter. As organic matter increase, more DO is needed, which reduces DO in water and leads to eutrophic condition in the river. Anthropogenic activities also affected the DO in the river due to the deposition of domestic, industrial, and agricultural waste, which contains oxygen-consuming organic waste (Gupta et al., 2017).

According to the IS: 10500:2012, an optimal DO level for preserving aquatic life is 5 mg/l. When the DO concentration falls below the ideal range, a water sample is deemed polluted (Bora and Goswami, 2017). During the study period, the DO values at S1, S2, S3, S4, S5, S6, and S7 were 2.8-11.4 mg/l, 2.9-10.9 mg/l, 0.7-9.5 mg/l, 1.3-8.4 mg/l, 1.1-6.0 mg/l, 0.6-5.1 mg/l, and 0.3-3.8 mg/l, respectively. The minimum average value observed at all sample stations was in July. The value of DO was found to be minimal at the last sampling station, S7 (Figure 5.10).



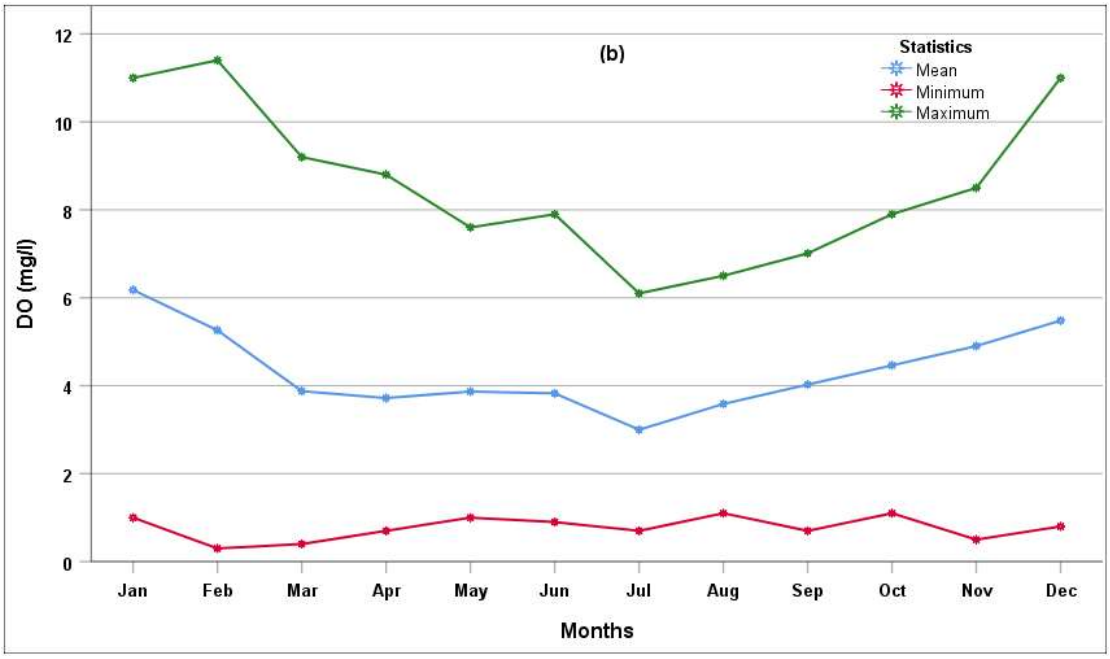


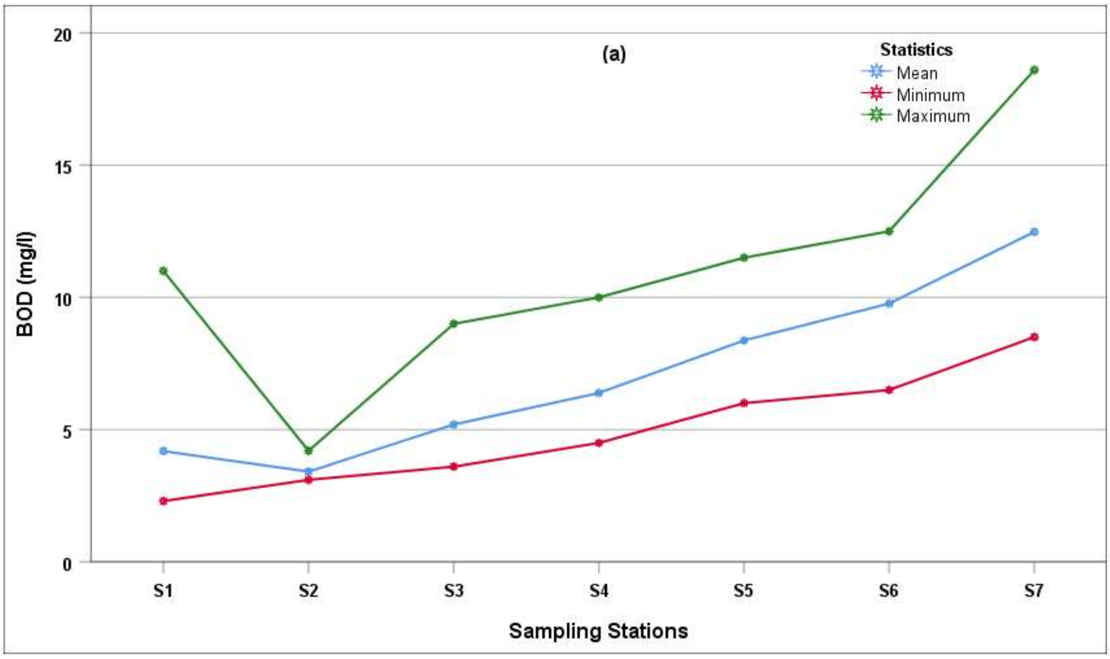
Figure 5.10: Variation of DO for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

The minimum value at all sample points throughout the hot and dry periods was far below the suggested range (5 mg/l). The trend of obtained results was in accordance with the study done by Singh et al. (2005), Singh and Singh (2007), Goel et al. (2018), Iqbal et al. (2019), Kumar et al. (2021c) and Kumar et al. (2022a) on Gomti river and by Joseph and Jacob (2010) on Pennar river, Kerala. High organic loads, drain discharges, and religious rituals along the riverbank all contributed to the current trends of DO depletion at most sampling locations (Shah and Joshi, 2017). Sufficient oxygen is necessary for the survival of aquatic fauna and the decomposition of organic matter by microorganisms. For higher life forms to survive, a stream's dissolved oxygen concentration must be at least 2 mg/l (Shivayogimath et al., 2012).

The DO observations were within the permissible limit of Class A (DO > 6 mg/l) at S1, S2, S3, S4, and S5 during monsoon season and lie under Class D & E (DO > 4 mg/l) during the non-monsoon season (IS: 2296:1992). This outcome may be attributable to the monsoon's wave action, enough turbulence, and significant oxygen diffusion from the surrounding environment (Sharma and Kansal, 2011). These sites receive water from 28 drains (Nagariya drain, Sarkata drain, Pata drain, Wazirganj drain, Ghasiyari mandi drain, Cis-Gomati Pumping Station, G. H. canal, Daliganj drain I, Kukrail drain, Gomti Nagar drainage, etc.) containing low organic pollution, and they could therefore be utilized for various purposes, such as outdoor swimming. However, the DO levels declined for the site S6 and S7 and reached Class D & E (DO > 4 mg/l) during the non-monsoon season, but during monsoon season, S6 lies in Class B (DO > 5 mg/l), and S7 lies in Class D & E (IS: 2296:1992).

5.2.10 Biochemical oxygen demand (BOD)

BOD is the total amount of oxygen needed by aerobic microorganisms in a water body to metabolize biodegradable organic wastes (Wang et al., 2013). BOD is a gauge for organic pollution as higher results indicate higher levels (Ravikumar et al., 2013; Bora and Goswami, 2017). Thus, BOD is an indicator of organic pollution in a river. The increased value of BOD indicates higher organic pollution in the river (Bora and Goswami, 2017). Typically, the waste material predominantly has two types of biodegradable compounds - carbonaceous compound and nitrogenous compound, which are metabolic byproducts or standard components. In general, we only measure CBOD in the BOD test. The decomposition of organic material induces high BOD in municipal and industrial effluents (Rasmussen et al., 2009; Sallam and Elsayed, 2018). BOD levels of more than 5 mg/l are unfavorable. During this study, the BOD values in river water ranged from 2.3-11.0 mg/l, 3.1-4.2 mg/l, 3.6-9.0 mg/l, 4.5-10.0 mg/l, 6.0-11.5 mg/l, 6.5-12.5 mg/l, and 8.5-18.6 mg/l at S1, S2, S3, S4, S5, S6, and S7, respectively (Figure 5.11).



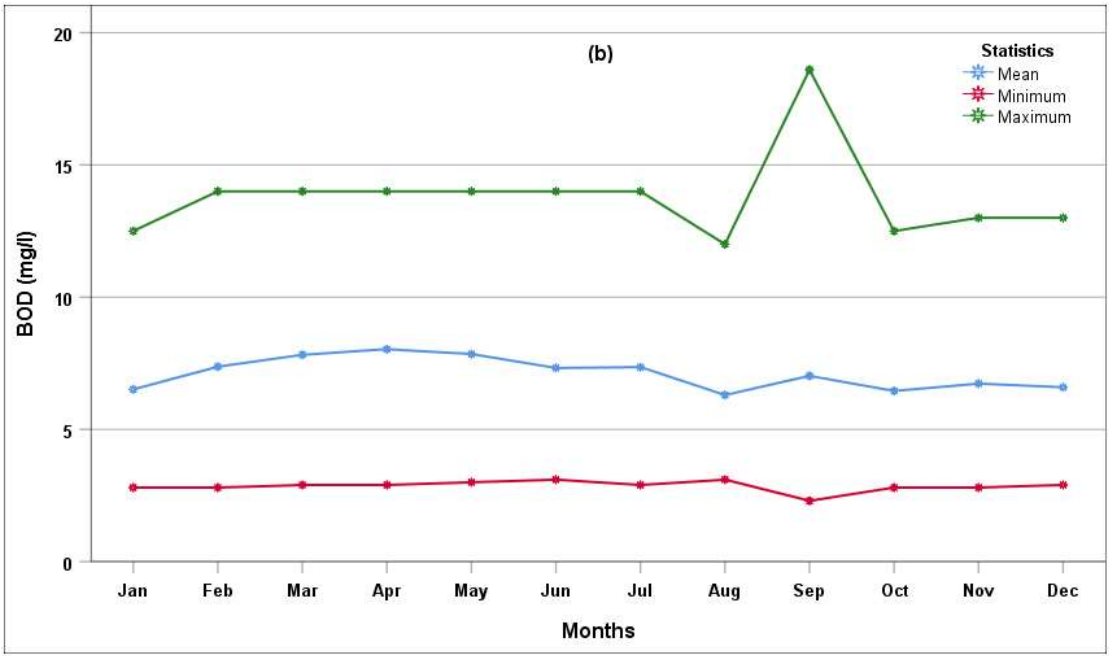


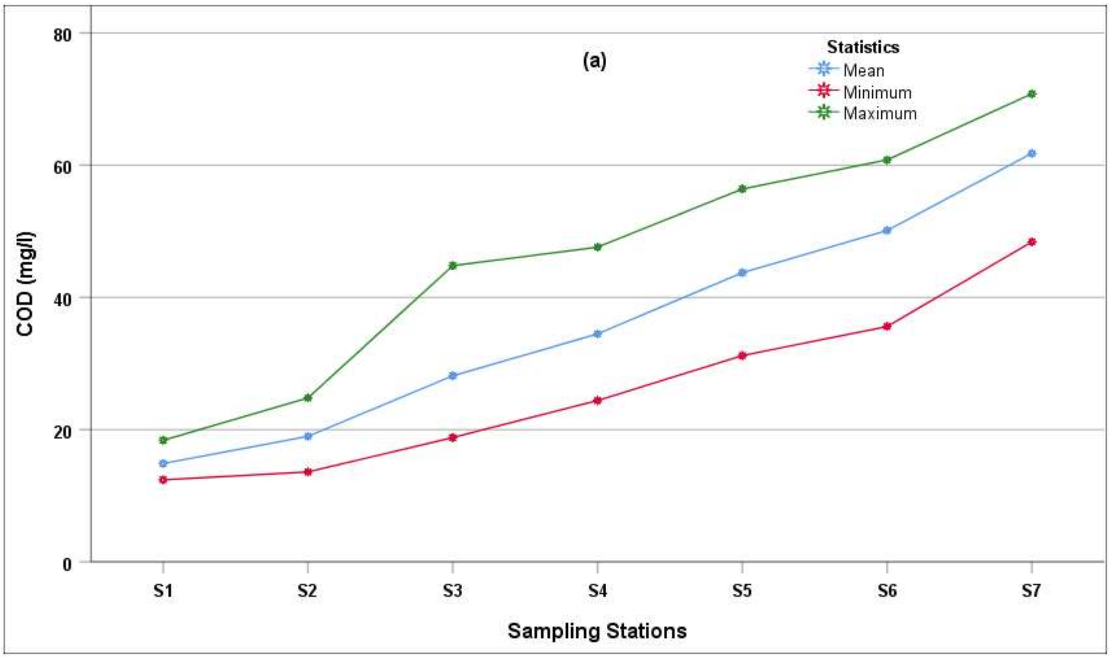
Figure 5.11: Variation of BOD for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

According to IS: 10500:2012, the maximum BOD value observed at all sampling stations during the study period was unacceptable and increased from S1 to S7. The trend of obtained results was in accordance with the study done by Singh et al. (2005), Singh and Singh (2007), Goel et al. (2018), Iqbal et al. (2019), Kumar et al. (2021c) and Kumar et al. (2022a) on Gomti river. A high score in each sampling point indicates that irreparable harm has been done due to the discharge of untreated organic waste and religious ceremonies close to the riverside. A rise in BOD in river water bodies may be due to many factors, including the degradation of DO, increased TDS, high quantum discharge, low water flow, and debris mounds along the river. Dead people and animals may also contribute to this occurrence (Singh et al., 2018). The concentration of BOD was recorded in all seasons under Class B, C, D, and E (BOD> 3 mg/l) at all sites except in site S1. In the case of S1, BOD lies under Class A (BOD> 2 mg/l) during the monsoon season (IS: 2296:1992). An increase in BOD value was observed after S3, which could be attributed to its journey through the city, which receives wastewater from 28 drains till S7.

5.2.11 Chemical oxygen demand (COD)

COD measures the amount of oxygen needed to completely oxidize all organic matter into water and carbon dioxide. It is typically employed to gauge how much organic material is present in water (Kumar et al., 2021c). By measuring almost all of the organic matter in sewage and industrial waste, COD is a useful tool for determining the extent of pollution. COD is a sign of declining water quality brought on by industrial wastewater discharge (Kumar et al., 2022a). The COD parameter measures both biodegradable and non-biodegradable organic materials. For the same sample, COD readings are always greater than BOD values (Omer, 2019).

In the present study, COD levels in the river were measured and found to be varied from 12.4-18.4 mg/l (mean value of 14.89 mg/l) at S1, 13.6-24.8 mg/l (mean value 18.99 mg/l) at S2, 18.8-44.8 mg/l (mean value 28.14 mg/l) at S3, 24.4-47.6 mg/l (mean value 34.49 mg/l) at S4, 31.2-56.4 mg/l (mean value 43.74 mg/l) at S5, 35.6-60.8 mg/l (mean value 50.12 mg/l) at S6 and 48.4-70.8 mg/l (mean value 61.79 mg/l) at S7. S7 had the highest COD of 70.8 mg/l, while the lowest (12.4 mg/l) was observed at S1, exceeding the maximum permissible limit (10 mg/l) during the study period (WHO, 2011). No permissible limit of COD has been identified by the Indian Standards (IS: 2296:1992 and IS: 10500:2012). The trend of obtained results was in accordance with the study done by Singh et al. (2005), Singh and Singh (2007), Kumar et al. (2021c), and Kumar et al. (2022a) on the Gomti River. Site-wise variation showed that the COD was comparable from S1 to S2 and increased substantially at S3, showing the mixing of industrial wastewater into the stream through various drains (Figure 5.12).



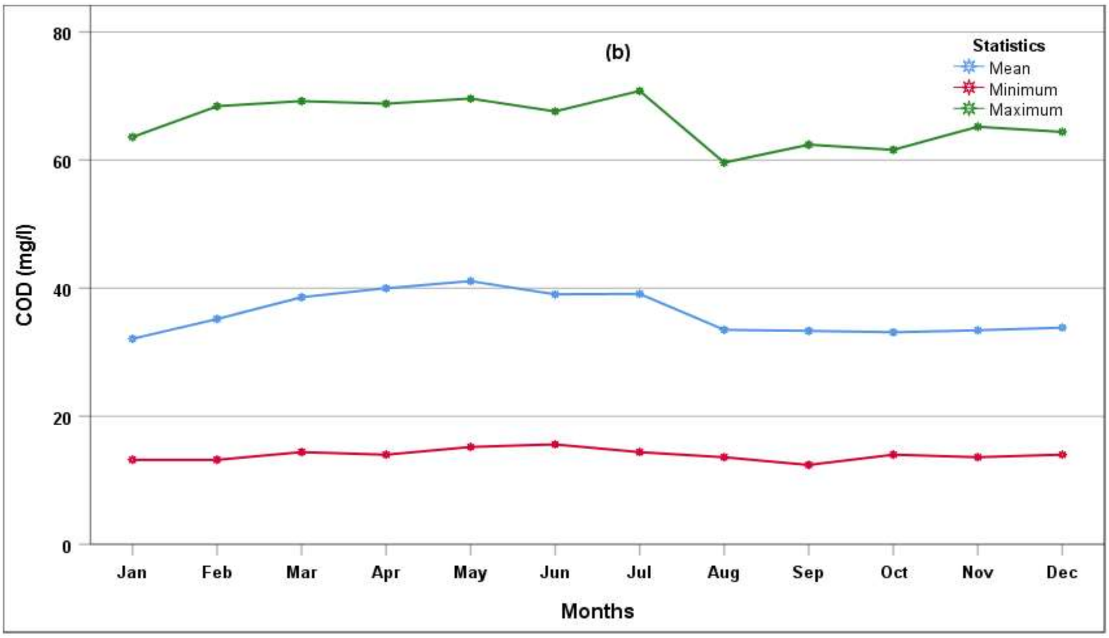


Figure 5.12: Variation of COD for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

The downstream (S7), which had higher levels of organic wastes, showed current trends in the rise of COD concentrations. Untreated industrial, municipal, and religious rituals near the riverbed produced significant amounts of inorganic and organic carbon. Kumar et al. (2015) and Sophia et al. (2017) reported similar results while studying River Varuna and Adyar Estuary, respectively.

5.2.12 Bacteriological analysis (Total coliforms and fecal coliforms)

Bacteria, unicellular microorganisms, are very abundant, diversified, and widely distributed in nature. They are found on almost every surface of the Earth, such as soil, ocean, glacier, human gut, etc. Bacteria found in the aquatic environment may be used as an indicator of water quality (Kumar et al., 2022a). Bacteria with beneficial and pathogenic characteristics are entered into the water by natural or through human activities. Pathogenic bacteria are the cause of dangerous diseases in human and aquatic animals (Baker-Austin et al., 2006). The indicator bacteria are of two types- fecal coliform and non-fecal coliform. The fecal coliform bacteria, Escherichia and Klebsiella are essentially found in the human intestine and other warm-blooded animals. In contrast, non-fecal coliform bacteria include Enterobacter and Citrobacter, which are distributed in nature and can be populated in organic matter (Islam et al., 2018).

Water without fecal matter contamination is the critical parameter of water quality because human feces are commonly considered a higher risk for human health. After all, it usually contains human enteric pathogens (Haque et al., 2019). The presence of indicator bacteria in the water sources indicates fecal contamination and the potential presence of the pathogenic organism. So, their presence can be used as a signal to determine why such contamination is present, how severe it is, and what steps can be taken to eliminate it. The increased value of indicator bacteria shows a higher level of fecal contamination and the vital risks of waterborne diseases (Singh and Singh, 2014). Water-prone diseases (typhoid fever, paratyphoids, dysentery, infectious hepatitis, and cholera) are caused by drinking contaminated water and by participating in recreational activities such as swimming, boating, and aquatic sports in contaminated water (Haque et al., 2019). Due to household sewage overflows or other nonpoint human and animal waste sources, coliform bacteria may appear in ambient water (Shivayogimath et al., 2012).

Analytical results showed that the total coliform (TC) in the present study ranged from 1400- 4000 MPN/100 ml with the average of 2618 MPN/100 ml at S1, 2400-7000 MPN/100 ml with the average of 4015 MPN/100 ml at S2, 4900-40000 MPN/100 ml with the average of 15953 MPN/100 at S3, 13000- 58000 MPN/100 ml with the average of 30583 MPN/100 ml at S4, 32000- 110000 MPN/100 ml with the average of 74933 MPN/100 ml at S5, 70000- 130000 MPN/100 ml with the average of 99450 MPN/100 ml at S6, and 94000- 240000 MPN/100 ml with the average of 151033 MPN/100 ml at S7. A high population of TC showed that the river was severely polluted with sewage in all the seasons; however, the concentration of TC was highest in February, March, and July (Figure 5.13). High TC in July is attributed to the indiscriminate discarding of waste along with open defecation around the river bank, which tends to wash off into the river during rainfall. The finding was in accordance with the studies of Venkatesharaju et al. (2010) on the Cauvery River and Mishra and Tripathi (2007) on the Ganga River in Varanasi. Site-wise variation showed the comparable population of TC at the first two sites (i.e., S1, S2). According to water quality criteria given by IS: 2296:1992, sites S1 and S2 lie under Class B (TC > 500 MPN/l00 ml), but sites S3, S4, S5, S6, and S7 exceeded the criteria of Class C (TC > 5000 MPN/l00 ml) with respect to TC and thus classified under D and E class throughout the study period.

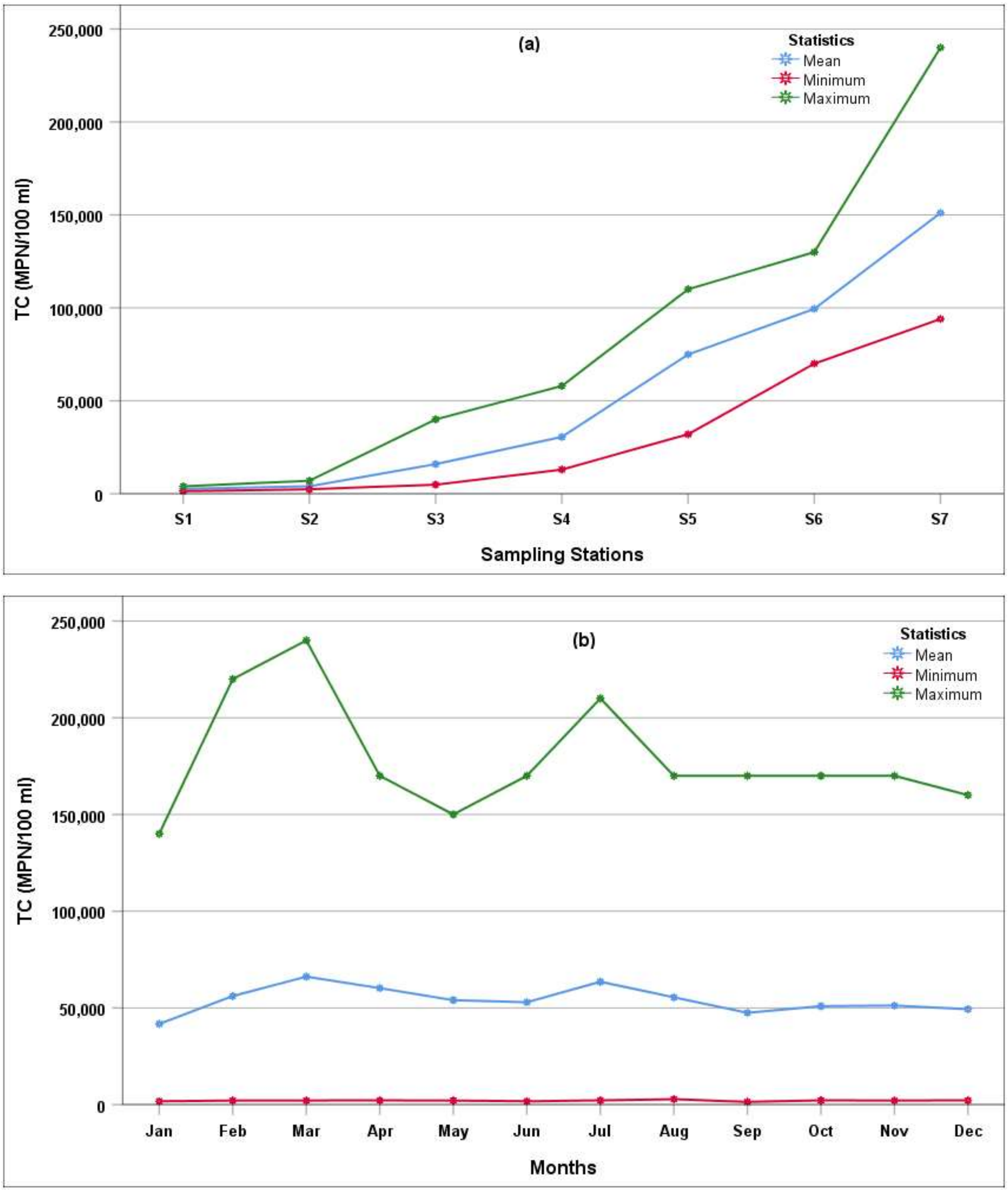


Figure 5.13: Variation of TC for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

Results showed that the fecal coliform (FC) in the present study ranged from 700- 2700 MPN/100 ml with an average of 1467 MPN/100 ml at S1, 1300-4900 MPN/100 ml with an average of 2595 MPN/100 ml at S2, 2600-34000 MPN/100 ml with an average of 11710 MPN/100 at S3, 7900- 43000 MPN/100 ml with an average of 22655 MPN/100 ml at S4, 22000- 79000 MPN/100 ml with an average of 48983 MPN/100 ml at S5, 33000- 79000 MPN/100 ml with an average of 67800 MPN/100 ml at S6, and 49000-170000 MPN/100 ml with an average of 108083 MPN/100 ml at S7 (Figure 5.14).

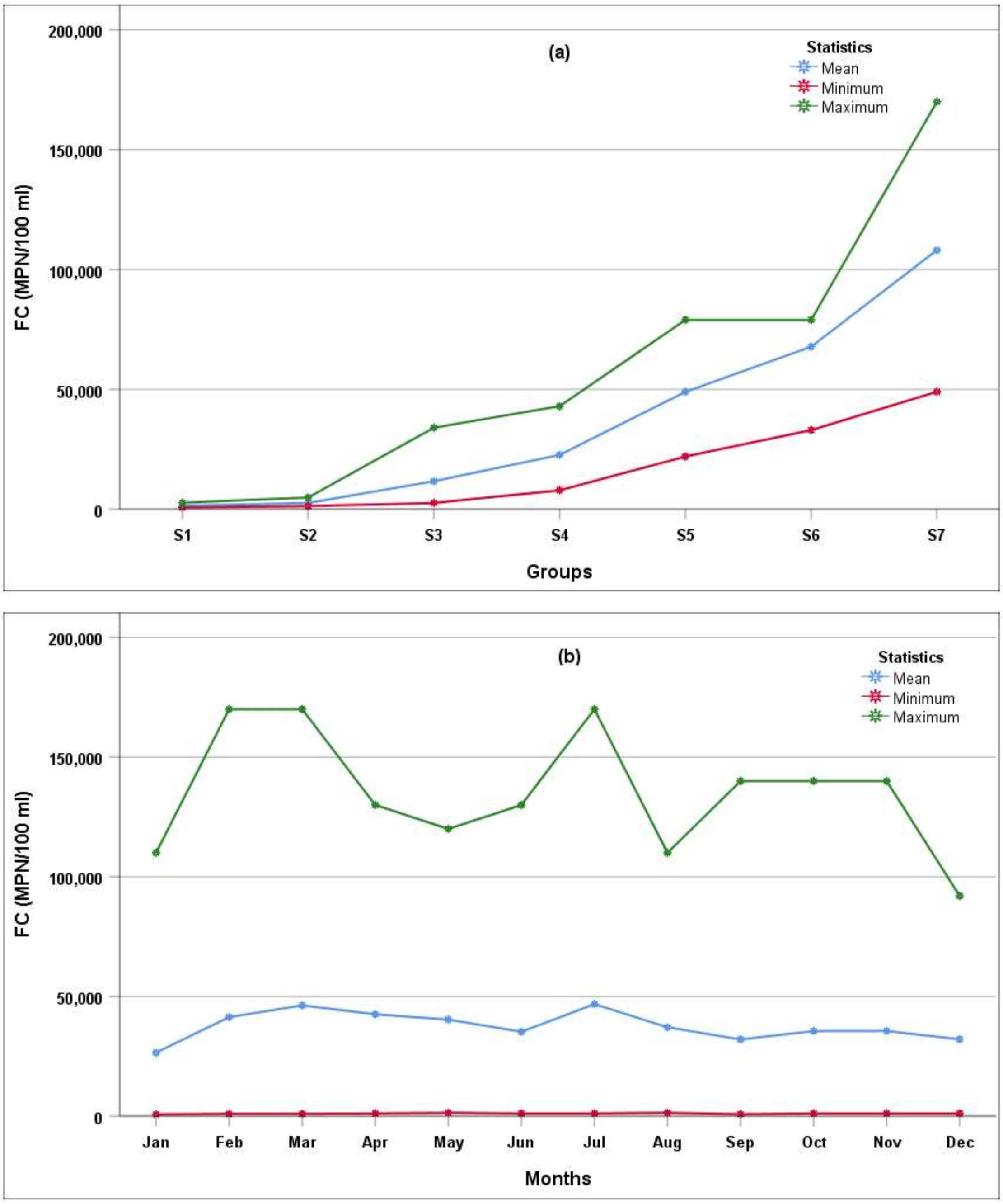


Figure 5.14: Variation of FC for the period 2013-2017 (a) Spatial (b) Temporal, along river Gomti

The findings of the enumeration revealed that the coliform count levels were greater than expected at each location. The acceptable limit of no-coliform/100 ml (IS: 10500:2012) was found to be exceeded by the coliform MPN (most probable number) index during the study period. The coliform count was much higher at S7 compared to the other sampling stations. Summertime high temperatures and significant microbial activity may cause the material cycling of pollutants, reducing the amount of nutrients in rivers (Islam et al., 2018). Similar results were also investigated by Singh and Singh (2014) through their studies on Gomti river pollution at Jaunpur, at Lucknow by Goel et al. (2018) and Kumar et al. (2022a), at Barak River in Assam by Rajkumar and Sharma (2013) and Gola River in Uttarakhand by Chandra et al. (2006) in India.

Additionally, the total fecal coliform counts gradually increased from upstream sites (S1), which received less municipal sewage, to downstream locations (S7), which received a significant amount of municipal sewage through 28 drains. Thus, it is hypothesized that excessive bacterial pollution occurred as a result of open defecation as well as the discharge of untreated sewage in the Gomti River's downstream basin. The discharge of untreated home sewage and open defecation along the river's banks are the two leading causes of fecal coliform (Kumar et al., 2022a).

5.3 ANOVA analysis

The ANOVA test was used to assess the variability in the water quality from 7 sampling points. For water quality assessments, one-way ANOVA is suggested as a more efficient approach than two-way ANOVA (Rizvi et al., 2016; Pujar et al., 2020). One-way ANOVA was applied to each water quality parameter, and the peculiarity between the sampling stations, months, and years was estimated. At a level of significance of 0.05%, the amount of variance between the mean values of several parameters was examined. The predominant site, month, and year-specific sources along the Gomti River's flow were highlighted using the test statistics of an ANOVA (Chaudhary et al., 2019; Kumar et al., 2022a). Results of one-way ANOVA with respect to years, months, and sampling stations are presented in Table 5.2, Table 5.3, and Table 5.4, respectively. The EC, TDS, Ca, Mg, and Cl of the water samples displayed a significant variance compared to the other parameters, according to the F-statistic of the ANOVA test at ≤ 0.05 of the water quality parameters. The excess value of F-statistics for the EC, TDS, Ca, Mg, and Cl parameters showed that the river Gomti was significantly polluted from extraneous sources over the study period of 2013–2017. Significant annual fluctuation for water quality metrics from 2013 to 2017 was shown by one-way ANOVA F-statistics values ($p \leq 0.05$), showing sources of pollution due to growth in urbanization and industrialization (Ali et al., 2021).

Table 5.2: One-way ANOVA values for parameters showing annual variation

Variables	Sum of Squares	df*	Mean Square	F	Sig.*
WT	83.94	4	20.99	0.70	0.60
pH	0.29	4	0.07	0.54	0.71
EC	1460916.03	4	365229.01	17.95	0.00
TDS	480869.68	4	120217.42	18.07	0.00
TA	8125.30	4	2031.32	1.65	0.16
TH	6968.90	4	1742.22	1.35	0.25
Ca	1008.89	4	252.22	3.10	0.02
Mg	3542.77	4	885.69	15.29	0.00
Cl	380.32	4	95.08	3.38	0.01
DO	31.86	4	7.97	1.08	0.36
BOD	109.33	4	27.33	2.36	0.05
COD	1844.05	4	461.01	1.70	0.15
TC	8941350142.86	4	2235337535.71	0.75	0.56
FC	6623731484.76	4	1655932871.19	1.07	0.37

*df - degree of freedom; Sig. - significance level

The WT, pH, EC, TDS, TA, TH, Ca, Mg, Cl, and DO of the water samples displayed a significant variance compared to the other parameters, according to the F-statistic of the ANOVA test at ≤ 0.05 of the water quality parameters. The excess value of F-statistics for these parameters indicated that extraneous source-induced pollution is considerable for different seasons of the study area. One-way ANOVA F-statistics values ($p \leq 0.05$) for water quality measures demonstrated considerable seasonal volatility, pointing to sources of pollution brought on by weather changes (Rizvi et al., 2016; Chaudhary et al., 2019).

The water quality metrics all demonstrated significant fluctuation, except for WT, according to the F-statistic of the ANOVA test at ≤ 0.05. The excess value of the F-statistics for these parameters showed significant pollution caused by extraneous sources from the Gomti River's headwaters (S1) to downstream (S7). Significant differences between sampling locations were found for water quality indicators according to one-way ANOVA F-statistics values ($p \leq 0.05$), indicating possible sources of pollution. Kumar et al. (2022a) found a similar result for the Gomti River.

Table 5.3: One-way ANOVA values for parameters showing seasonal variation

Variables	Sum of Squares	df*	Mean Square	F	Sig.*
WT	12071.24	11	1097.39	847.18	0.00
pH	14.59	11	1.33	13.28	0.00
EC	2767692.12	11	251608.38	14.38	0.00
TDS	679551.28	11	61777.39	9.83	0.00
TA	317897.25	11	28899.75	58.51	0.00
TH	349252.80	11	31750.26	67.17	0.00
Ca	11589.94	11	1053.63	18.52	0.00
Mg	4250.66	11	386.42	6.76	0.00
Cl	975.02	11	88.64	3.27	0.00
DO	329.25	11	29.93	4.43	0.00
BOD	137.77	11	12.53	1.07	0.39
COD	4073.64	11	370.33	1.37	0.18
TC	18113844190.48	11	1646713108.23	0.55	0.87
FC	14134535663.57	11	1284957787.60	0.83	0.61

*df - degree of freedom; Sig. - significance level

Table 5.4: One-way ANOVA values for parameters showing spatial variation

Variables	Sum of Squares	df*	Mean Square	F	Sig.*
WT	8.10	6	1.35	0.04	1.00
pH	25.14	6	4.19	57.28	0.00
EC	1405550.19	6	234258.36	11.38	0.00
TDS	586484.91	6	97747.49	15.20	0.00
TA	128309.79	6	21384.97	22.58	0.00
TH	121469.33	6	20244.89	19.88	0.00
Ca	4995.39	6	832.57	11.54	0.00
Mg	2026.69	6	337.78	5.46	0.00
Cl	9104.76	6	1517.46	213.59	0.00
DO	1701.35	6	283.56	84.75	0.00
BOD	3832.36	6	638.73	241.49	0.00
COD	103418.62	6	17236.44	649.78	0.00
TC	1143227434238.10	6	190537905706.35	785.30	0.00
FC	566042873870.00	6	94340478978.33	482.89	0.00

*df - degree of freedom; Sig. - significance level

Additionally, the F-statistics of an ANOVA determined a significant difference between the sites in terms of pollutants, a justified load of pesticide pollution, and urban sewage runoff. The findings recommend reducing the sources of toxins that pour into the Gomti River and creating remediation plans to lessen the pollution of the river. Every housing society needs a primary sewage treatment facility and a place to dump solid waste. A grid-based inventory for each section of the river's course, from its source to its confluence, can help lower the pollution load (Ali et al., 2021; Kumar et al., 2022a).

5.4 Correlation analysis

It measures the degree of closeness between two variables; one is taken as the dependent variable and the other as an independent variable (Isaac and Siddiqui, 2022). The dependent variable provides a basis for estimating the regression coefficients with each independent variable that maximizes the dependent variable (Gholizadeh et al., 2016; Sharma et al., 2021b). A higher correlation coefficient value symbolizes a better-fit relationship between the regression variables. In this work, correlation analysis is carried out to find the significant correlation between different water quality parameters (Bhandari and Nayal, 2008; Jaiswal et al., 2019). The correlation coefficient is close to +1 (positive correlation), indicating that as one variable rises, the other rises almost linearly. However, a correlation value close to -1 (negative correlation) denotes that when one variable rises, the other variable falls almost linearly. Values close to zero indicate little or no linear association between the variables (Maity et al., 2021). The correlation between data points is zero, suggesting that data are truly independent of each other.

Since water quality parameters showed spatiotemporal variations, it was necessary to derive a relationship between them. For this reason, the Pearson correlation was calculated for water quality parameters at a 0.05 significance level. Correlation analysis facilitates locating the critically important parameters on which other parameters depend. Once the degree of relationship is established, for the value of one given variable, the value of another can be detected.

Strong positive correlations ($p \geq 0.9$) between the water quality measures, such as EC, TDS, TA, Cl, BOD, COD, TC, and FC for the water samples collected during 2013 - 2017 in Table 5.5, were identified, respectively.

Table 5.5: Correlation coefficient matrix of physicochemical and biological parameters of the river Gomti

	WT	pH	EC	TDS	TA	TH	Ca	Mg	Cl	DO	BOD	COD	TC	FC
WT	**1.00**													
pH	-0.22	**1.00**												
EC	0.03	-0.12	**1.00**											
TDS	0.08	-0.18	**0.97**	**1.00**										
TA	-0.23	0.03	0.62	0.59	**1.00**									
TH	-0.19	0.04	0.64	0.61	**0.98**	**1.00**								
Ca	-0.12	0.03	0.44	0.42	**0.70**	0.62	**1.00**							
Mg	-0.01	-0.01	0.33	0.38	0.45	0.37	**0.83**	**1.00**						
Cl	0.08	-0.48	0.55	0.56	0.62	0.61	0.45	0.31	**1.00**					
DO	-0.31	0.68	-0.38	-0.42	-0.37	-0.38	-0.32	-0.27	**-0.71**	**1.00**				
BOD	0.06	-0.56	0.50	0.55	0.55	0.53	0.46	0.41	**0.85**	**-0.83**	**1.00**			
COD	0.10	-0.62	0.49	0.54	0.60	0.59	0.42	0.31	**0.91**	**-0.79**	**0.92**	**1.00**		
TC	0.07	-0.62	0.43	0.47	0.49	0.49	0.34	0.24	**0.86**	**-0.72**	**0.88**	**0.93**	**1.00**	
FC	0.08	-0.60	0.44	0.48	0.49	0.50	0.33	0.23	**0.86**	**-0.71**	**0.87**	**0.92**	**0.98**	**1.00**

In particular, the correlation matrix showed that some parameters are significantly correlated with each other. pH was found to be negatively and moderately correlated with BOD, COD, TC, and FC; however, it was positively and moderately correlated with DO. EC is found to be significantly correlated only with TDS and moderately correlated with TA, TH, Cl, and BOD. This could be well understood by the study of Bhandari and Nayal (2008) on the Kosi River, where they indicated a high correlation of EC with TDS.

TH was found to be moderately correlated with Ca, Cl, BOD, COD, and Ca is strongly correlated with Mg. These ions regulate the mineralization of water (Varol, 2020). Natural and human-made sources contribute to the fluctuation of these ions (Maity et al., 2021). Cl was recorded to exhibit a strong correlation with BOD, COD, TC, and FC but a strong negative correlation with DO. TDS exhibited a moderate correlation with TA, TH, Cl, BOD, and COD (Cadraku, 2021), while TA exhibited a strong correlation with TH and Ca and a moderate correlation with Cl, BOD, and COD, which illustrates how residential sewage affects the Gomti river. Effluent discharge from the residential, industrial, and agricultural regions is caused by COD (Bellos and Sawidis, 2005). BOD and COD show a strong correlation with TC and FC. This is supported by the study of Tajmunnaher and Chowdhury (2017) on the Kushiyara River (Bangladesh) and by Jaiswal et al. (2019) on the Yamuna River (India), where they reported a positive correlation between BOD and COD, which shows that there is a serious industrial effluent pollution of the river. The negative relationship between WT and DO suggests that rising WT promotes the biological activity of aquatic organisms, which results in an intake of DO. The fact that WT and DO are inversely correlated may be because cooler water tends to dissolve larger amounts of oxygen.

The low DO levels at numerous locations were consistently associated with high BOD values, according to the DO-BOD association, which could be because aerobic species consume DO during the assimilation of organics in polluted water (Brandt et al., 2017). TC and FC show a very strong correlation between them. The behavior of polluting sources and their dissipation is comparable at all seven water sampling locations, according to the total statistical correlations of water samples between the physicochemical characteristics.

5.5 Multivariate statistical techniques

MSTs are data analysis techniques utilized in water quality investigations to fully comprehend two or more variables (Kwon and Jo, 2023). They provide clear and straightforward answers for interpreting environmental data, identifying potential influences on water systems, the foundation for further water quality management, and a solution to pollution issues in many nations throughout the world, including India (De Andrade et al., 2008; Venkatesharaju et al., 2010; Bodrud-Doza et al., 2016; Liu et al., 2021). The statistical analysis tool SPSS, version 26.0, was used to calculate PCA and CA to statistically analyze the water quality results. They have been extensively utilized in recent years to analyze data on water quality and explain the pertinent information (Kazi et al., 2009; Varol et al., 2012; Sharma and Ravichandran, 2021). PCA was used for each sampling point to determine the most important factor affecting the deterioration of the water quality and to foretell the source of pollution in the river system (Tripathi and Singal, 2019). Additionally, CA was used to create a cluster of sample stations that shows how comparable the pollutant loads are at the various locations (Kumar et al., 2020b).

5.5.1 Principal component analysis

In pattern recognition, PCA is a frequently used method for decreasing input dimensions and generating related features (Mustapha et al., 2013; Arora and Keshari, 2021). PCA can also identify the pattern and highlight the differences and similarities between the data (Singh et al., 2005; Kannel et al., 2007; Malik and Hashmi, 2017; Kwon and Jo, 2023). A covariance matrix is created from the initial variables to obtain the eigenvalues and eigenvectors using the square Euclidean distance. Correlated variables and eigenvector coefficients are used to create new variables called principal components (PCs) (Jaiswal et al., 2019). A smaller collection of information is created to determine dependencies on the data sets and extract information about the essential parameters' interactions with other parameters from the new uncorrelated variable without losing any crucial information (Sharma and Ravichandran, 2021).

Depending on the values of the correlation matrix, the cumulative factor variance of greater than 0.85, 0.65-0.85, and less than 0.65 are classified as having strong, moderate, and weak correlations, respectively. Table 5.6 and Table 5.7 displays the PCA results, which reveal the parameter and matching factor loading rates. The eigenvalues and variance factors for each site are generated from the data sets. According to the water quality parameter displayed in the scree plots, the number of factors is designed, as shown in Figure 5.15. Results of PCA suggest that three eigenvalues are significant. PCA's component loading plots to estimate the pollutants' origin are shown in Figure 5.16. PCA yielded the three principal components, which accounted for 80.37 % of the total variance associated with all parameters. The first three components explained about 80.37 % of the variance, while the rest explained only 19.63 %.

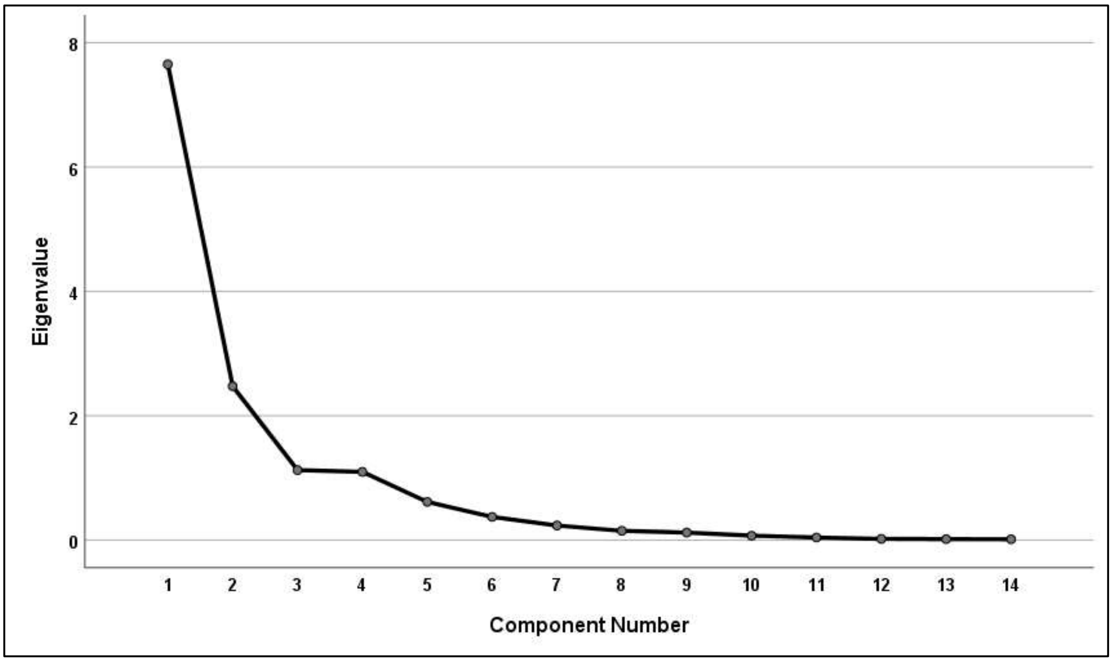


Figure 5.15: Scree plot of the eigenvalues

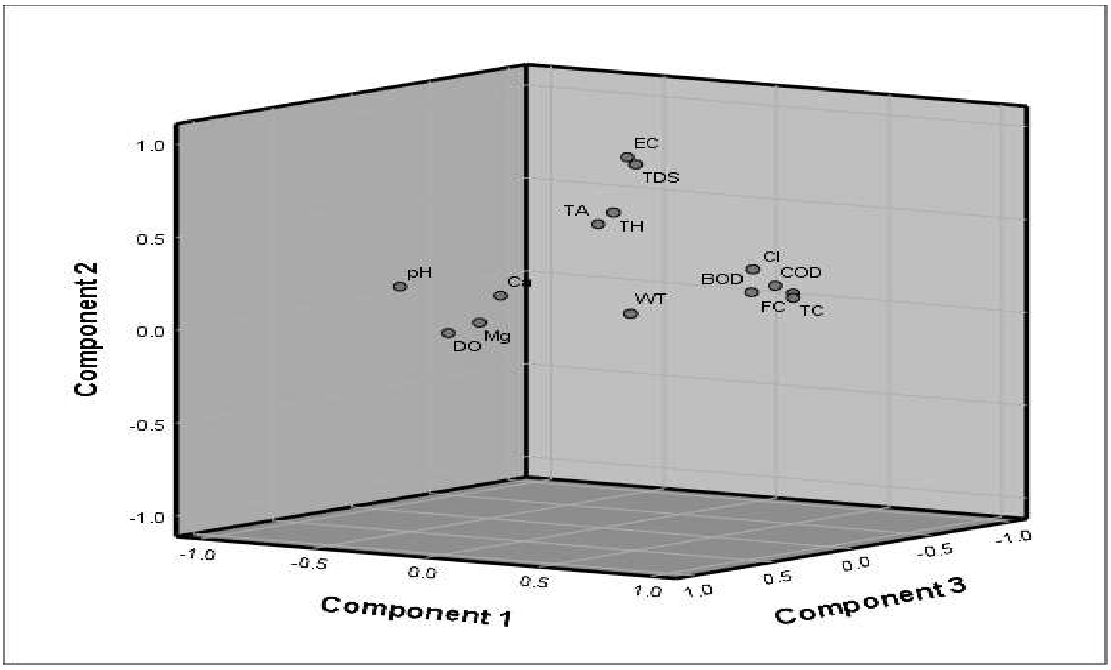


Figure 5.16: Component loading plots of PCA to estimate the origin of pollutants

Table 5.6: Extracted values of various PCA parameters

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	7.65	54.65	54.65	7.65	54.65	54.65	5.58	39.82	39.82
2	2.48	17.68	72.33	2.48	17.68	72.33	3.10	22.12	61.94
3	1.13	8.04	80.37	1.13	8.04	80.37	2.28	16.25	78.19

Table 5.7: Rotated component matrix of the water quality factor loadings

Variables		**WT**	**pH**	**EC**	**TDS**	**TA**	**TH**	**Ca**	**Mg**	**Cl**	**DO**	**BOD**	**COD**	**TC**	**FC**
Component	PC1	0.13	**-0.80**	0.22	0.27	0.30	0.30	0.18	0.11	**0.81**	**-0.82**	**0.86**	**0.90**	**0.92**	**0.91**
	PC2	0.05	0.13	**0.93**	**0.90**	**0.62**	**0.67**	0.29	0.14	0.39	-0.17	0.28	0.31	0.24	0.26
	PC3	-0.01	0.14	0.15	0.17	0.45	0.36	**0.89**	**0.93**	0.20	-0.20	0.28	0.19	0.10	0.09

*Statistically significant loadings are marked by bold

The first component consisted of pH, Cl, DO, BOD, COD, TC, and FC with a total variation of 54.65 % within the dataset, which explains strong positive loadings for BOD, COD, TC, and FC and moderate positive loading for Cl while moderate negative loading for pH and DO. This component represented organic pollution from domestic wastewater and sewage pollution. This finding could be supported by the study of Gupta et al. (2009) on the Mumbai coast. This component also correlated with Cl, which could be due to the release of domestic effluents into the river water. This component contains variables with probable sources of origin and attributed to the runoff from the fields with high solids load and waste disposal activities. Strong loading of BOD and COD were grouped together in a component that indicated organic pollution load, which could be supported by the similar findings of Venkatramanan et al. (2014) for the Nakdong River (Korea). This component was attributed to the anthropogenic pollution source and could be supported by the positive correlation between BOD and COD (Arora and Keshari, 2021). A high concentration of organic chemicals in the water body suggested that oxidizable organic and inorganic pollutants extensively pollutes the river. Nominally treated or often untreated effluent discharge from industries and direct waste dumping into the stream was the main reason for elevated levels of COD and BOD.

The second component accounted for 17.68 % of the total variance in the dataset. It has strong positive EC and TDS loading and moderate positive TA and TH loading. A similar finding was reported in a study on the Tigris River (Bhagdad) by Ismail et al. (2014) and River Gharasoo (Iran) by Rezaei and Sayadi (2015), in which EC and TDS were grouped in a component. According to Ismail et al. (2014), this could be linked to point-source pollution from domestic and industrial wastewater and nonpoint sources such as agricultural activities (Chakravarty and Gupta, 2021).

The third component was responsible for 8.04 % of the total variance and had strong positive loading of Ca and Mg. This component represented the point and nonpoint pollution of the river. Phosphorus-rich bedrock, human and animal waste, industrial runoff, agricultural runoff, and washing clothes could be some probable causes (Jaiswal et al., 2019).

5.5.2 Cluster analysis

CA is one of the most effective methods for categorizing water quality metrics (Shrestha and Kazama, 2007; Sharma and Ravichandran, 2021). Each data point in the

CA defines a single-membered cluster, which then combines to produce a multimembered cluster, and so on, until all of the data points are combined to form a single huge cluster. Hierarchical clustering (HCA), the most popular method of CA, offers intuitive correlations between any sample and the complete data set (Shrestha and Kazama, 2007; Liu et al., 2021). Thus, HCA was performed to find out the water quality characteristics. HCA was used in the current study to analyze the five years of the dataset from 2013 to 2017. The created clusters were shown using dendrograms (Singh et al., 2004, 2005; Arora and Keshari, 2021). The squared Euclidean approach was employed as a distance matrix, and Ward's method of CA was used to analyze variance. The Euclidean distance matrix and transformation of dimensions on a comparable scale were computed using the normalized data (Jaiswal et al., 2019). The results obtained from the cluster analysis yielded a dendrogram are shown in Figure 5.17, which noticeably indicates that the sampling stations are grouped into three heterogeneous clusters.

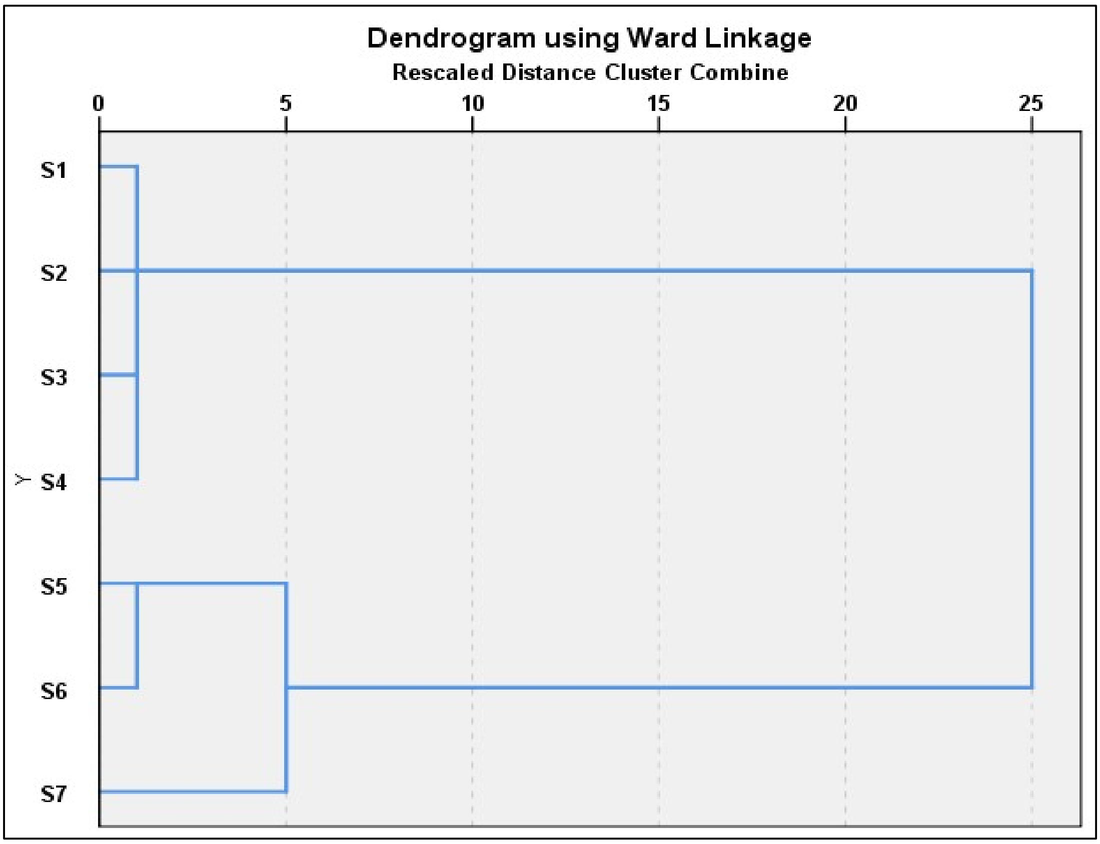


Figure 5.17: Dendrogram showing spatial clustering of sampling stations

Group A comprised S1, S2, S3, and S4; Group B comprised S5 and S6; Group C comprised only S7. It can be seen from Figure 5.17 that Group A was less polluted than Group B and Group C. Group C was the most polluted stretch of the river because the discharges from 28 drains finally reached this site. The Gomti River stretch was divided into three categories. The first category, which included S1, S2, S3, and S4, were moderately polluted areas. The second category included S5 and S6, polluted areas, and the last category, which included S7, referred to as the most polluted stretch.

The primary source of pollution in the high-pollution zones was the direct release of neighboring rural home sewage into rivers and the sewage from nearby cities after treatment/partial treatment by sewage treatment plants. Urban domestic water consumption has surpassed sewage treatment facilities' carrying capacity due to rising urban living standards. A new sewage treatment plant is now being built, which will worsen the water quality. The M/s. Hindustan Aeronautics Ltd. (HAL), Tata Motors, Railway Carriage and Wagon Shop (C&W), the battery industry, numerous small- to medium-sized companies, bakeries, auto repair shops, and dairy farms were the main discharge businesses. The Gomti River is heavily polluted by sources such as vegetable waste, oil, grease, and surfactants used for washing clothes at the river site, biomedical/animal waste, fish/meat markets, and cattle barns.

5.6 Assessment of water quality indices

A large number of water quality parameters assessed over different seasons resulted in a large number of multidimensional data. Interpretation of every single water quality parameter, its seasonal variability, and compliance with the prescribed guideline value given by national and international organizations was very complex and time-consuming (Kamboj and Kamboj, 2019; Kamboj et al., 2020). In order to gather information about the water quality of the river Gomti understandably, it was essential to assess its water quality using Water Quality Indices (WQIs) as well as to get a single value that could reflect the overall water quality of the river and facilitates easy interpretation (Khan et al., 2003; Shah and Joshi, 2017; Semy and Singh, 2021). Based on the available literature on the use of WQIs in assessing the water quality of rivers, the four most suitable WQIs [Arithmetic water quality index (Arithmetic WQI), Synthetic pollution index (SPI), Comprehensive Pollution Index (CPI) and Ved Prakash water quality index (CPCB-WQI)] were selected to compare and check their suitability in defining water quality data of the river Gomti.

5.6.1 Assessment of Arithmetic WQI

The summary of the Arithmetic WQI values of the water samples from all seven sampling stations (S1 – S7) for each year (2013–2017) is presented in Table 5.8. Arithmetic WQI values for the all-selected sampling stations S1, S2, S3, S4, S5, S6, and S7 ranged between 78.99 to 175.61 with an average of 120.81, 83.70 to 148.23 with an average of 117.52, 92.86 to 184.85 with an average of 137.62, 102.99 to 196.60 with an average of 152.33, 123.35 to 220.99 with an average of 176.66, 132.49 to 228.69 with an average of 192.49, and 154.66 to 249.39 with an average 221.12 respectively for the whole study period. The results revealed that all the water samples fall into category E (>100), which is unsuitable for drinking and fish culture and requires proper treatment before use. These stations recorded the highest arithmetic WQI values during 2017, ranging from 175.61 at Station S1 to 249.39 at Station S7. The arithmetic WQI of the water samples collected at stations S1 and S2 were better than other sampling stations. Samples collected at stations S1 and S2 have better water quality conditions, as these stations are present in the outskirts of Lucknow city and have less urban agglomeration. Similar results were also observed by Dutta et al. (2018a), Goel et al. (2018), and Iqbal et al. (2019) for the river Gomti. The pollutants in the water at the sampling stations were added primarily due to various anthropogenic activities like the inflow of untreated sewerage from residential and commercial establishments, unavailability of proper sanitation systems, agricultural runoff, direct disposal of untreated outflow from industries, and unabated dumping of solid waste by the communities residing alongside the river, etc. (Tangri et al., 2018; Iqbal et al., 2019).

The arithmetic WQI analysis unveiled that sampling stations S5, S6, and S7 have the highest levels of pollutants along the entire reach of the Gomti River. Not only high sewage disposal and eutrophication but the lack of sufficient flow leads to the stagnancy of river water, which results in a high pollution level of sampling stations, which in turn reduces the self-purification capacity of the river Gomti. Rehana and Majumdar (2011) reported similar impacts of altered river flow on Tunga Bhadra. In addition to the above reasons, a continuous increase in the population, which resulted in riverbed encroachment and exploitation of river water for various chores, contributed to the deterioration of the water quality of the river Gomti (LDA, 2016; UPPCB, 2019). Figure 5.18 indicates, from 2013 to 2017, how the pollution level increased when we moved downstream from station S1 to S7.

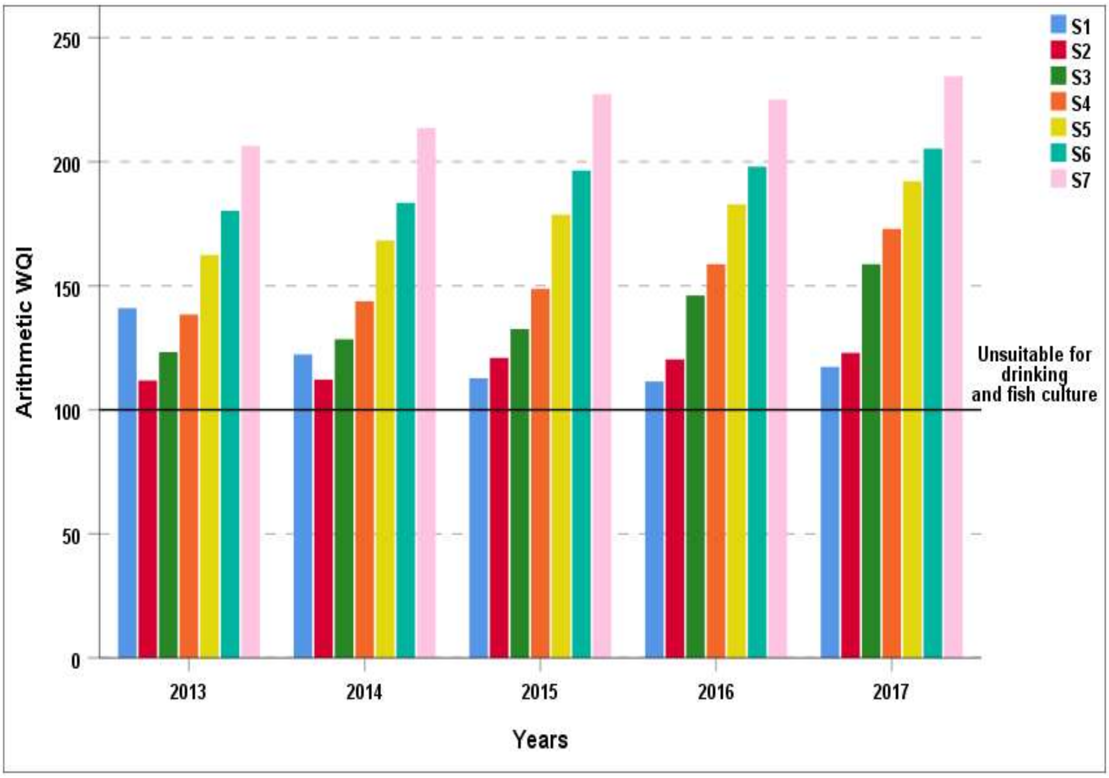


Figure 5.18: Variation of Arithmetic WQI of studied stations in the Gomti River for the period 2013-2017

A similar study has been reported by Kumar and Dua (2009), Kumar and Bahadur (2013), Rizvi et al. (2016); Bhutiani et al. (2016), Shah and Joshi (2017), Gupta et al. (2017) Lkr et al. (2018), Chaudhary et al. (2019), Sharma et al. (2020), Gupta et al. (2020), Pramanik et al. (2020), Chabuk et al. (2020), Ali et al. (2021), Semy and Singh (2021) and Kumar et al. (2021b) on other rivers in India.

5.6.2 Assessment of SPI

The SPI was estimated for seven water sampling stations using 12 physicochemical parameters. SPI comparisons among sampling locations between 12 months of 5 years (2013-2017) are presented in Table 5.9. The SPI values ranged from 0.868 to 1.277 at S1, 0.908 to 1.312 at S2, 0.987 to 1.465 at S3, 1.07 to 1.601 at S4, 1.254 to 1.859 at S5, 1.338 to 2.02 at S6 and 1.513 to 2.177 at S7. The mean values of SPI are 1.112, 1.151, 1.250, 1.367, 1.532, 1.662 and 1.927 at S1, S2, S3, S4, S5, S6 and S7, respectively, which indicates "very poor" (1.0-3.0) status at all sampling sites during the study period (Figure 5.19).

The water quality is severely polluted and can only be used for irrigation. During the study period, a gradual increase of SPI was found from S1 to S7 sampling stations, which specify the degree of water quality deterioration of the Gomti River downstream. As more sewage-discharging drains merged with the river from the S1 to S7 site, a considerable shift in SPI value was noticed. In contrast to earlier published studies, a considerable SPI divergence was seen between the seasons in the current study. During the study period, SPI falls only under the poor (0.5-1.0) and very poor (1.0-3.0), i.e., moderately polluted to severely polluted, and can be used only for irrigation and industrial purposes.

The outcomes of the SPI studies, as well as the regional and seasonal evaluation of the relevant physicochemical parameters, were validated with similar data from the literature (Ali et al., 2021). Ma et al. (2009) developed this method to assess the impact of pollutants on water quality, and due to its simplicity, it has since been widely employed in numerous research studies (Solangi et al., 2018; Solangi et al., 2020; Hui et al., 2020; Sunar et al., 2020).

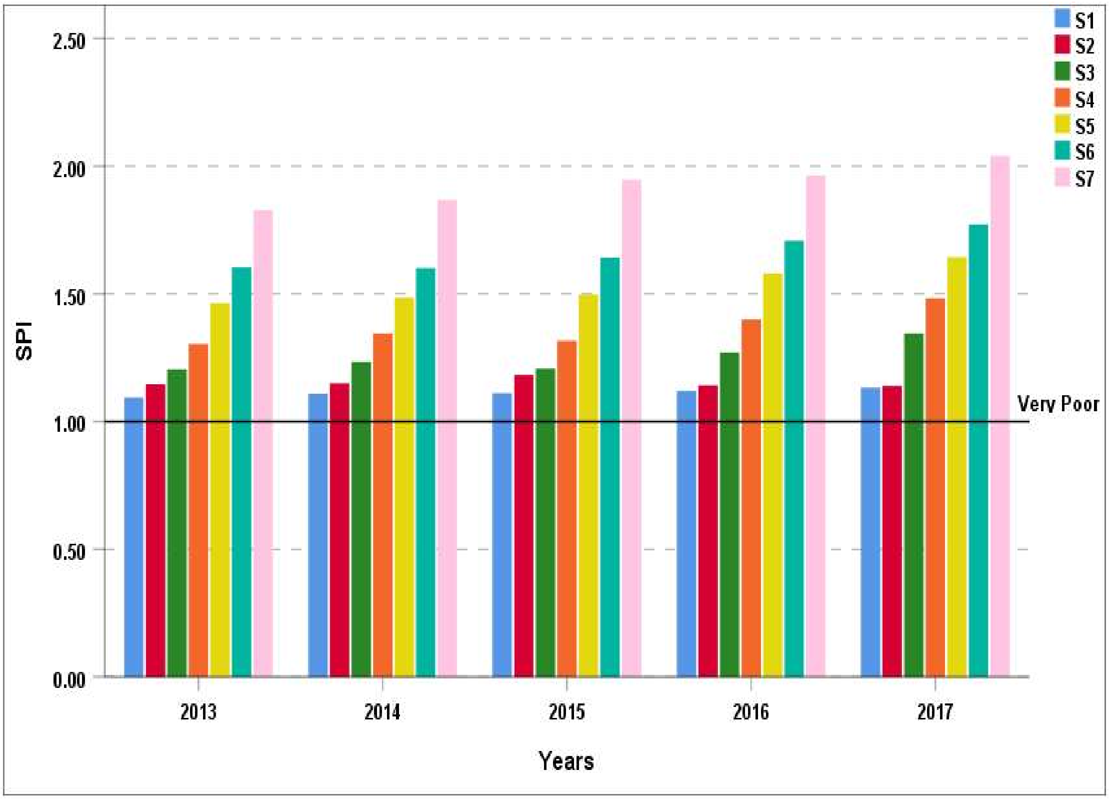


Figure 5.19: Variation of SPI of studied stations in the Gomti River for the period 2013-2017

Table 5.8: Water quality status of the river Gomti during the study period as per Arithmetic WQI

	2013		2014		2015		2016		2017	
	WQI	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**
S1										
Jan	168.75	Unsuitable	168.75	Unsuitable	88.07	Very poor	88.07	Very poor	111.28	Unsuitable
Feb	173.07	Unsuitable	173.07	Unsuitable	91.88	Very poor	113.76	Unsuitable	112.11	Unsuitable
Mar	164.57	Unsuitable	164.57	Unsuitable	118.40	Unsuitable	113.68	Unsuitable	122.85	Unsuitable
Apr	119.45	Unsuitable	121.90	Unsuitable	119.45	Unsuitable	121.90	Unsuitable	115.74	Unsuitable
May	128.36	Unsuitable	137.71	Unsuitable	128.36	Unsuitable	128.36	Unsuitable	137.71	Unsuitable
Jun	147.47	Unsuitable	116.47	Unsuitable	128.68	Unsuitable	128.68	Unsuitable	140.75	Unsuitable
Jul	128.83	Unsuitable	107.05	Unsuitable	114.60	Unsuitable	126.31	Unsuitable	126.31	Unsuitable
Aug	92.40	Very poor	78.99	Very poor	116.18	Unsuitable	95.54	Very poor	95.54	Very poor
Sep	115.78	Unsuitable	100.68	Unsuitable	110.65	Unsuitable	97.43	Very poor	113.35	Unsuitable
Oct	137.24	Unsuitable	90.73	Very poor	111.70	Unsuitable	105.17	Unsuitable	105.17	Unsuitable
Nov	139.74	Unsuitable	100.45	Unsuitable	116.76	Unsuitable	109.72	Unsuitable	109.72	Unsuitable
Dec	175.61	Unsuitable	107.74	Unsuitable	108.34	Unsuitable	108.34	Unsuitable	108.34	Unsuitable
S2										
Jan	108.12	Unsuitable	108.12	Unsuitable	95.36	Very poor	95.36	Very poor	116.67	Unsuitable
Feb	113.90	Unsuitable	113.90	Unsuitable	101.49	Unsuitable	124.46	Unsuitable	116.01	Unsuitable

	2013		2014		2015		2016		2017	
	WQI	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**
Mar	119.09	Unsuitable	119.09	Unsuitable	127.85	Unsuitable	126.06	Unsuitable	130.65	Unsuitable
Apr	129.71	Unsuitable	131.87	Unsuitable	129.71	Unsuitable	131.87	Unsuitable	122.34	Unsuitable
May	138.47	Unsuitable	135.42	Unsuitable	138.47	Unsuitable	138.47	Unsuitable	135.40	Unsuitable
Jun	121.61	Unsuitable	121.61	Unsuitable	137.98	Unsuitable	137.98	Unsuitable	148.23	Unsuitable
Jul	112.00	Unsuitable	112.00	Unsuitable	124.47	Unsuitable	139.81	Unsuitable	139.81	Unsuitable
Aug	83.70	Very poor	83.70	Very poor	124.57	Unsuitable	102.12	Unsuitable	102.12	Unsuitable
Sep	97.63	Very poor	105.10	Unsuitable	117.07	Unsuitable	104.05	Unsuitable	114.02	Unsuitable
Oct	107.11	Unsuitable	97.46	Very poor	117.88	Unsuitable	112.12	Unsuitable	112.13	Unsuitable
Nov	96.88	Very poor	105.38	Unsuitable	121.66	Unsuitable	116.12	Unsuitable	116.12	Unsuitable
Dec	112.95	Unsuitable	112.95	Unsuitable	114.98	Unsuitable	114.98	Unsuitable	114.98	Unsuitable
S3										
Jan	113.37	Unsuitable	113.37	Unsuitable	105.25	Unsuitable	105.25	Unsuitable	155.49	Unsuitable
Feb	126.21	Unsuitable	126.21	Unsuitable	113.87	Unsuitable	158.31	Unsuitable	145.75	Unsuitable
Mar	134.97	Unsuitable	134.97	Unsuitable	141.73	Unsuitable	155.34	Unsuitable	184.06	Unsuitable
Apr	140.03	Unsuitable	160.23	Unsuitable	140.03	Unsuitable	160.22	Unsuitable	184.85	Unsuitable
May	151.86	Unsuitable	176.08	Unsuitable	151.86	Unsuitable	151.86	Unsuitable	176.06	Unsuitable
Jun	138.48	Unsuitable	138.48	Unsuitable	154.10	Unsuitable	154.10	Unsuitable	169.38	Unsuitable

	2013		2014		2015		2016		2017	
	WQI	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**
Jul	125.57	Unsuitable	125.57	Unsuitable	133.24	Unsuitable	168.74	Unsuitable	168.74	Unsuitable
Aug	92.86	Very poor	92.86	Very poor	135.20	Unsuitable	129.01	Unsuitable	129.01	Unsuitable
Sep	108.45	Unsuitable	121.17	Unsuitable	125.94	Unsuitable	141.52	Unsuitable	152.58	Unsuitable
Oct	119.43	Unsuitable	112.02	Unsuitable	126.14	Unsuitable	146.79	Unsuitable	146.80	Unsuitable
Nov	106.78	Unsuitable	118.71	Unsuitable	123.22	Unsuitable	141.51	Unsuitable	141.52	Unsuitable
Dec	121.23	Unsuitable	121.23	Unsuitable	139.89	Unsuitable	139.89	Unsuitable	139.89	Unsuitable
S4										
Jan	131.53	Unsuitable	131.53	Unsuitable	125.39	Unsuitable	125.39	Unsuitable	167.54	Unsuitable
Feb	142.30	Unsuitable	142.30	Unsuitable	130.47	Unsuitable	166.63	Unsuitable	166.49	Unsuitable
Mar	151.96	Unsuitable	151.96	Unsuitable	158.02	Unsuitable	167.52	Unsuitable	194.00	Unsuitable
Apr	157.34	Unsuitable	164.54	Unsuitable	157.34	Unsuitable	164.54	Unsuitable	196.60	Unsuitable
May	166.87	Unsuitable	194.14	Unsuitable	166.87	Unsuitable	166.87	Unsuitable	194.13	Unsuitable
Jun	154.61	Unsuitable	154.61	Unsuitable	169.42	Unsuitable	169.42	Unsuitable	185.49	Unsuitable
Jul	144.76	Unsuitable	144.76	Unsuitable	151.32	Unsuitable	179.31	Unsuitable	179.31	Unsuitable
Aug	102.99	Unsuitable	102.99	Unsuitable	153.57	Unsuitable	147.05	Unsuitable	147.05	Unsuitable
Sep	120.89	Unsuitable	137.19	Unsuitable	139.82	Unsuitable	156.84	Unsuitable	174.50	Unsuitable
Oct	128.70	Unsuitable	125.77	Unsuitable	137.88	Unsuitable	156.20	Unsuitable	156.19	Unsuitable

	2013		2014		2015		2016		2017	
	WQI	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**
Nov	121.58	Unsuitable	137.84	Unsuitable	143.88	Unsuitable	152.47	Unsuitable	152.31	Unsuitable
Dec	137.15	Unsuitable	137.15	Unsuitable	151.58	Unsuitable	151.58	Unsuitable	151.58	Unsuitable
S5										
Jan	154.09	Unsuitable	154.09	Unsuitable	147.24	Unsuitable	147.24	Unsuitable	186.09	Unsuitable
Feb	164.31	Unsuitable	164.31	Unsuitable	160.83	Unsuitable	198.64	Unsuitable	190.53	Unsuitable
Mar	176.73	Unsuitable	176.73	Unsuitable	198.72	Unsuitable	194.75	Unsuitable	211.45	Unsuitable
Apr	196.69	Unsuitable	199.15	Unsuitable	196.69	Unsuitable	199.15	Unsuitable	220.99	Unsuitable
May	199.72	Unsuitable	214.75	Unsuitable	199.72	Unsuitable	199.72	Unsuitable	214.72	Unsuitable
Jun	180.65	Unsuitable	180.65	Unsuitable	192.20	Unsuitable	192.20	Unsuitable	204.05	Unsuitable
Jul	167.79	Unsuitable	167.79	Unsuitable	179.85	Unsuitable	195.25	Unsuitable	195.25	Unsuitable
Aug	123.35	Unsuitable	123.35	Unsuitable	181.68	Unsuitable	163.80	Unsuitable	163.80	Unsuitable
Sep	142.31	Unsuitable	163.50	Unsuitable	166.46	Unsuitable	174.13	Unsuitable	177.34	Unsuitable
Oct	146.54	Unsuitable	150.00	Unsuitable	165.96	Unsuitable	168.93	Unsuitable	168.93	Unsuitable
Nov	139.07	Unsuitable	166.96	Unsuitable	175.44	Unsuitable	181.51	Unsuitable	181.51	Unsuitable
Dec	157.92	Unsuitable	157.92	Unsuitable	178.82	Unsuitable	178.82	Unsuitable	178.82	Unsuitable
S6										
Jan	172.86	Unsuitable	172.86	Unsuitable	172.43	Unsuitable	172.43	Unsuitable	197.25	Unsuitable

	2013		2014		2015		2016		2017	
	WQI	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**
Feb	182.88	Unsuitable	182.88	Unsuitable	179.20	Unsuitable	210.53	Unsuitable	207.42	Unsuitable
Mar	192.45	Unsuitable	192.45	Unsuitable	215.89	Unsuitable	211.69	Unsuitable	223.67	Unsuitable
Apr	218.36	Unsuitable	192.45	Unsuitable	218.36	Unsuitable	215.97	Unsuitable	228.69	Unsuitable
May	219.56	Unsuitable	228.06	Unsuitable	219.56	Unsuitable	219.56	Unsuitable	228.06	Unsuitable
Jun	197.64	Unsuitable	197.64	Unsuitable	207.21	Unsuitable	207.21	Unsuitable	217.99	Unsuitable
Jul	188.07	Unsuitable	188.07	Unsuitable	206.61	Unsuitable	206.72	Unsuitable	206.72	Unsuitable
Aug	132.49	Unsuitable	132.49	Unsuitable	202.07	Unsuitable	176.19	Unsuitable	176.19	Unsuitable
Sep	155.36	Unsuitable	181.48	Unsuitable	181.58	Unsuitable	183.92	Unsuitable	194.19	Unsuitable
Oct	164.17	Unsuitable	169.18	Unsuitable	170.10	Unsuitable	178.72	Unsuitable	178.72	Unsuitable
Nov	161.58	Unsuitable	186.56	Unsuitable	188.61	Unsuitable	197.06	Unsuitable	197.06	Unsuitable
Dec	177.33	Unsuitable	177.33	Unsuitable	195.88	Unsuitable	195.88	Unsuitable	195.88	Unsuitable
S7										
Jan	198.65	Unsuitable	198.65	Unsuitable	206.71	Unsuitable	206.71	Unsuitable	227.42	Unsuitable
Feb	216.48	Unsuitable	216.48	Unsuitable	209.82	Unsuitable	242.15	Unsuitable	245.41	Unsuitable
Mar	231.15	Unsuitable	231.15	Unsuitable	246.57	Unsuitable	227.80	Unsuitable	246.80	Unsuitable
Apr	243.56	Unsuitable	232.16	Unsuitable	243.56	Unsuitable	232.16	Unsuitable	243.41	Unsuitable
May	246.52	Unsuitable	242.57	Unsuitable	246.52	Unsuitable	246.52	Unsuitable	242.57	Unsuitable

	2013		2014		2015		2016		2017	
	WQI	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**	**WQI**	**Status**
Jun	219.61	Unsuitable	219.61	Unsuitable	230.51	Unsuitable	230.51	Unsuitable	249.39	Unsuitable
Jul	226.72	Unsuitable	226.72	Unsuitable	237.33	Unsuitable	228.70	Unsuitable	228.70	Unsuitable
Aug	154.66	Unsuitable	154.66	Unsuitable	217.34	Unsuitable	195.54	Unsuitable	195.54	Unsuitable
Sep	175.48	Unsuitable	219.97	Unsuitable	210.45	Unsuitable	211.45	Unsuitable	242.13	Unsuitable
Oct	187.47	Unsuitable	208.04	Unsuitable	217.75	Unsuitable	219.81	Unsuitable	219.81	Unsuitable
Nov	182.63	Unsuitable	218.60	Unsuitable	231.81	Unsuitable	231.96	Unsuitable	231.96	Unsuitable
Dec	193.79	Unsuitable	193.79	Unsuitable	227.83	Unsuitable	227.83	Unsuitable	227.83	Unsuitable

Table 5.9: Water quality status of the river Gomti during the study period as per SPI

	2013		2014		2015		2016		2017	
	SPI	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**
S1										
Jan	1.232	Very Poor	1.232	Very Poor	1.233	Very Poor	1.233	Very Poor	1.262	Very Poor
Feb	1.245	Very Poor	1.245	Very Poor	1.226	Very Poor	1.263	Very Poor	1.277	Very Poor
Mar	1.189	Very Poor	1.189	Very Poor	1.040	Very Poor	1.207	Very Poor	1.197	Very Poor
Apr	1.049	Very Poor	1.191	Very Poor	1.049	Very Poor	1.191	Very Poor	1.109	Very Poor
May	1.103	Very Poor	1.129	Very Poor	1.103	Very Poor	1.103	Very Poor	1.129	Very Poor

	2013		2014		2015		2016		2017	
	SPI	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**
Jun	1.079	Very Poor	1.079	Very Poor	1.095	Very Poor	1.095	Very Poor	1.174	Very Poor
Jul	0.968	Poor	0.968	Poor	1.023	Very Poor	1.026	Very Poor	1.026	Very Poor
Aug	0.868	Poor	0.868	Poor	1.068	Very Poor	0.997	Poor	0.997	Poor
Sep	0.952	Poor	0.974	Poor	1.075	Very Poor	0.977	Poor	0.973	Poor
Oct	1.066	Very Poor	1.061	Very Poor	1.065	Very Poor	1.033	Very Poor	1.033	Very Poor
Nov	1.106	Very Poor	1.123	Very Poor	1.135	Very Poor	1.098	Very Poor	1.098	Very Poor
Dec	1.254	Very Poor	1.254	Very Poor	1.223	Very Poor	1.223	Very Poor	1.223	Very Poor
S2										
Jan	1.277	Very Poor	1.277	Very Poor	1.294	Very Poor	1.294	Very Poor	1.302	Very Poor
Feb	1.312	Very Poor	1.312	Very Poor	1.305	Very Poor	1.235	Very Poor	1.305	Very Poor
Mar	1.267	Very Poor	1.267	Very Poor	1.130	Very Poor	1.175	Very Poor	1.171	Very Poor
Apr	1.149	Very Poor	1.168	Very Poor	1.149	Very Poor	1.168	Very Poor	1.057	Very Poor
May	1.171	Very Poor	1.148	Very Poor	1.171	Very Poor	1.171	Very Poor	1.148	Very Poor
Jun	1.119	Very Poor	1.119	Very Poor	1.173	Very Poor	1.173	Very Poor	1.193	Very Poor
Jul	1.003	Very Poor	1.003	Very Poor	1.118	Very Poor	1.010	Very Poor	1.010	Very Poor
Aug	0.908	Poor	0.908	Poor	1.137	Very Poor	0.973	Poor	0.973	Poor
Sep	0.999	Poor	1.014	Very Poor	1.131	Very Poor	1.022	Very Poor	0.974	Poor

	2013		2014		2015		2016		2017	
	SPI	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**
Oct	1.110	Very Poor	1.117	Very Poor	1.115	Very Poor	1.044	Very Poor	1.044	Very Poor
Nov	1.141	Very Poor	1.169	Very Poor	1.181	Very Poor	1.144	Very Poor	1.144	Very Poor
Dec	1.300	Very Poor	1.300	Very Poor	1.285	Very Poor	1.285	Very Poor	1.285	Very Poor
S3										
Jan	1.298	Very Poor	1.298	Very Poor	1.317	Very Poor	1.317	Very Poor	1.418	Very Poor
Feb	1.324	Very Poor	1.324	Very Poor	1.287	Very Poor	1.213	Very Poor	1.397	Very Poor
Mar	1.328	Very Poor	1.328	Very Poor	1.174	Very Poor	1.200	Very Poor	1.465	Very Poor
Apr	1.204	Very Poor	1.270	Very Poor	1.204	Very Poor	1.270	Very Poor	1.420	Very Poor
May	1.242	Very Poor	1.393	Very Poor	1.242	Very Poor	1.242	Very Poor	1.393	Very Poor
Jun	1.229	Very Poor	1.229	Very Poor	1.263	Very Poor	1.263	Very Poor	1.388	Very Poor
Jul	1.111	Very Poor	1.111	Very Poor	1.160	Very Poor	1.368	Very Poor	1.368	Very Poor
Aug	0.987	Poor	0.987	Poor	1.163	Very Poor	1.195	Very Poor	1.195	Very Poor
Sep	1.066	Very Poor	1.135	Very Poor	1.153	Very Poor	1.370	Very Poor	1.198	Very Poor
Oct	1.178	Very Poor	1.185	Very Poor	1.142	Very Poor	1.288	Very Poor	1.288	Very Poor
Nov	1.165	Very Poor	1.231	Very Poor	1.199	Very Poor	1.350	Very Poor	1.350	Very Poor
Dec	1.301	Very Poor	1.301	Very Poor	1.163	Very Poor	1.163	Very Poor	1.163	Very Poor
S4										

	2013		2014		2015		2016		2017	
	SPI	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**
Jan	1.383	Very Poor	1.383	Very Poor	1.363	Very Poor	1.363	Very Poor	1.474	Very Poor
Feb	1.340	Very Poor	1.340	Very Poor	1.331	Very Poor	1.483	Very Poor	1.518	Very Poor
Mar	1.417	Very Poor	1.417	Very Poor	1.256	Very Poor	1.337	Very Poor	1.581	Very Poor
Apr	1.328	Very Poor	1.399	Very Poor	1.328	Very Poor	1.399	Very Poor	1.560	Very Poor
May	1.367	Very Poor	1.601	Very Poor	1.367	Very Poor	1.367	Very Poor	1.601	Very Poor
Jun	1.381	Very Poor	1.381	Very Poor	1.411	Very Poor	1.411	Very Poor	1.559	Very Poor
Jul	1.267	Very Poor	1.267	Very Poor	1.315	Very Poor	1.485	Very Poor	1.485	Very Poor
Aug	1.070	Very Poor	1.070	Very Poor	1.292	Very Poor	1.378	Very Poor	1.378	Very Poor
Sep	1.167	Very Poor	1.247	Very Poor	1.269	Very Poor	1.483	Very Poor	1.454	Very Poor
Oct	1.257	Very Poor	1.284	Very Poor	1.247	Very Poor	1.377	Very Poor	1.377	Very Poor
Nov	1.271	Very Poor	1.352	Very Poor	1.326	Very Poor	1.417	Very Poor	1.415	Very Poor
Dec	1.396	Very Poor	1.396	Very Poor	1.285	Very Poor	1.285	Very Poor	1.285	Very Poor
S5										
Jan	1.467	Very Poor	1.467	Very Poor	1.346	Very Poor	1.346	Very Poor	1.555	Very Poor
Feb	1.457	Very Poor	1.457	Very Poor	1.354	Very Poor	1.762	Very Poor	1.657	Very Poor
Mar	1.565	Very Poor	1.565	Very Poor	1.537	Very Poor	1.605	Very Poor	1.727	Very Poor
Apr	1.649	Very Poor	1.743	Very Poor	1.649	Very Poor	1.743	Very Poor	1.859	Very Poor

	2013		2014		2015		2016		2017	
	SPI	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**
May	1.648	Very Poor	1.828	Very Poor	1.648	Very Poor	1.648	Very Poor	1.828	Very Poor
Jun	1.513	Very Poor	1.513	Very Poor	1.587	Very Poor	1.587	Very Poor	1.797	Very Poor
Jul	1.438	Very Poor	1.438	Very Poor	1.539	Very Poor	1.646	Very Poor	1.646	Very Poor
Aug	1.254	Very Poor	1.254	Very Poor	1.525	Very Poor	1.545	Very Poor	1.545	Very Poor
Sep	1.373	Very Poor	1.376	Very Poor	1.491	Very Poor	1.610	Very Poor	1.513	Very Poor
Oct	1.402	Very Poor	1.335	Very Poor	1.376	Very Poor	1.484	Very Poor	1.484	Very Poor
Nov	1.384	Very Poor	1.415	Very Poor	1.421	Very Poor	1.486	Very Poor	1.486	Very Poor
Dec	1.423	Very Poor	1.423	Very Poor	1.496	Very Poor	1.496	Very Poor	1.496	Very Poor
S6										
Jan	1.578	Very Poor	1.578	Very Poor	1.497	Very Poor	1.497	Very Poor	1.651	Very Poor
Feb	1.595	Very Poor	1.595	Very Poor	1.541	Very Poor	1.874	Very Poor	1.786	Very Poor
Mar	1.664	Very Poor	1.664	Very Poor	1.687	Very Poor	1.755	Very Poor	1.840	Very Poor
Apr	1.803	Very Poor	1.664	Very Poor	1.803	Very Poor	1.903	Very Poor	2.020	Very Poor
May	1.794	Very Poor	1.971	Very Poor	1.794	Very Poor	1.794	Very Poor	1.971	Very Poor
Jun	1.669	Very Poor	1.669	Very Poor	1.721	Very Poor	1.721	Very Poor	1.951	Very Poor
Jul	1.619	Very Poor	1.619	Very Poor	1.778	Very Poor	1.791	Very Poor	1.791	Very Poor
Aug	1.338	Very Poor	1.338	Very Poor	1.703	Very Poor	1.663	Very Poor	1.663	Very Poor

	2013		2014		2015		2016		2017	
	SPI	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**	**SPI**	**Status**
Sep	1.497	Very Poor	1.526	Very Poor	1.614	Very Poor	1.651	Very Poor	1.622	Very Poor
Oct	1.558	Very Poor	1.447	Very Poor	1.366	Very Poor	1.579	Very Poor	1.579	Very Poor
Nov	1.541	Very Poor	1.548	Very Poor	1.543	Very Poor	1.615	Very Poor	1.615	Very Poor
Dec	1.579	Very Poor	1.579	Very Poor	1.645	Very Poor	1.645	Very Poor	1.645	Very Poor
S7										
Jan	1.715	Very Poor	1.715	Very Poor	1.821	Very Poor	1.821	Very Poor	1.945	Very Poor
Feb	1.809	Very Poor	1.809	Very Poor	1.838	Very Poor	2.022	Very Poor	2.114	Very Poor
Mar	2.000	Very Poor	2.000	Very Poor	2.032	Very Poor	2.013	Very Poor	2.084	Very Poor
Apr	2.070	Very Poor	2.027	Very Poor	2.070	Very Poor	2.027	Very Poor	2.125	Very Poor
May	2.096	Very Poor	2.109	Very Poor	2.096	Very Poor	2.096	Very Poor	2.109	Very Poor
Jun	1.927	Very Poor	1.927	Very Poor	1.996	Very Poor	1.996	Very Poor	2.177	Very Poor
Jul	1.999	Very Poor	1.999	Very Poor	2.093	Very Poor	1.992	Very Poor	1.992	Very Poor
Aug	1.513	Very Poor	1.513	Very Poor	1.847	Very Poor	1.830	Very Poor	1.830	Very Poor
Sep	1.647	Very Poor	1.874	Very Poor	1.831	Very Poor	1.903	Very Poor	2.130	Very Poor
Oct	1.716	Very Poor	1.851	Very Poor	1.840	Very Poor	1.938	Very Poor	1.938	Very Poor
Nov	1.704	Very Poor	1.858	Very Poor	1.941	Very Poor	1.971	Very Poor	1.971	Very Poor
Dec	1.728	Very Poor	1.728	Very Poor	1.950	Very Poor	1.950	Very Poor	1.950	Very Poor

5.6.3 Assessment of CPI

According to the approach used to categorize the overall water quality status of the river Gomti, the CPI value was assessed for each location using water quality measures (from January 2013 to December 2017) (Table 5.10). The monthly CPI data were organized to examine the seasonal variations in water quality, and the mean CPI of each year during the study period was calculated using this data (Figure 5.20).

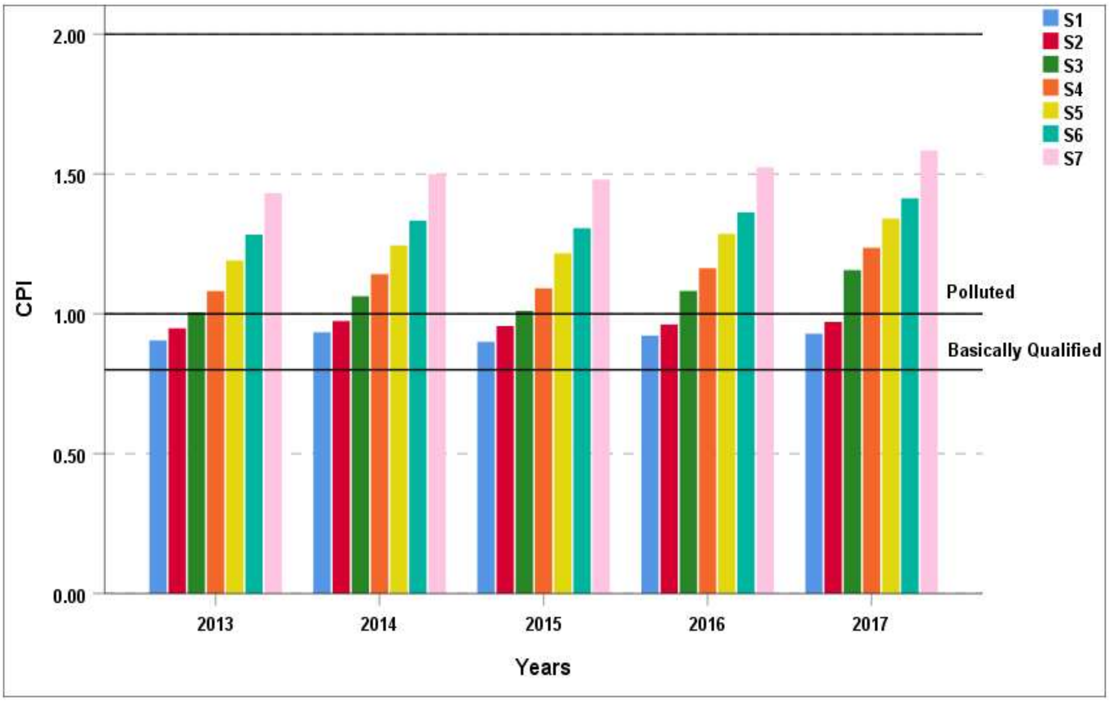


Figure 5.20: Variation of CPI of studied stations in the Gomti River for the period 2013-2017

The CPI values at S1 and S2 for all seasons were found in the range of 0.688 to 1.054 with an average of 0.918 and 0.725 to 1.087 with an average of 0.962 respectively, indicating basically qualified (0.81-1.0), i.e., poor quality and only allowable for irrigation purposes. Comparably, the CPI values at sampling stations S3, S4, S5, S6, and S7 were observed 0.787 to 1.348 with an average of 1.063, 0.846 to 1.455 with an average of 1.143, 0.955 to 1.577 with an average of 1.256, 1.014 to 1.662 with an average of 1.340 and 1.132 to 1.836 with an average of 1.504 respectively, indicating polluted (1.01-2.0), i.e., very poor quality (polluted) and can be used restrictedly for irrigation. It was also noticed that the river Gomti water was found only in three categories: qualified (0.41-0.8), basically qualified (0.81-1.0), and polluted (1.01-2.0) during the study period at different locations and months. Moreover, the water quality of the rivers during the year 2013–17 was found to be in the polluted category, and CPI values increased from sampling stations S1 to S7, showing an increase in pollutant load as a result of recent, excessive human activity. Additionally, similar remarks regarding the unsuitability of water were made by Sidabutar et al. (2017), Wang et al. (2018), Matta et al. (2018), Kumar et al. (2020a), Pramanik et al. (2020) and Kumar et al. (2021b) during their investigation of water quality by CPI.

5.6.4 Assessment of CPCB-WQI

CPCB-WQI was developed for the evaluation of the water quality of River Ganga by Ved Prakash et al. (1990), which was the modified version of NSF-WQI (Abbasi and Abbasi, 2012). The index was modified in terms of the set of parameters and weights. This index model calculated water quality based on only four parameters (pH, DO, BOD, and FC). CPCB-WQI value was evaluated for each location using selected water quality parameters (between January 2013 and December 2017) according to the technique used to categorize the river Gomti's overall water quality condition (Table 5.11). This model aggregated the index value based on the weighted product method, which usually worked well for low values with great variability and followed a linear scale for classification.

The CPCB-WQI values for all seasons were found in range of 30.31 to 100.44 with a mean of 54.61 at S1, 38.81 to 94.99 with a mean of 55.14 at S2, 29.68 to 63.10 with a mean of 45.38 at S3, 28.92 to 54.71 with a mean of 40.86 at S4, 27.65 to 45.97 with a mean of 34.43 at S5, 26.22 to 40.60 with a mean of 31.88 at S6 and 25.66 to 34.35 with a mean of 29.18 at S7. The mean values of CPCB-WQI at S1 and S2 lie under the category medium to good, Class -B (50-63), S3 and S4 under the category bad, Class -C (38-50), S5, S6, and S7 under category bad to very bad, Class – D & E (<38). It was also noticed that the river Gomti water was found in all categories classified by CPCB-WQI for different sampling stations during different months of the study period. The result of CPCB-WQI could be well related to the biological and physicochemical results. Also, well-defined annual and site-wise variation was observed in the CPCB-WQI values (Figure 5.21); thus, any little change in the pollution concentration could be well noticed. According to CPCB-WQI values, the water quality of river Gomti is deteriorating during its course to Lucknow (UP) from upstream (S1) to downstream (S7). Several researchers used this index, Bhutiani et al. (2016), Singh et al. (2018), and Kharake and Raut (2021) on other rivers in India.

Table 5.10: Water quality status of the river Gomti during the study period as per CPI

	2013		2014		2015		2016		2017	
	CPI	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**
S1										
Jan	0.944	Basically Qualified	0.944	Basically Qualified	0.924	Basically Qualified	0.924	Basically Qualified	0.950	Basically Qualified
Feb	0.990	Basically Qualified	0.990	Basically Qualified	0.964	Basically Qualified	1.007	Polluted	0.983	Basically Qualified
Mar	0.991	Basically Qualified	0.991	Basically Qualified	0.905	Basically Qualified	1.054	Polluted	0.995	Basically Qualified
Apr	0.912	Basically Qualified	1.050	Polluted	0.912	Basically Qualified	1.050	Polluted	1.020	Polluted
May	0.925	Basically Qualified	1.012	Polluted	0.925	Basically Qualified	0.925	Basically Qualified	1.012	Polluted
Jun	1.023	Polluted	1.023	Polluted	0.933	Basically Qualified	0.933	Basically Qualified	1.017	Polluted
Jul	0.938	Basically Qualified	0.938	Basically Qualified	0.799	Qualified	0.931	Basically Qualified	0.931	Basically Qualified
Aug	0.688	Qualified	0.688	Qualified	0.922	Basically Qualified	0.773	Qualified	0.773	Qualified
Sep	0.770	Qualified	0.843	Basically Qualified	0.856	Basically Qualified	0.766	Qualified	0.768	Qualified
Oct	0.871	Basically Qualified	0.876	Basically Qualified	0.858	Basically Qualified	0.853	Basically Qualified	0.853	Basically Qualified
Nov	0.877	Basically Qualified	0.924	Basically Qualified	0.869	Basically Qualified	0.912	Basically Qualified	0.912	Basically Qualified
Dec	0.926	Basically Qualified	0.926	Basically Qualified	0.930	Basically Qualified	0.930	Basically Qualified	0.930	Basically Qualified
S2										
Jan	0.984	Basically Qualified	0.984	Basically Qualified	0.970	Basically Qualified	0.970	Basically Qualified	0.991	Basically Qualified
Feb	1.041	Polluted	1.041	Polluted	1.026	Polluted	1.038	Polluted	1.015	Polluted
Mar	1.048	Polluted	1.048	Polluted	0.971	Basically Qualified	1.087	Polluted	1.010	Polluted

	2013		2014		2015		2016		2017	
	CPI	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**
Apr	0.976	Basically Qualified	1.073	Polluted	0.976	Basically Qualified	1.073	Polluted	1.047	Polluted
May	0.984	Basically Qualified	1.066	Polluted	0.984	Basically Qualified	0.984	Basically Qualified	1.065	Polluted
Jun	1.062	Polluted	1.062	Polluted	0.995	Basically Qualified	0.995	Basically Qualified	1.078	Polluted
Jul	0.969	Basically Qualified	0.969	Basically Qualified	0.867	Basically Qualified	0.985	Basically Qualified	0.985	Basically Qualified
Aug	0.725	Qualified	0.725	Qualified	0.983	Basically Qualified	0.781	Qualified	0.781	Qualified
Sep	0.812	Basically Qualified	0.880	Basically Qualified	0.906	Basically Qualified	0.804	Basically Qualified	0.850	Basically Qualified
Oct	0.902	Basically Qualified	0.916	Basically Qualified	0.898	Basically Qualified	0.888	Basically Qualified	0.888	Basically Qualified
Nov	0.907	Basically Qualified	0.966	Basically Qualified	0.911	Basically Qualified	0.959	Basically Qualified	0.959	Basically Qualified
Dec	0.961	Basically Qualified	0.961	Basically Qualified	0.980	Basically Qualified	0.980	Basically Qualified	0.980	Basically Qualified
S3										
Jan	1.024	Polluted	1.024	Polluted	1.021	Polluted	1.021	Polluted	1.125	Polluted
Feb	1.088	Polluted	1.088	Polluted	1.064	Polluted	1.132	Polluted	1.162	Polluted
Mar	1.114	Polluted	1.114	Polluted	1.038	Polluted	1.205	Polluted	1.316	Polluted
Apr	1.035	Polluted	1.235	Polluted	1.035	Polluted	1.235	Polluted	1.339	Polluted
May	1.051	Polluted	1.348	Polluted	1.051	Polluted	1.051	Polluted	1.347	Polluted
Jun	1.149	Polluted	1.149	Polluted	1.076	Polluted	1.076	Polluted	1.343	Polluted
Jul	1.046	Polluted	1.046	Polluted	0.922	Basically Qualified	1.236	Polluted	1.236	Polluted
Aug	0.787	Qualified	0.787	Qualified	1.044	Polluted	0.911	Basically Qualified	0.911	Basically Qualified
Sep	0.862	Basically Qualified	0.962	Basically Qualified	0.951	Basically Qualified	0.987	Basically Qualified	0.962	Basically Qualified

	2013		2014		2015		2016		2017	
	CPI	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**
Oct	0.961	Basically Qualified	0.985	Basically Qualified	0.947	Basically Qualified	1.029	Polluted	1.029	Polluted
Nov	0.945	Basically Qualified	1.022	Polluted	0.963	Basically Qualified	1.086	Polluted	1.086	Polluted
Dec	0.993	Basically Qualified	0.993	Basically Qualified	1.018	Polluted	1.018	Polluted	1.018	Polluted
S4										
Jan	1.099	Polluted	1.099	Polluted	1.081	Polluted	1.081	Polluted	1.179	Polluted
Feb	1.135	Polluted	1.135	Polluted	1.123	Polluted	1.266	Polluted	1.249	Polluted
Mar	1.192	Polluted	1.192	Polluted	1.102	Polluted	1.287	Polluted	1.378	Polluted
Apr	1.117	Polluted	1.300	Polluted	1.117	Polluted	1.300	Polluted	1.388	Polluted
May	1.139	Polluted	1.455	Polluted	1.139	Polluted	1.139	Polluted	1.455	Polluted
Jun	1.257	Polluted	1.257	Polluted	1.183	Polluted	1.183	Polluted	1.434	Polluted
Jul	1.151	Polluted	1.151	Polluted	1.024	Polluted	1.306	Polluted	1.306	Polluted
Aug	0.846	Basically Qualified	0.846	Basically Qualified	1.132	Polluted	1.006	Polluted	1.006	Polluted
Sep	0.929	Basically Qualified	1.035	Polluted	1.027	Polluted	1.062	Polluted	1.119	Polluted
Oct	1.022	Polluted	1.064	Polluted	1.015	Polluted	1.090	Polluted	1.090	Polluted
Nov	1.018	Polluted	1.111	Polluted	1.055	Polluted	1.144	Polluted	1.141	Polluted
Dec	1.064	Polluted	1.064	Polluted	1.090	Polluted	1.090	Polluted	1.090	Polluted
S5										
Jan	1.173	Polluted	1.173	Polluted	1.129	Polluted	1.129	Polluted	1.260	Polluted
Feb	1.227	Polluted	1.227	Polluted	1.188	Polluted	1.429	Polluted	1.354	Polluted

	2013		2014		2015		2016		2017	
	CPI	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**
Mar	1.301	Polluted	1.301	Polluted	1.270	Polluted	1.449	Polluted	1.478	Polluted
Apr	1.297	Polluted	1.508	Polluted	1.297	Polluted	1.508	Polluted	1.563	Polluted
May	1.319	Polluted	1.577	Polluted	1.319	Polluted	1.319	Polluted	1.576	Polluted
Jun	1.355	Polluted	1.355	Polluted	1.321	Polluted	1.321	Polluted	1.575	Polluted
Jul	1.271	Polluted	1.271	Polluted	1.161	Polluted	1.400	Polluted	1.400	Polluted
Aug	0.955	Basically Qualified	0.955	Basically Qualified	1.278	Polluted	1.103	Polluted	1.103	Polluted
Sep	1.050	Polluted	1.129	Polluted	1.160	Polluted	1.156	Polluted	1.165	Polluted
Oct	1.118	Polluted	1.131	Polluted	1.118	Polluted	1.174	Polluted	1.174	Polluted
Nov	1.106	Polluted	1.191	Polluted	1.144	Polluted	1.225	Polluted	1.225	Polluted
Dec	1.123	Polluted	1.123	Polluted	1.213	Polluted	1.213	Polluted	1.213	Polluted
S6										
Jan	1.259	Polluted	1.259	Polluted	1.230	Polluted	1.230	Polluted	1.322	Polluted
Feb	1.322	Polluted	1.322	Polluted	1.301	Polluted	1.502	Polluted	1.433	Polluted
Mar	1.369	Polluted	1.369	Polluted	1.363	Polluted	1.531	Polluted	1.549	Polluted
Apr	1.397	Polluted	1.595	Polluted	1.397	Polluted	1.595	Polluted	1.645	Polluted
May	1.415	Polluted	1.659	Polluted	1.415	Polluted	1.415	Polluted	1.659	Polluted
Jun	1.458	Polluted	1.458	Polluted	1.415	Polluted	1.415	Polluted	1.662	Polluted
Jul	1.389	Polluted	1.389	Polluted	1.291	Polluted	1.480	Polluted	1.480	Polluted
Aug	1.014	Polluted	1.014	Polluted	1.388	Polluted	1.169	Polluted	1.169	Polluted

	2013		2014		2015		2016		2017	
	CPI	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**	**CPI**	**Status**
Sep	1.126	Polluted	1.219	Polluted	1.241	Polluted	1.191	Polluted	1.212	Polluted
Oct	1.211	Polluted	1.212	Polluted	1.115	Polluted	1.232	Polluted	1.232	Polluted
Nov	1.206	Polluted	1.276	Polluted	1.223	Polluted	1.298	Polluted	1.298	Polluted
Dec	1.227	Polluted	1.227	Polluted	1.298	Polluted	1.298	Polluted	1.298	Polluted
S7										
Jan	1.370	Polluted	1.370	Polluted	1.419	Polluted	1.419	Polluted	1.537	Polluted
Feb	1.487	Polluted	1.487	Polluted	1.470	Polluted	1.654	Polluted	1.630	Polluted
Mar	1.590	Polluted	1.590	Polluted	1.558	Polluted	1.684	Polluted	1.700	Polluted
Apr	1.554	Polluted	1.699	Polluted	1.554	Polluted	1.699	Polluted	1.739	Polluted
May	1.586	Polluted	1.799	Polluted	1.586	Polluted	1.586	Polluted	1.799	Polluted
Jun	1.633	Polluted	1.633	Polluted	1.575	Polluted	1.575	Polluted	1.836	Polluted
Jul	1.630	Polluted	1.630	Polluted	1.461	Polluted	1.608	Polluted	1.608	Polluted
Aug	1.132	Polluted	1.132	Polluted	1.462	Polluted	1.277	Polluted	1.277	Polluted
Sep	1.240	Polluted	1.417	Polluted	1.382	Polluted	1.346	Polluted	1.451	Polluted
Oct	1.322	Polluted	1.433	Polluted	1.389	Polluted	1.444	Polluted	1.444	Polluted
Nov	1.308	Polluted	1.463	Polluted	1.432	Polluted	1.519	Polluted	1.519	Polluted
Dec	1.337	Polluted	1.337	Polluted	1.474	Polluted	1.474	Polluted	1.474	Polluted

Table 5.11: Water quality status of the river Gomti during the study period as per CPCB-WQI

	2013		2014		2015		2016		2017	
	CPCB-WQI	Status	CPCB-WQI	Status	CPCB-WQI	Status	CPCB-WQI	Status	CPCB-WQI	Status
S1										
Jan	31.03	Bad to very bad	31.03	Bad to very bad	100.44	Good to excellent	100.44	Good to excellent	95.51	Good to excellent
Feb	30.39	Bad to very bad	30.39	Bad to very bad	68.63	Good to excellent	63.87	Good to excellent	94.41	Good to excellent
Mar	31.32	Bad to very bad	31.32	Bad to very bad	52.92	Medium to good	59.75	Medium to good	59.11	Medium to good
Apr	52.90	Medium to good	58.00	Medium to good	52.90	Medium to good	58.00	Medium to good	56.68	Medium to good
May	52.90	Medium to good	52.12	Medium to good	52.90	Medium to good	52.90	Medium to good	52.13	Medium to good
Jun	36.41	Bad to very bad	53.95	Medium to good	51.91	Medium to good	51.91	Medium to good	52.73	Medium to good
Jul	39.54	Bad	51.65	Medium to good	50.57	Medium to good	49.00	Bad	49.00	Bad
Aug	44.53	Bad	52.26	Medium to good	52.92	Medium to good	54.04	Medium to good	54.04	Medium to good
Sep	40.96	Bad	53.69	Medium to good	55.18	Medium to good	54.39	Medium to good	54.32	Medium to good
Oct	37.23	Bad to very bad	60.84	Medium to good	55.55	Medium to good	55.26	Medium to good	55.26	Medium to good
Nov	35.59	Bad to very bad	61.07	Medium to good	57.95	Medium to good	58.20	Medium to good	58.20	Medium to good
Dec	30.31	Bad to very bad	96.19	Good to excellent	63.36	Good to excellent	63.36	Good to excellent	63.36	Good to excellent
S2										
Jan	64.69	Good to excellent	64.69	Good to excellent	68.58	Good to excellent	68.58	Good to excellent	64.05	Good to excellent
Feb	64.33	Good to excellent	64.33	Good to excellent	66.53	Good to excellent	56.08	Medium to good	94.99	Good to excellent
Mar	59.82	Medium to good	59.82	Medium to good	51.09	Medium to good	51.41	Medium to good	53.81	Medium to good

	2013		2014		2015		2016		2017	
	CPCB-WQI	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**
Apr	50.87	Medium to good	51.14	Medium to good	50.87	Medium to good	51.14	Medium to good	48.42	Bad
May	50.05	Medium to good	48.60	Bad	50.05	Medium to good	50.05	Medium to good	48.60	Bad
Jun	52.54	Medium to good	52.54	Medium to good	49.41	Bad	49.41	Bad	46.08	Bad
Jul	49.84	Bad	49.84	Bad	48.74	Bad	38.81	Bad	38.81	Bad
Aug	50.86	Medium to good	50.86	Medium to good	50.88	Medium to good	46.59	Bad	46.59	Bad
Sep	52.60	Medium to good	52.23	Medium to good	53.37	Medium to good	52.26	Medium to good	47.50	Bad
Oct	55.80	Medium to good	59.03	Medium to good	53.68	Medium to good	51.47	Medium to good	51.47	Medium to good
Nov	60.73	Medium to good	60.04	Medium to good	56.70	Medium to good	56.08	Medium to good	56.08	Medium to good
Dec	64.87	Good to excellent	64.87	Good to excellent	61.73	Medium to good	61.73	Medium to good	61.73	Medium to good
S3										
Jan	61.72	Medium to good	61.72	Medium to good	63.10	Good to excellent	63.10	Good to excellent	44.21	Bad
Feb	57.29	Medium to good	57.27	Medium to good	58.04	Medium to good	33.30	Bad to very bad	46.96	Bad
Mar	53.08	Medium to good	53.08	Medium to good	44.60	Bad	34.43	Bad to very bad	30.33	Bad to very bad
Apr	46.27	Bad	34.06	Bad to very bad	46.27	Bad	34.06	Bad to very bad	29.68	Bad to very bad
May	44.29	Bad	31.56	Bad to very bad	44.29	Bad	44.29	Bad	31.56	Bad to very bad
Jun	45.49	Bad	45.49	Bad	43.55	Bad	43.55	Bad	33.12	Bad to very bad
Jul	43.52	Bad	43.52	Bad	42.54	Bad	33.58	Bad to very bad	33.58	Bad to very bad
Aug	45.95	Bad	45.95	Bad	42.76	Bad	40.37	Bad	40.37	Bad

	2013		2014		2015		2016		2017	
	CPCB-WQI	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**
Sep	49.00	Bad	48.25	Bad	48.23	Bad	44.48	Bad	33.91	Bad to very bad
Oct	51.38	Medium to good	53.09	Medium to good	48.78	Bad	38.87	Bad	38.87	Bad
Nov	55.77	Medium to good	55.12	Medium to good	51.45	Medium to good	46.35	Bad	46.35	Bad
Dec	60.01	Medium to good	60.01	Medium to good	40.40	Bad	40.40	Bad	40.40	Bad
S4										
Jan	54.71	Medium to good	54.71	Medium to good	53.84	Medium to good	53.84	Medium to good	39.25	Bad
Feb	48.62	Bad	48.62	Bad	49.13	Bad	35.86	Bad to very bad	40.44	Bad
Mar	46.16	Bad	46.16	Bad	36.77	Bad to very bad	32.25	Bad to very bad	29.76	Bad to very bad
Apr	38.09	Bad	34.37	Bad to very bad	38.09	Bad	34.37	Bad to very bad	28.92	Bad to very bad
May	36.78	Bad to very bad	30.07	Bad to very bad	36.78	Bad to very bad	36.78	Bad to very bad	30.07	Bad to very bad
Jun	39.41	Bad	39.41	Bad	37.10	Bad to very bad	37.10	Bad to very bad	31.94	Bad to very bad
Jul	39.55	Bad	39.55	Bad	38.37	Bad	32.22	Bad to very bad	32.22	Bad to very bad
Aug	42.14	Bad	42.14	Bad	38.32	Bad	38.16	Bad	38.16	Bad
Sep	45.57	Bad	41.30	Bad	43.73	Bad	41.57	Bad	32.08	Bad to very bad
Oct	48.26	Bad	48.56	Bad	44.85	Bad	37.36	Bad to very bad	37.36	Bad to very bad
Nov	51.11	Bad	48.48	Bad	44.45	Bad	42.90	Bad	42.90	Bad
Dec	53.98	Bad	53.98	Bad	37.61	Bad to very bad	37.614	Bad to very bad	37.61	Bad to very bad

	2013		2014		2015		2016		2017	
	CPCB-WQI	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**
S5										
Jan	45.31	Bad	45.31	Bad	38.94	Bad	38.94	Bad	31.47	Bad to very bad
Feb	39.62	Bad	39.62	Bad	33.60	Bad to very bad	31.86	Bad to very bad	31.73	Bad to very bad
Mar	35.15	Bad to very bad	35.15	Bad to very bad	27.65	Bad to very bad	28.74	Bad to very bad	28.12	Bad to very bad
Apr	30.41	Bad to very bad	31.53	Bad to very bad	30.41	Bad to very bad	31.53	Bad to very bad	29.32	Bad to very bad
May	30.78	Bad to very bad	30.12	Bad to very bad	30.78	Bad to very bad	30.78	Bad to very bad	30.12	Bad to very bad
Jun	33.10	Bad to very bad	33.01	Bad to very bad	31.98	Bad to very bad	31.98	Bad to very bad	31.86	Bad to very bad
Jul	35.33	Bad to very bad	35.33	Bad to very bad	32.85	Bad to very bad	29.54	Bad to very bad	29.540	Bad to very bad
Aug	38.34	Bad	38.34	Bad	33.39	Bad to very bad	35.75	Bad to very bad	35.75	Bad to very bad
Sep	39.83	Bad	34.33	Bad to very bad	36.69	Bad	35.18	Bad to very bad	31.77	Bad to very bad
Oct	43.99	Bad	37.25	Bad	34.69	Bad to very bad	34.91	Bad to very bad	34.91	Bad to very bad
Nov	45.97	Bad	35.15	Bad	32.08	Bad to very bad	31.30	Bad to very bad	31.30	Bad to very bad
Dec	43.28	Bad	43.28	Bad	32.25	Bad to very bad	32.25	Bad to very bad	32.25	Bad to very bad
S6										
Jan	39.82	Bad	39.82	Bad	33.60	Bad to very bad	33.60	Bad to very bad	29.72	Bad to very bad
Feb	33.48	Bad to very bad	33.48	Bad to very bad	30.05	Bad to very bad	31.37	Bad to very bad	30.26	Bad to very bad
Mar	32.08	Bad to very bad	32.08	Bad to very bad	26.22	Bad to very bad	28.27	Bad to very bad	27.57	Bad to very bad

	2013 CPCB-WQI	Status	2014 CPCB-WQI	Status	2015 CPCB-WQI	Status	2016 CPCB-WQI	Status	2017 CPCB-WQI	Status
Apr	28.14	Bad to very bad	30.56	Bad to very bad	28.14	Bad to very bad	30.56	Bad to very bad	30.52	Bad to very bad
May	27.95	Bad to very bad	29.88	Bad to very bad	27.95	Bad to very bad	27.95	Bad to very bad	29.88	Bad to very bad
Jun	30.15	Bad to very bad	30.15	Bad to very bad	29.26	Bad to very bad	29.26	Bad to very bad	31.75	Bad to very bad
Jul	31.79	Bad to very bad	31.79	Bad to very bad	30.07	Bad to very bad	30.41	Bad to very bad	30.41	Bad to very bad
Aug	36.30	Bad to very bad	36.30	Bad to very bad	30.35	Bad to very bad	34.41	Bad to very bad	34.41	Bad to very bad
Sep	38.21	Bad	31.26	Bad to very bad	34.37	Bad to very bad	32.86	Bad to very bad	30.13	Bad to very bad
Oct	40.59	Bad	33.07	Bad to very bad	31.07	Bad to very bad	33.13	Bad to very bad	33.13	Bad to very bad
Nov	40.60	Bad	30.73	Bad to very bad	30.22	Bad to very bad	28.56	Bad to very bad	28.56	Bad to very bad
Dec	39.50	Bad	39.50	Bad	29.26	Bad to very bad	29.26	Bad to very bad	29.26	Bad to very bad
S7										
Jan	30.35	Bad to very bad	30.35	Bad to very bad	30.25	Bad to very bad	30.25	Bad to very bad	28.22	Bad to very bad
Feb	27.84	Bad to very bad	27.84	Bad to very bad	27.62	Bad to very bad	26.32	Bad to very bad	27.79	Bad to very bad
Mar	28.36	Bad to very bad	28.36	Bad to very bad	25.66	Bad to very bad	29.47	Bad to very bad	26.68	Bad to very bad
Apr	27.07	Bad to very bad	28.64	Bad to very bad	27.07	Bad to very bad	28.64	Bad to very bad	28.43	Bad to very bad
May	27.05	Bad to very bad	28.49	Bad to very bad	27.05	Bad to very bad	27.05	Bad to very bad	28.49	Bad to very bad
Jun	29.44	Bad to very bad	29.44	Bad to very bad	29.03	Bad to very bad	29.03	Bad to very bad	28.44	Bad to very bad
Jul	28.75	Bad to very bad	28.75	Bad to very bad	28.76	Bad to very bad	28.83	Bad to very bad	28.83	Bad to very bad
Aug	31.02	Bad to very bad	31.02	Bad to very bad	28.94	Bad to very bad	32.76	Bad to very bad	32.76	Bad to very bad

	2013		2014		2015		2016		2017	
	CPCB-WQI	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**	**CPCB-WQI**	**Status**
Sep	34.36	Bad to very bad	28.75	Bad to very bad	30.35	Bad to very bad	31.40	Bad to very bad	28.95	Bad to very bad
Oct	33.48	Bad to very bad	30.62	Bad to very bad	28.74	Bad to very bad	29.69	Bad to very bad	29.69	Bad to very bad
Nov	33.480	Bad to very bad	29.00	Bad to very bad	26.96	Bad to very bad	27.79	Bad to very bad	27.79	Bad to very bad
Dec	32.657	Bad to very bad	32.66	Bad to very bad	28.50	Bad to very bad	28.50	Bad to very bad	28.50	Bad to very bad

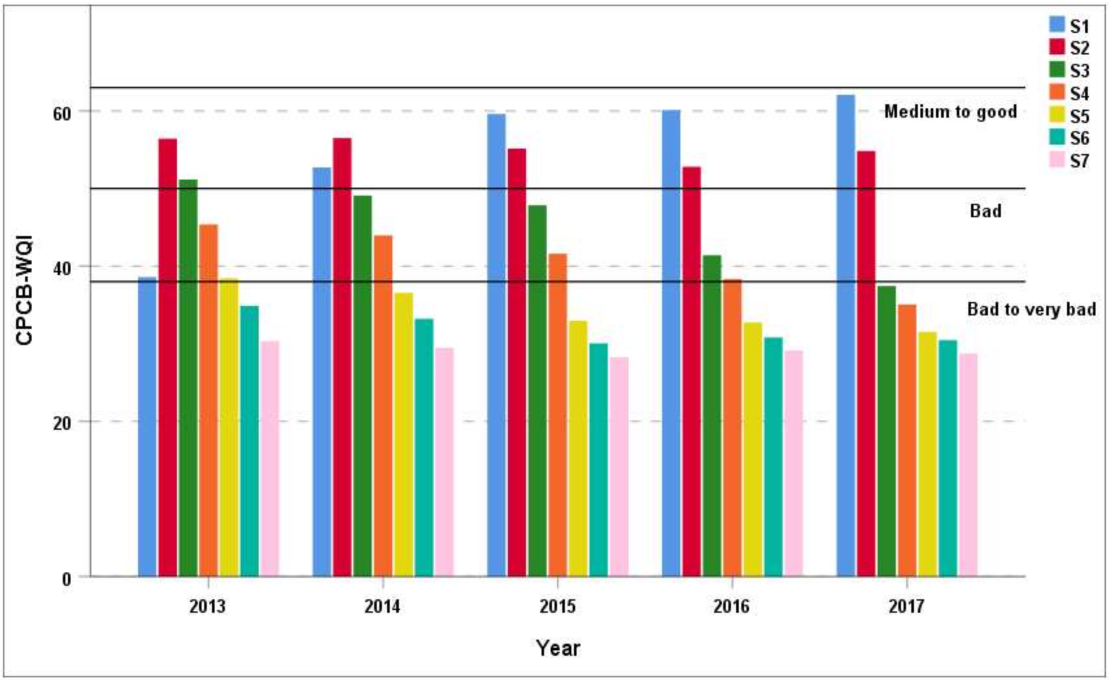


Figure 5.21: Variation of CPCB-WQI of studied stations in the Gomti River for the period 2013-2017

5.7 Geospatial assessment of water quality indices

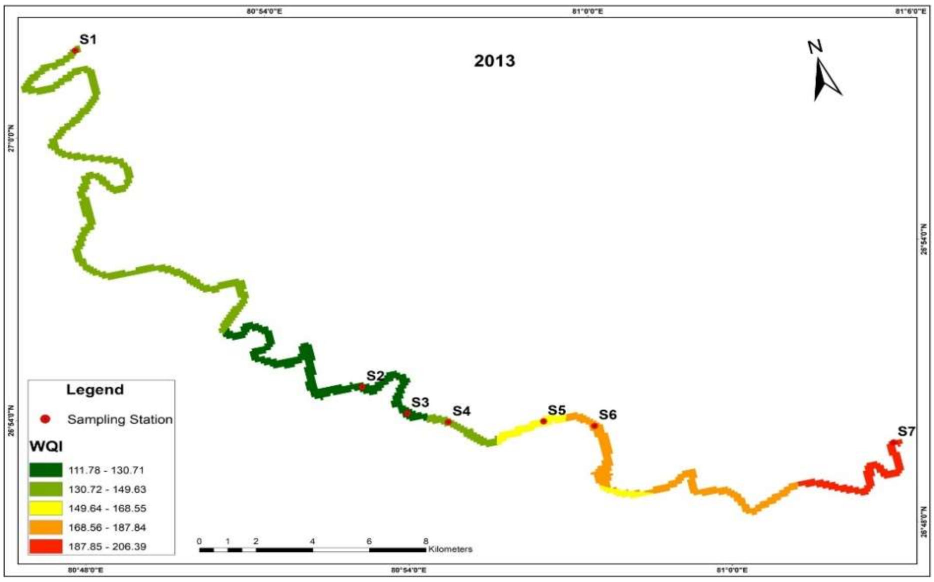
To manage river water sustainably, it is crucial to monitor pollution patterns and their trends in relation to urbanization. The locational distribution of water pollutants is delineated using spatial distribution maps of estimated water quality indices (Arithmetic WQI, SPI, CPI, and CPCB-WQI), which also aid in the holistic suggestion of surface water pollution prevention and treatment actions.

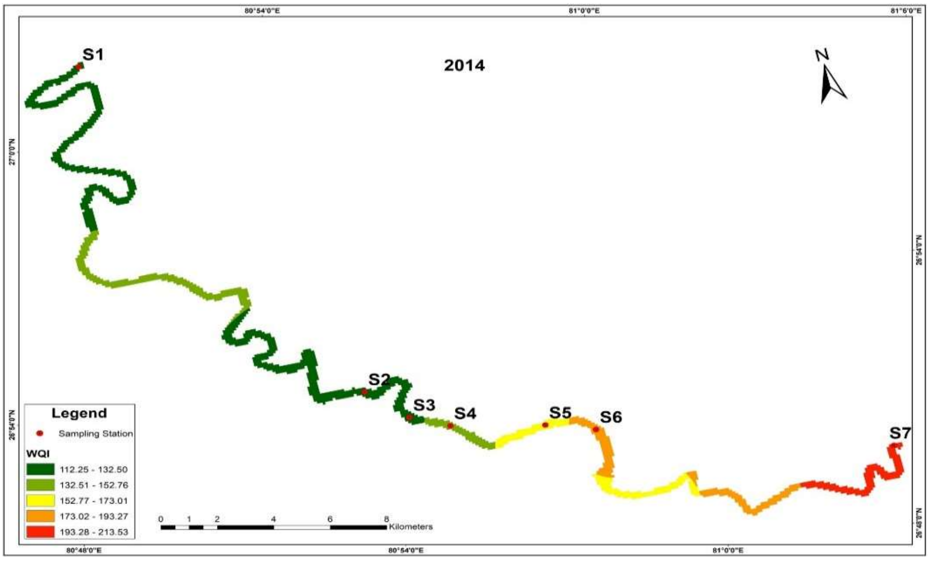
Integration of the Arithmetic WQI, SPI, CPI, and CPCB-WQI data collecting with GIS can enable policymakers or stakeholders to assess the water quality situation of the river Gomti in Lucknow (UP). In ArcGIS 10.4, the spatial analyst tool's IDW interpolation method is used to perform the spatial interpolation. IDW predicts the values of the measured and unmeasured sites using a weighted distance (Chabuk et al., 2020; Ali et al., 2021). Although the indices described above show the quality of the water, they do not really convey that quality. As a result, the data set's integration with a GIS aid in letting the public and policymakers know the actual status of the river Gomti's water quality. Policymakers and the general public can easily access and comprehend the study's output (Chabuk et al., 2020; Ali et al., 2021).

For the given stretch of the river Gomti in Lucknow, WQIs were analyzed for five years in a row (2013–2017). The arithmetic WQI (Figure 5.22), SPI (Figure 5.23), CPI

(Figure 5.24), and CPCB-WQI (Figure 5.25) values were interpolated with IDW geostatistics in ArcGIS for improved interpretability. The results clearly exposed the pollution load of the river Gomti at all the sampling stations. Further, it is observed that water quality is deteriorating continually due to high anthropogenic activities at the sampling locations S1 – S7. The trends of pollution load indicate the change in river water quality from S1 to S7 during the study period (2013-2017).

The current WQIs can be used with GIS to create stronger water quality management plans. Recently, several researchers (Katyal et al., 2012; Alsaqqar et al., 2015; Jayalakshmi and Velappan, 2015; Shil et al., 2019; Chabuk et al., 2020; Ali et al., 2021; Oseke et al., 2021) stated the use of GIS in water quality assessment. GIS integrates geographical data with laboratory data exceptionally well and more correctly predicts the spatial distributions of water quality indicators.





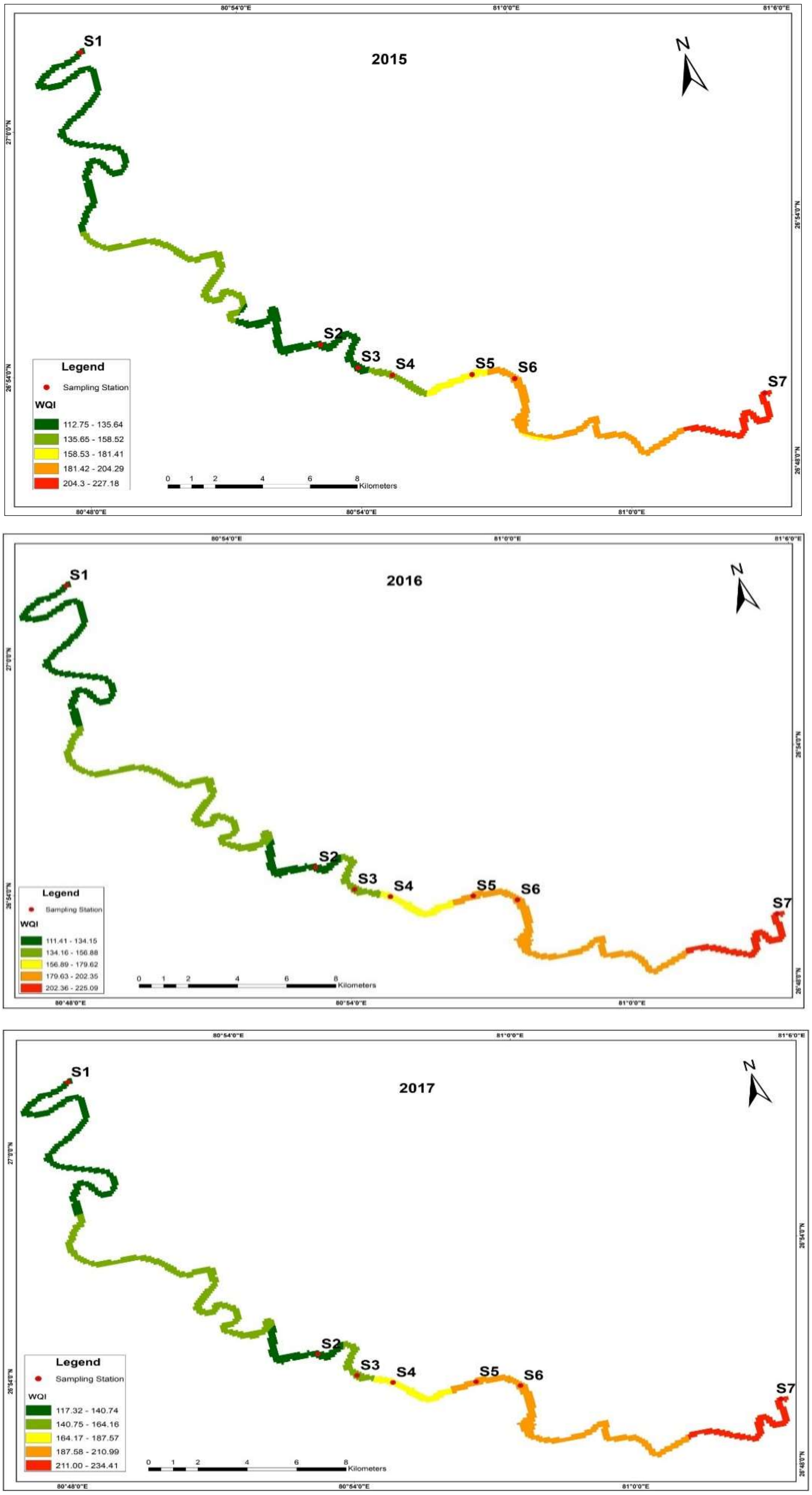
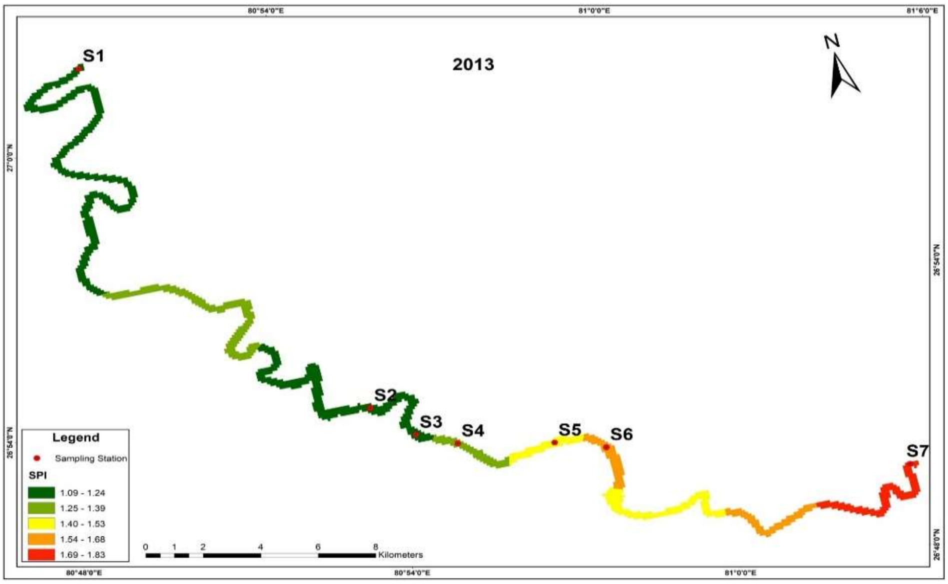
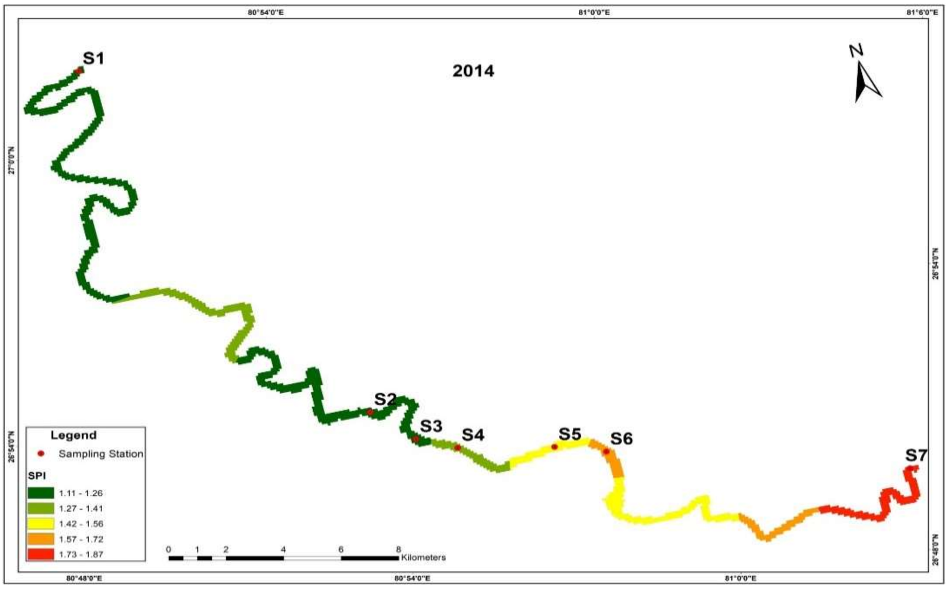
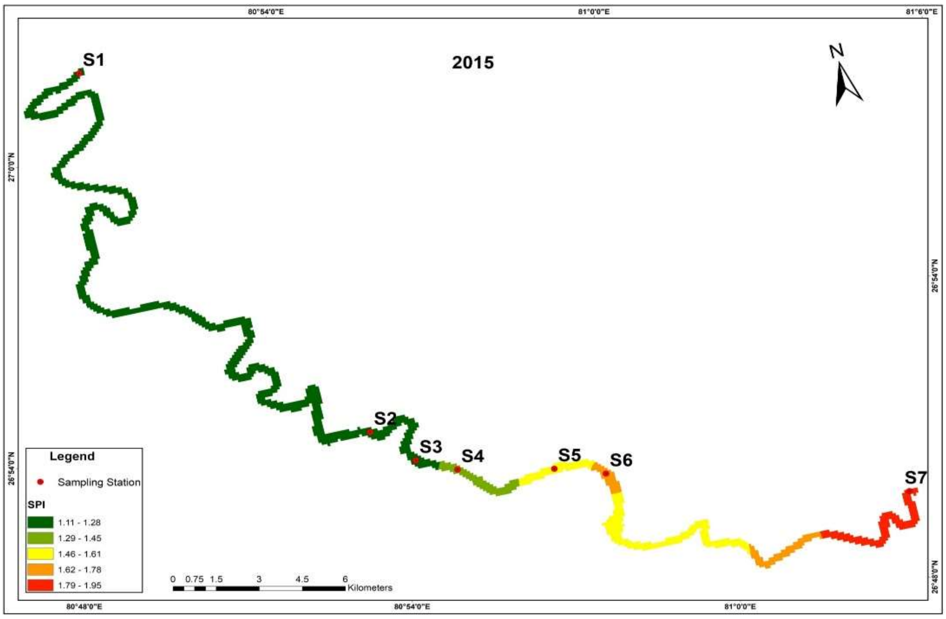
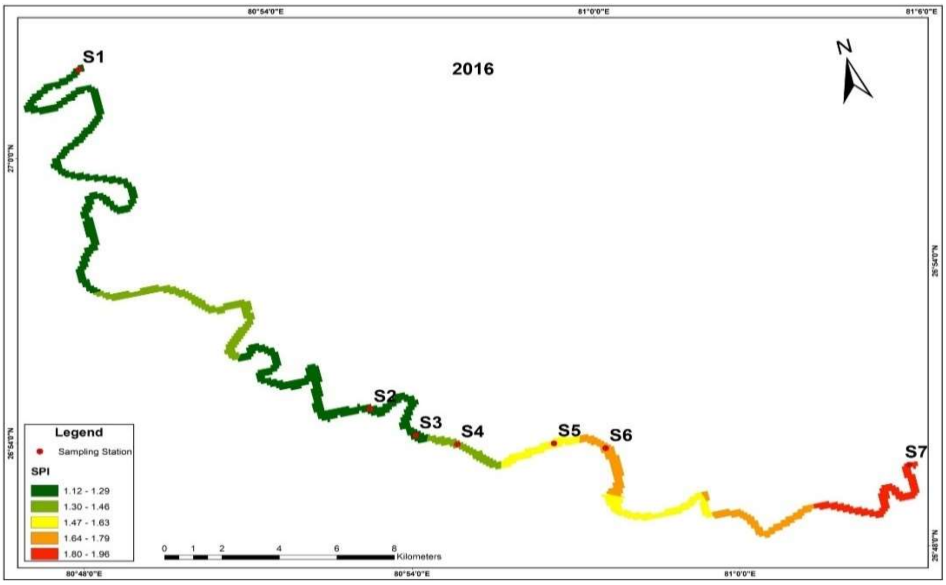


Figure 5.22: Arithmetic WQI of the river Gomti for suitability assessment (2013-2017)


2013
S1
S2
S3
S4
S5
S6
S7
Legend
Sampling Station
SPI
1.09 - 1.24
1.25 - 1.39
1.40 - 1.53
1.54 - 1.68
1.69 - 1.83
0 1 2 4 6 8 Kilometers
80°48'0"E
80°54'0"E
81°0'0"E
81°6'0"E
27°0'0"N
26°54'0"N
26°48'0"N


2014
S1
S2
S3
S4
S5
S6
S7
Legend
Sampling Station
SPI
1.11 - 1.26
1.27 - 1.41
1.42 - 1.56
1.57 - 1.72
1.73 - 1.87
0 1 2 4 6 8 Kilometers
80°48'0"E
80°54'0"E
81°0'0"E
81°6'0"E
27°0'0"N
26°54'0"N
26°48'0"N


2015
S1
S2
S3
S4
S5
S6
S7
Legend
Sampling Station
SPI
1.11 - 1.28
1.29 - 1.45
1.46 - 1.61
1.62 - 1.78
1.79 - 1.95
0 0.75 1.5 3 4.5 6 Kilometers
80°48'0"E
80°54'0"E
81°0'0"E
81°6'0"E
27°0'0"N
26°54'0"N
26°48'0"N



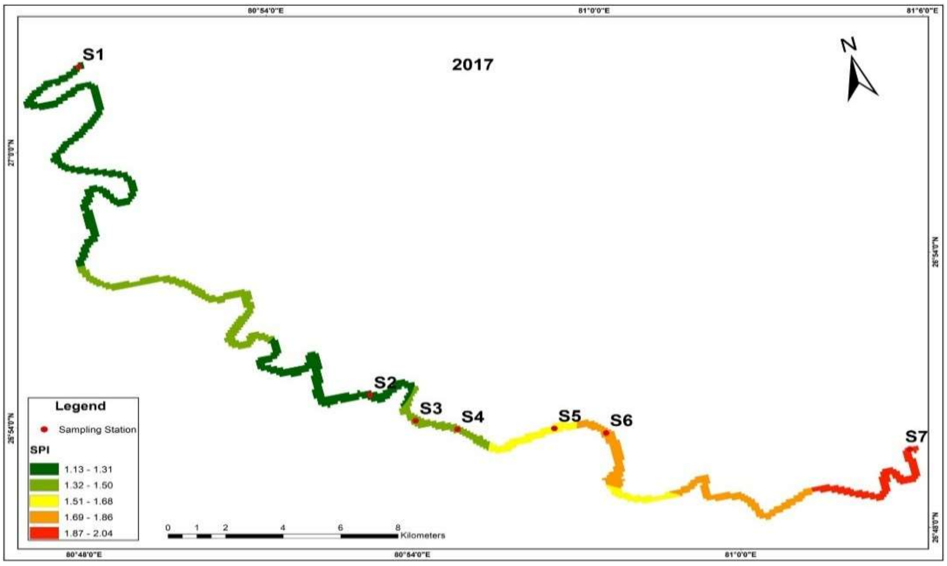
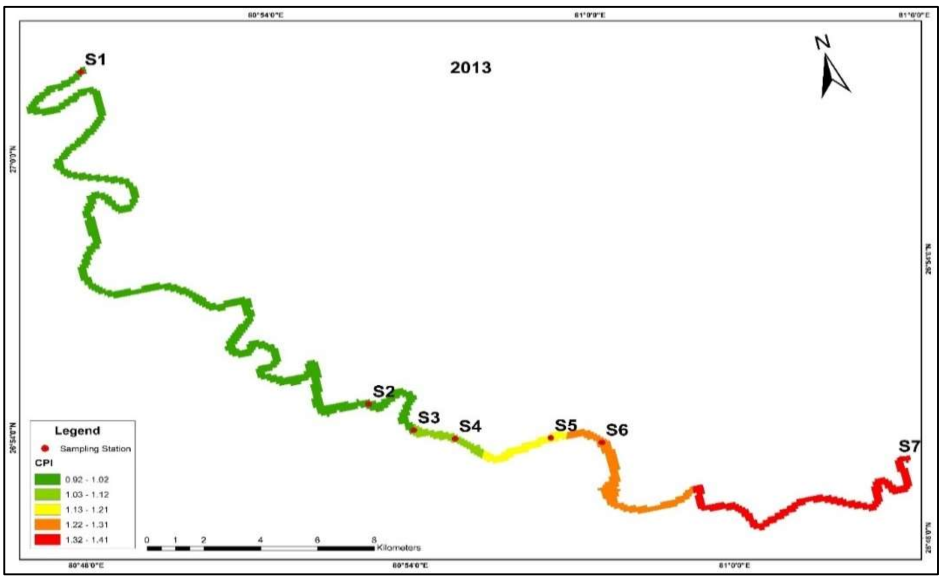
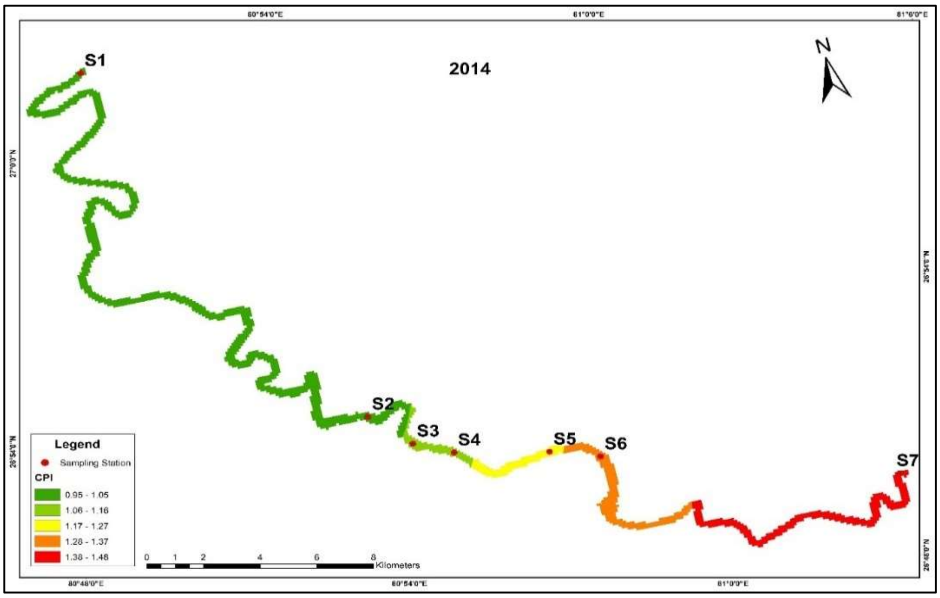
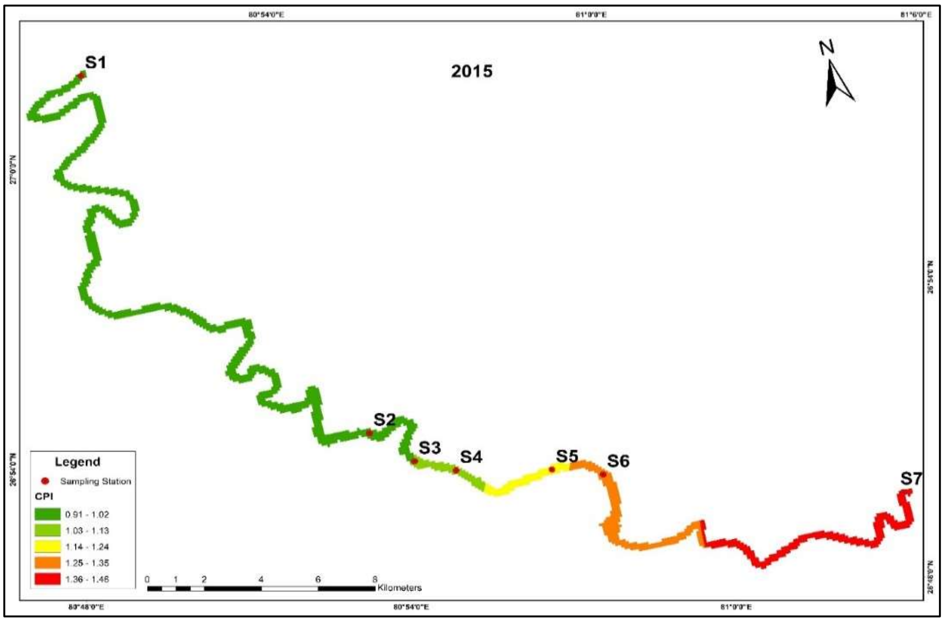
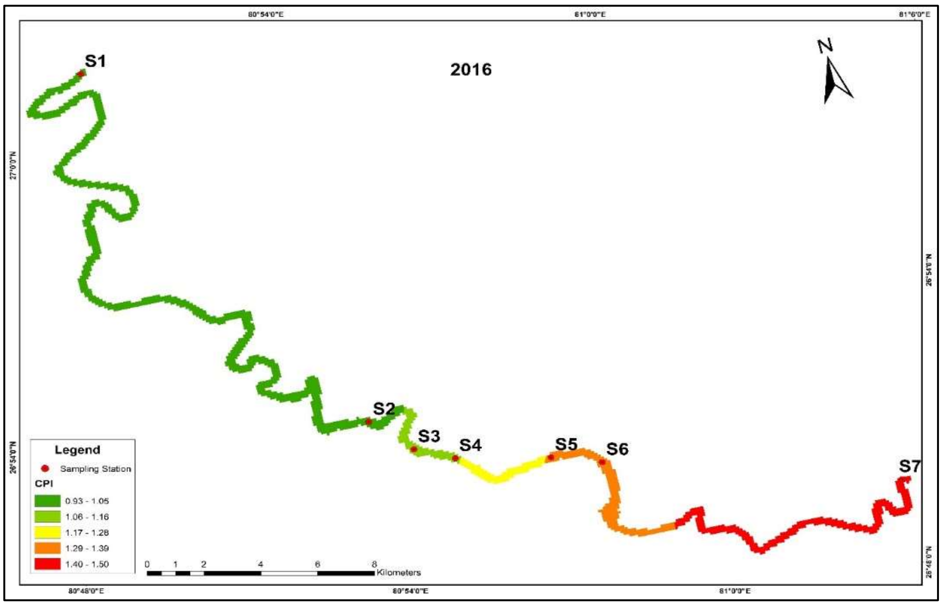


Figure 5.23: SPI of the river Gomti for suitability assessment (2013-2017)




2014
N
S1
S2
S3
S4
S5
S6
S7
Legend
Sampling Station
CPI
0.95 - 1.05
1.06 - 1.16
1.17 - 1.27
1.28 - 1.37
1.38 - 1.48
0 1 2 4 6 8 Kilometers
80°54'0"E
81°0'0"E
81°6'0"E
80°48'0"E
27°0'0"N
26°54'0"N


2015
N
S1
S2
S3
S4
S5
S6
S7
Legend
Sampling Station
CPI
0.91 - 1.02
1.03 - 1.13
1.14 - 1.24
1.25 - 1.35
1.36 - 1.46
0 1 2 4 6 8 Kilometers
80°54'0"E
81°0'0"E
81°6'0"E
80°48'0"E
27°0'0"N
26°54'0"N


2016
N
S1
S2
S3
S4
S5
S6
S7
Legend
Sampling Station
CPI
0.93 - 1.05
1.06 - 1.16
1.17 - 1.28
1.29 - 1.39
1.40 - 1.50
0 1 2 4 6 8 Kilometers
80°54'0"E
81°0'0"E
81°6'0"E
80°48'0"E
27°0'0"N
26°54'0"N

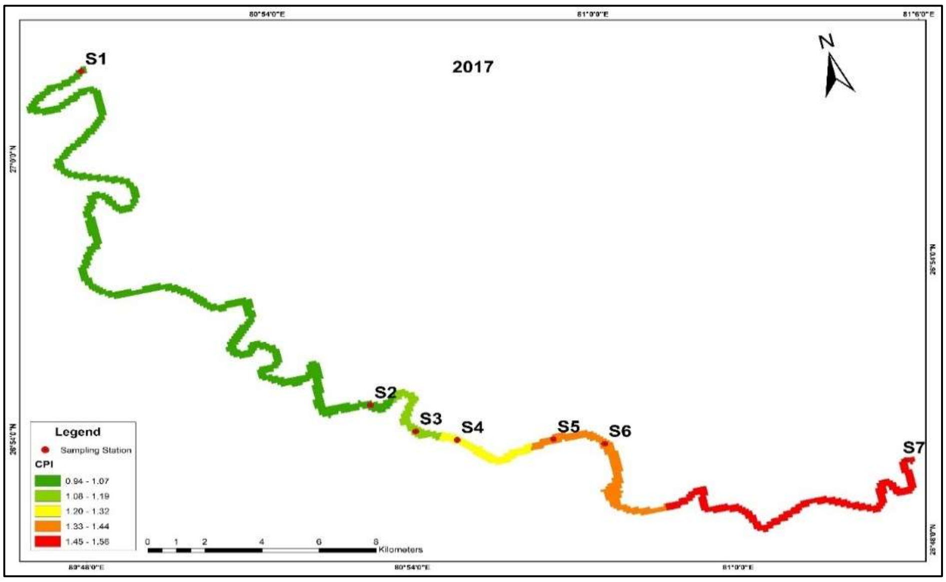
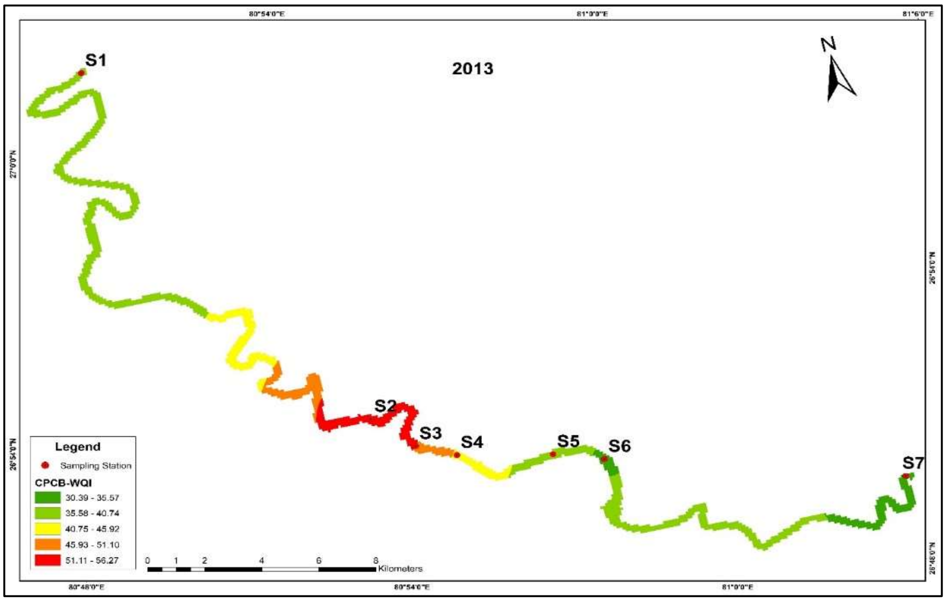
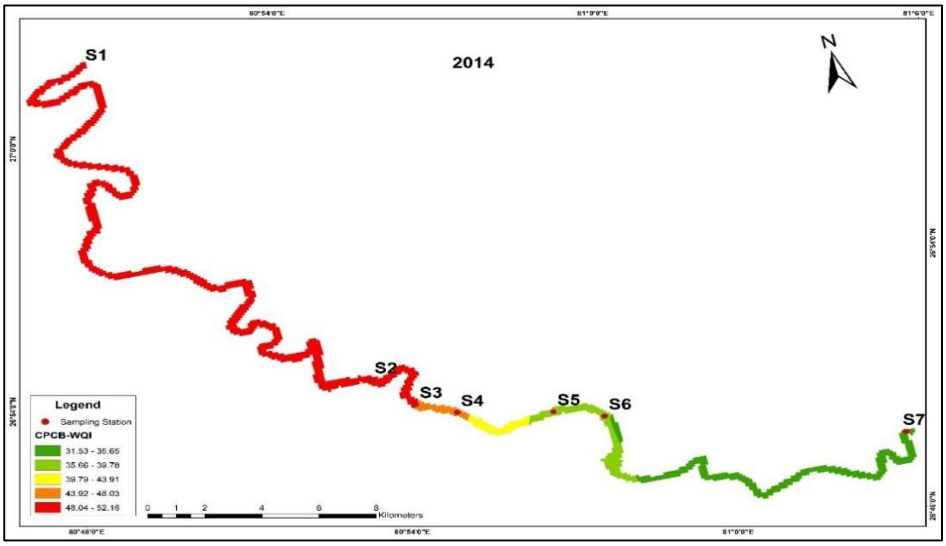


Figure 5.24: CPI of the river Gomti for suitability assessment (2013-2017)





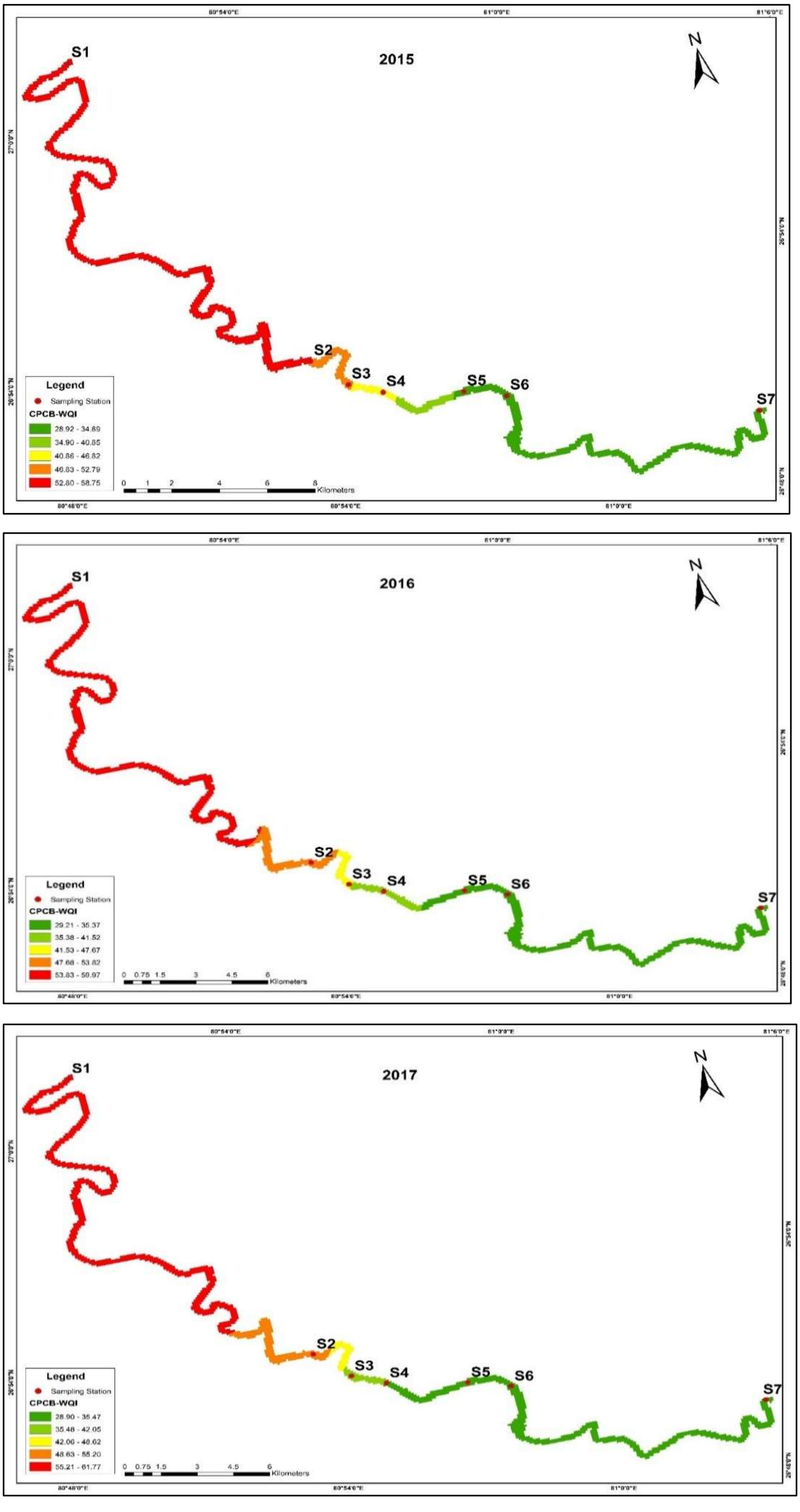


Figure 5.25: CPCB-WQI of the river Gomti for suitability assessment (2013-2017)

5.8 Statistical modeling

The water quality at all sampling stations along the Gomti River has been examined using statistical and time series analysis. Table 5.12 presents key statistical measures, including the mean, median, mode, minimum, maximum, range, standard deviation (SD), kurtosis, skewness, and coefficient of variation (CoV) for the calculated water quality indices, namely Arithmetic WQI, SPI, CPI, and CPCB-WQI, at each of the sampling stations. Table 5.13 explains the trend and time series analysis of the ARIMA model, stationary R-squared, R-squared, RMSE, MAPE, MAE, MaxAPE, MaxAE, Normalized BIC, and Ljung-Box Q(18) for all calculated water quality indices at all sampling stations.

Arithmetic WQI: In the case of S4 and S6, mean median and mode values are the same; thus, it shows normal behavior, low data points spread, and symmetrical and platykurtic curve, but for S1, S2, S3, S5, and S7, it is nonsymmetrical and platykurtic. Compared to the baseline model, the time series model performs better since stationary R-squared and R-squared values behave similarly. Due to the high RMSE value, the dependent series cannot be closed to the level anticipated by the model. Using the Ljung-Box model, for all sites, the value of statistics lies from 13.22 to 30.53, with a significance level ranging from 0.01 to 0.59, the degree of freedom is 15, and Winters' Additive ARIMA model was used for prediction. Using plot of residual ACF, residual PACF, forecast, observed, best fit, LCL, and UCL (ANNEXURE –II, and III), it is observed that the value of Arithmetic WQI lies between 86.20 to 130.24 for S1, 107.23 to 170.54 for S2, 142.25 to 256.93 for S3, 155.86 to 247.60 for S4, 172.66 to 291.95 for S5, 182.47 to 297.99 for S6 and 202.99 to 323.43 for S7 and at all sites, the water quality is impacted, as determined by the 95% confidence interval. In order to assess the annual variability in Arithmetic WQI, the monthly data were arranged, which were further used to calculate the mean Arithmetic WQI of each year during the predicted period (2018-2027), which is depicted in Figure 5.26.

It is observed by the predicted value that Arithmetic WQI falls under Category E (above 100), which is unsuitable for drinking and fish culture and requires proper treatment before use at all sampling stations except S1 in the monsoon season, which falls under Category D (76–100), i.e., very poor which is only used for irrigation. The results reflect that the water quality of the river Gomti is gradually degrading for the predicted future compared to the baseline period.

Table 5.12: Statistical analysis of Arithmetic WQI, SPI, CPI and CPCB-WQI

	Mean	Median	Mode	Minimum	Maximum	Range	SD*	Kurtosis	Skewness	CoV*
S1										
Arithmetic WQI	120.81	115.98	128.36	78.99	175.61	96.61	22.90	0.40	0.85	0.19
SPI	1.11	1.10	1.10	0.87	1.28	0.41	0.10	-0.66	-0.25	0.09
CPI	0.92	0.93	0.93	0.69	1.05	0.37	0.08	0.59	-0.80	0.09
CPCB-WQI	54.61	53.30	52.90	30.31	100.44	70.14	16.21	2.23	1.16	0.30
S2										
Arithmetic WQI	117.52	116.12	138.47	83.70	148.23	64.53	14.40	-0.29	-0.14	0.12
SPI	1.15	1.15	1.17	0.91	1.31	0.40	0.11	-0.71	-0.28	0.10
CPI	0.96	0.98	0.98	0.73	1.09	0.36	0.09	0.77	-0.99	0.09
CPCB-WQI	55.14	52.40	50.05	38.81	95.00	56.17	8.60	6.60	1.73	0.16
S3										
Arithmetic WQI	137.62	139.18	151.86	92.86	184.85	91.99	21.43	-0.31	0.14	0.67
SPI	1.25	1.24	1.24	0.98	1.47	0.48	0.10	0.02	-0.26	0.38
CPI	1.06	1.04	1.05	0.79	1.35	0.56	0.13	0.46	0.52	0.53
CPCB-WQI	45.38	44.54	44.29	29.67	63.10	33.42	8.94	-0.60	0.22	0.74
S4										
Arithmetic WQI	152.33	152.14	166.87	102.99	196.60	93.61	20.72	0.15	0.01	0.14
SPI	1.37	1.37	1.37	1.07	1.60	0.53	0.11	0.98	-0.16	0.08

	Mean	Median	Mode	Minimum	Maximum	Range	SD*	Kurtosis	Skewness	CoV*
CPI	1.14	1.12	1.14	0.85	1.46	0.61	0.13	0.61	0.47	0.11
CPCB-WQI	40.86	39.33	36.78	28.92	54.71	25.79	6.95	-0.56	0.44	0.17
S5										
Arithmetic WQI	176.66	178.08	199.72	123.35	220.99	97.64	21.83	-0.17	-0.27	0.12
SPI	1.53	1.51	1.65	1.25	1.86	0.61	0.14	-0.22	0.40	0.09
CPI	1.26	1.23	1.32	0.96	1.58	0.62	0.15	-0.02	0.52	0.12
CPCB-WQI	34.43	33.01	30.78	27.65	45.97	18.32	4.53	0.39	1.01	0.13
S6										
Arithmetic WQI	192.49	193.32	192.45	132.49	228.69	96.20	21.55	0.40	-0.50	0.11
SPI	1.66	1.65	1.66	1.34	2.02	0.68	0.15	0.26	0.247	0.90
CPI	1.34	1.31	1.42	1.01	1.66	0.65	0.15	-0.10	0.338	0.11
CPCB-WQI	31.88	30.56	27.95	26.22	40.60	14.38	3.57	0.54	1.103	0.11
S7										
Arithmetic WQI	221.12	227.61	246.52	154.66	249.39	94.73	21.75	1.40	-1.16	0.10
SPI	1.93	1.95	2.10	1.51	2.18	0.66	0.15	0.38	-0.76	0.08
CPI	1.50	1.49	1.59	1.13	1.84	0.70	0.15	0.00	-0.17	0.10
CPCB-WQI	29.18	28.75	27.05	25.66	34.36	8.70	1.88	0.59	0.91	0.06

*SD - Standard Deviation; CoV - Coefficient of variation

Table 5.13: Trend and time series analysis of the Gomti River Arithmetic WQI, SPI, CPI, and CPCB-WQI

	S1	S2	S3	S4	S5	S6	S7
Model Fit Statistics for Arithmetic WQI							
Stationary R-squared	0.59	0.70	0.77	0.75	0.81	0.80	0.78
R-squared	0.71	0.73	0.78	0.78	0.83	0.81	0.73
RMSE	12.54	7.55	10.16	9.82	9.19	9.52	11.42
MAPE	7.95	5.13	5.73	4.96	3.98	3.55	4.07
MAE	9.42	5.85	7.71	7.28	6.76	6.53	8.63
MaxAPE	24.08	21.79	19.36	20.80	17.80	19.37	15.56
MaxAE	29.21	27.15	26.17	27.67	32.34	39.14	33.81
Normalized BIC	5.26	4.25	4.84	4.77	4.64	4.71	5.08
Ljung-Box Q(18) for Arithmetic WQI							
Statistics	23.09	25.33	18.94	14.00	30.53	13.22	23.97
df*	15	15	15	15	15	15	15
Sig.*	0.08	0.05	0.22	0.53	0.01	0.59	0.07
Model Fit Statistics for SPI							
Stationary R-squared	0.56	0.50	0.52	0.53	0.69	0.73	0.71
R-squared	0.85	0.87	0.56	0.55	0.76	0.75	0.79
RMSE	0.04	0.04	0.07	0.07	0.07	0.08	0.07
MAPE	2.82	2.88	4.24	4.36	3.54	3.35	2.96

	S1	S2	S3	S4	S5	S6	S7
MAE	0.03	0.03	0.05	0.06	0.05	0.06	0.06
MaxAPE	11.71	8.16	13.06	11.56	12.33	12.38	9.32
MaxAE	0.12	0.09	0.18	0.16	0.21	0.18	0.16
Normalized BIC	-6.17	-6.16	-5.13	-5.01	-5.09	-4.98	-5.13
Ljung-Box Q(18) for SPI							
Statistics	37.44	18.69	23.59	41.19	15.36	13.35	16.32
df*	15	15	15	15	15	15	15
Sig.*	0.00	0.23	0.07	0.00	0.43	0.58	0.36
Model Fit Statistics for CPI							
Stationary R-squared	0.78	0.79	0.71	0.72	0.74	0.74	0.77
R-squared	0.73	0.76	0.66	0.67	0.76	0.77	0.81
RMSE	0.04	0.04	0.08	0.08	0.07	0.07	0.07
MAPE	3.60	3.30	5.16	4.85	4.23	4.07	3.39
MAE	0.03	0.03	0.06	0.06	0.05	0.06	0.05
MaxAPE	16.62	18.61	23.40	22.15	19.05	19.53	16.01
MaxAE	0.15	0.18	0.24	0.25	0.24	0.27	0.23
Normalized BIC	-6.01	-6.10	-4.98	-4.96	-5.03	-5.01	-5.15
Ljung-Box Q(18) for CPI							
Statistics	25.11	27.51	24.60	23.64	32.99	34.71	41.60

	S1	S2	S3	S4	S5	S6	S7
df*	15	15	15	15	15	15	15
Sig.*	0.05	0.03	0.06	0.07	0.01	0.00	0.00
Model Fit Statistics for CPCB-WQI							
Stationary R-squared	0.64	0.70	0.70	0.70	0.67	0.68	0.72
R-squared	0.59	0.71	0.69	0.77	0.75	0.63	0.54
RMSE	12.00	4.74	5.16	3.38	2.32	2.21	1.30
MAPE	13.36	4.27	9.26	6.63	5.19	5.16	3.15
MAE	7.35	2.48	3.91	2.59	1.78	1.67	0.93
MaxAPE	76.09	29.14	46.17	26.39	15.14	18.29	10.91
MaxAE	33.75	27.68	15.37	9.93	6.55	7.22	3.75
Normalized BIC	6.06	3.32	3.49	2.64	1.89	1.79	0.72
Ljung-Box Q(18) for CPCB-WQI							
Statistics	6.44	9.55	8.47	10.63	26.53	26.01	40.93
df*	3	15	15	15	15	15	15
Sig.*	0.09	0.85	0.90	0.78	0.03	0.04	0.00

*df - degree of freedom, Sig. - significance level

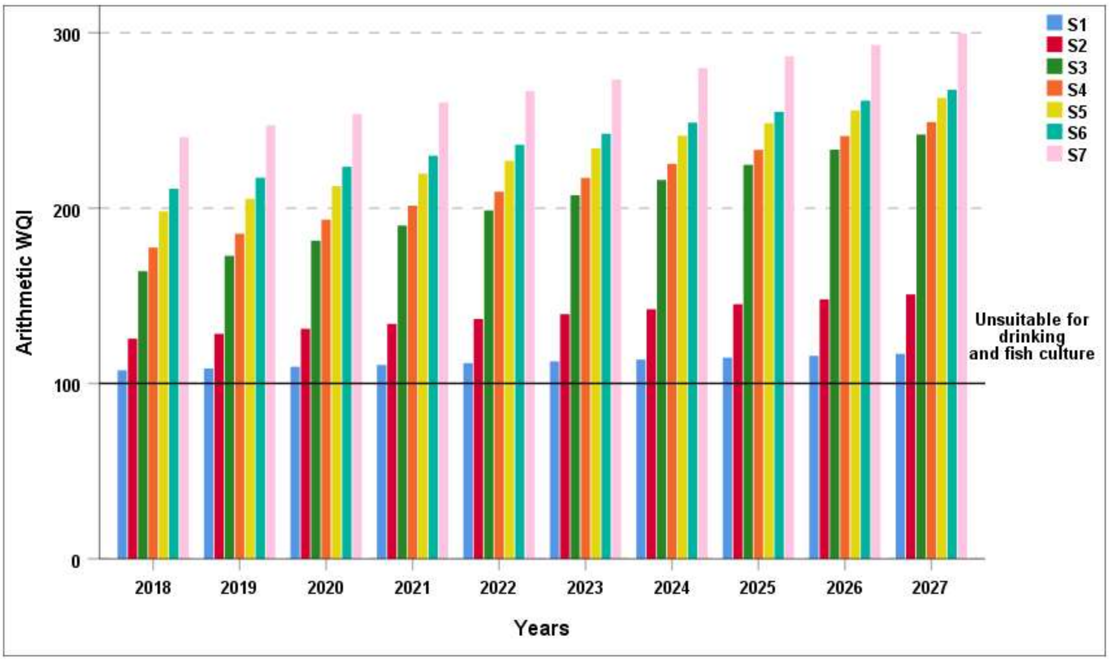


Figure 5.26: Variation of predicted annual mean values of Arithmetic WQI of studied stations in the Gomti River for the period 2018-2027

SPI: All sites display normal behavior and minimal data spread. The curve is symmetrical and platykurtic. Because stationary R-squared and R-squared values show the same behavior across all sites, the prediction model is superior to the baseline model. The dependent series is closed at the level predicted by the model because the RMSE value is low. Using the Ljung-Box model, statistics lie between 13.35 and 41.19, the significance level varies from 0.00 to 0.58, the degree of freedom is 15, and Winters' Additive ARIMA model was used for prediction. Using plot of residual ACF, residual PACF, forecast, observed, best fit, LCL, and UCL (ANNEXURE –IV and V), show that the value of SPI lies between 0.97 to 1.36 for S1, 0.97 to 1.32 for S2, 1.16 to 1.66 for S3, 1.29 to 1.87 for S4, 1.55 to 2.25 for S5, 1.64 to 2.38 for S6 and 1.86 to 2.71 for S7 and the quality of river water gets affected at all sampling stations during the predicted period (2018-2023), which is calculated at 95% confidence interval. The monthly data were arranged to assess the annual variability in SPI to calculate the mean SPI of each year during the predicted period (2018-2027), as shown in Figure 5.27.

The result of the predicted value of SPI revealed that the Gomti River water quality is gradually degrading as compared to the baseline period. It is observed that SPI falls under very poor (1.0-3.0), i.e., severely polluted water classification, which is only suitable for irrigation purposes. Water quality status (WQS) is very poor, i.e., severely polluted at all sampling stations in all seasons. However, in the case of stations S1 and S2, water quality is poor (0.5-1.0), i.e., moderately polluted during monsoon season.

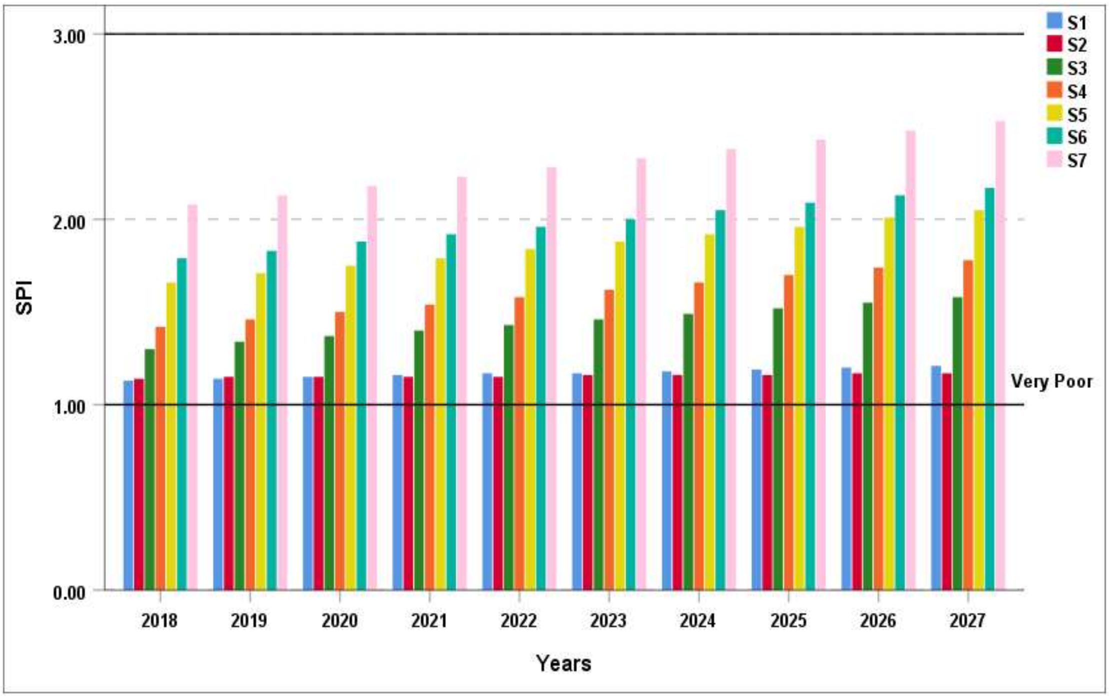


Figure 5.27: Variation of predicted annual mean values of SPI of studied stations in the Gomti River for the period 2018-2027

CPI: Every site displays a normal curve, low, symmetric, and platykurtic data dispersion. Because stationary R-squared and R-squared values show similar behavior, the prediction model performs better than the baseline model. Because the RMSE values are small, the dependent series is closed at the level predicted by the model. Using the Ljung-Box model, the value of statistics ranges from 23.64 to 41.60, the significance level lies from 0.00 to 0.07, the degree of freedom is 15, and Winters' Additive ARIMA model was used for prediction.

Using plot of residual ACF, residual PACF, forecast, observed, best fit, LCL, and UCL (ANNEXURE –VI and VII), show that the value of CPI lies between 0.78 to 1.05 for S1, 0.81 to 1.10 for S2, 0.98 to 1.56 for S3, 1.07 to 1.66 for S4, 1.18 to 1.84 for S5, 1.24 to 1.88 for S6 and 1.36 to 2.07 for S7 and the quality of river water gets effected at all sampling stations during the predicted period (2018-2023), which is calculated at 95% confidence limits. The monthly data were arranged to assess the annual variability in CPI to calculate the mean CPI of each year during the predicted period (2018-2027), as represented in Figure 5.28, which shows that water quality is deteriorating from S1 to S7 as well as from 2018-2027. CPI status at S4, S5, and S6 falls under polluted while S7 is under polluted and seriously polluted, suggesting that water from S4, S5, S6, and S7 can be used restrictedly for irrigation, and proper treatment is required before use. However, CPI status ranges between basically qualified and polluted at S3 and S2, which can be used for irrigation only, but S1 lies under three statuses: qualified, basically qualified, and polluted, which can be used for irrigation and industrial purposes.

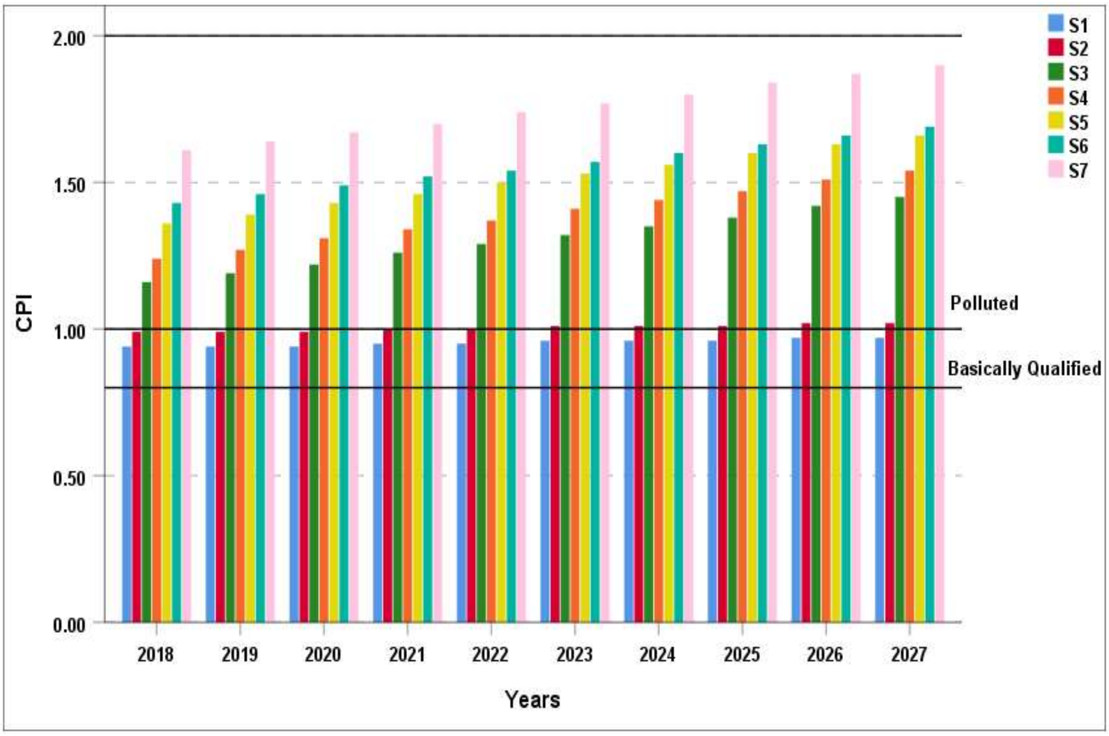


Figure 5.28: Variation of predicted annual mean values of CPI of studied stations in the Gomti River for the period 2018-2027

CPCB-WQI: The mean, median, and mode do not behave normally for any of the sites, the standard deviation is high, and the spread is uniform and asymmetrical. Except for S2, which possesses leptokurtic, the curve is platykurtic. Because stationary R-squared and R-squared values exhibit similar behavior, the model is superior to the baseline model. Due to excessive RMSE values, the dependent series cannot be closed to the level anticipated by the model. Using the Ljung-Box model, the value of statistics lies between 6.44 and 40.93, the significance level between 0.00 and 0.90, the degree of freedom is 15 except at S1, which is 3, and the Winters' Additive ARIMA model was used for prediction.

Using plot of residual ACF, residual PACF, forecast, observed, best fit, LCL, and UCL (ANNEXURE –VIII and IX), it is observed that the value of CPCB-WQI lies between 52.79 to 80.49 for S1, 36.94 to 67.14 for S2, 15.33 to 45.22 for S3, 16.43 to 41.59 for S4, 18.03 to 34.19 for S5, 20.47 to 30.75 for S6 and 22.61 to 29.65 for S7 and the river water quality gets effected at all sampling stations during the predicted period (2018-2023), which is calculated at 95% confidence limits. To calculate the mean CPCB-WQI of each year during the predicted period (2018-2027), the monthly data were arranged to assess the annual variability in CPCB-WQI, represented in Figure 5.29, which shows that water quality is deteriorating from S1 to S7.

This index classified the last three sites (S5 to S7) into bad to very bad categories classified as class D & E by CPCB, whereas S3 and S4 sites ranged between bad and bad to very bad categories. Sampling station S1 ranged between good to excellent and medium to good (Class A and B by CPCB), and the water quality of sampling station S2 falls under all categories of CPCB-WQI. The predicted period result of CPCB-WQI could be well related to the biological and physicochemical results. Also, well-defined seasonal and site-wise variation was observed in the CPCB-WQI values, and thus, any minor change in the pollution concentration could be well noticed.

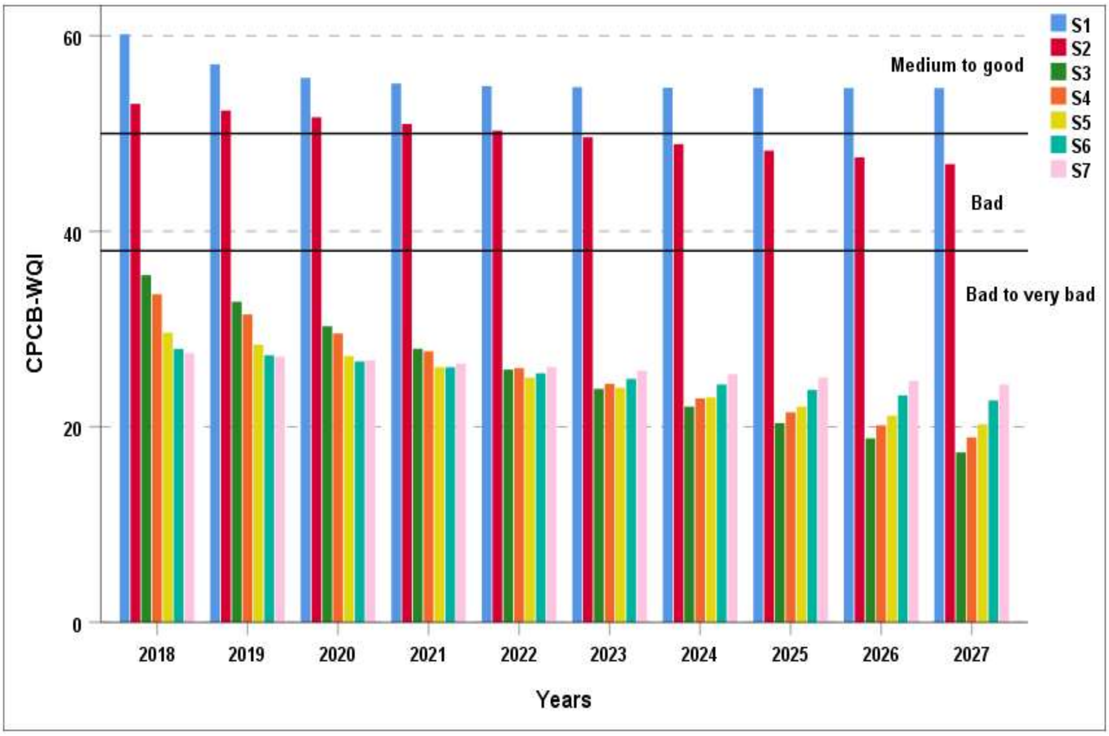


Figure 5.29: Variation of predicted annual mean values of CPCB-WQI of studied stations in the Gomti River for the period 2018-2027

5.9 Assimilative capacity

The outcomes of the simulated scenarios were compared with the quality criteria that apply to river water bodies in India, where the CPCB has identified water quality requirements in terms of a few chemical characteristics, known as primary water quality criteria, to assess the assimilative capacity. Additionally, the standard IS 2296:1992 from the Bureau of Indian Standards includes recommendations for water quality parameters for various uses. The quality standards that would serve as a guide for the use of the water resource were consolidated based on the current usage of the river and the legislation and guidelines reviewed.

5.9.1 Present scenarios and assimilative capacity (2013-2017)

Regarding the temporal variation, a rise in DO was seen in the current study at all sample locations during the rainy season. This finding is consistent with reports in the literature that precipitation benefits this parameter (Liu et al., 2020). Additionally, it is noted that concentrations at all sample stations are greater during the rainy season than they are during the dry season, which is consistent with reports in the literature that indicate precipitation has a favorable impact on DO (Liu et al., 2020). After analyzing the graphs in Figure 5.30, it is found that DO concentration varies from 2.8 – 11.4 mg/l at S1, 2.9 – 10.9 mg/l at S2, 0.7 – 9.5 mg/l at S3, 1.3 – 8.4 mg/l at S4, 1.1 – 6.0 mg/l at S5, 0.6 to 5.1 mg/l at S6 and 0.3 – 3.8 mg/l at S7 during the study period (2013-2017). The minimum DO concentration at all sampling stations lies below 4 mg/l while the maximum DO concentration is well above the reference limit (4 mg/l), but the scenario at S7 shows a lower concentration than the reference limit (4 mg/l) for both minimum and maximum concentrations.

In the case of BOD, the highest concentrations were reported during the dry season because of the lower flow rates during this time of year, which increases pollution loads and lowers DO while increasing BOD owing to decomposition processes (Liu et al., 2020). Additionally, Benjumea et al. (2018) assert that the lack of nutrient dilution is caused by a greater presence of organic materials at lower flow rates.

For the study period of 2013 – 2017, the minimum and maximum BOD concentrations vary from 2.3 – 11.0 mg/l, 3.10 – 4.2 mg/l, 3.6 – 9.0 mg/l, 4.5 – 10.0 mg/l, 6.0 – 11.5 mg/l, 6.5 – 12.5 mg/l and 8.5 – 18.6 mg/l at S1, S2, S3, S4, S5, S6 and S7 respectively. Figure 5.31 shows that the river water quality at selected sampling stations is unfit for all purposes according to the designated best-use criteria of CPCB for surface water.

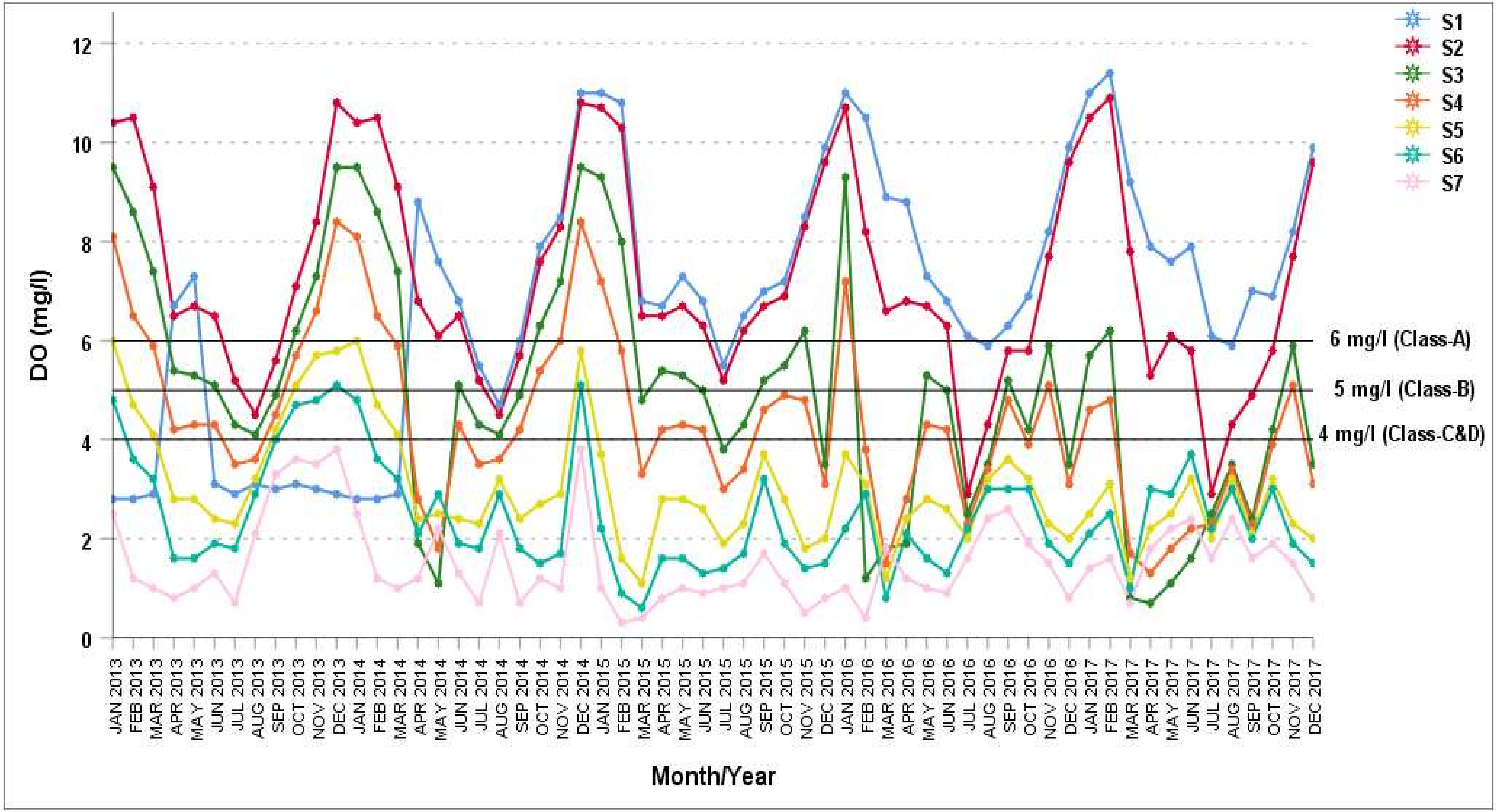


Figure 5.30: Variation of DO during 2013-17 along river Gomti

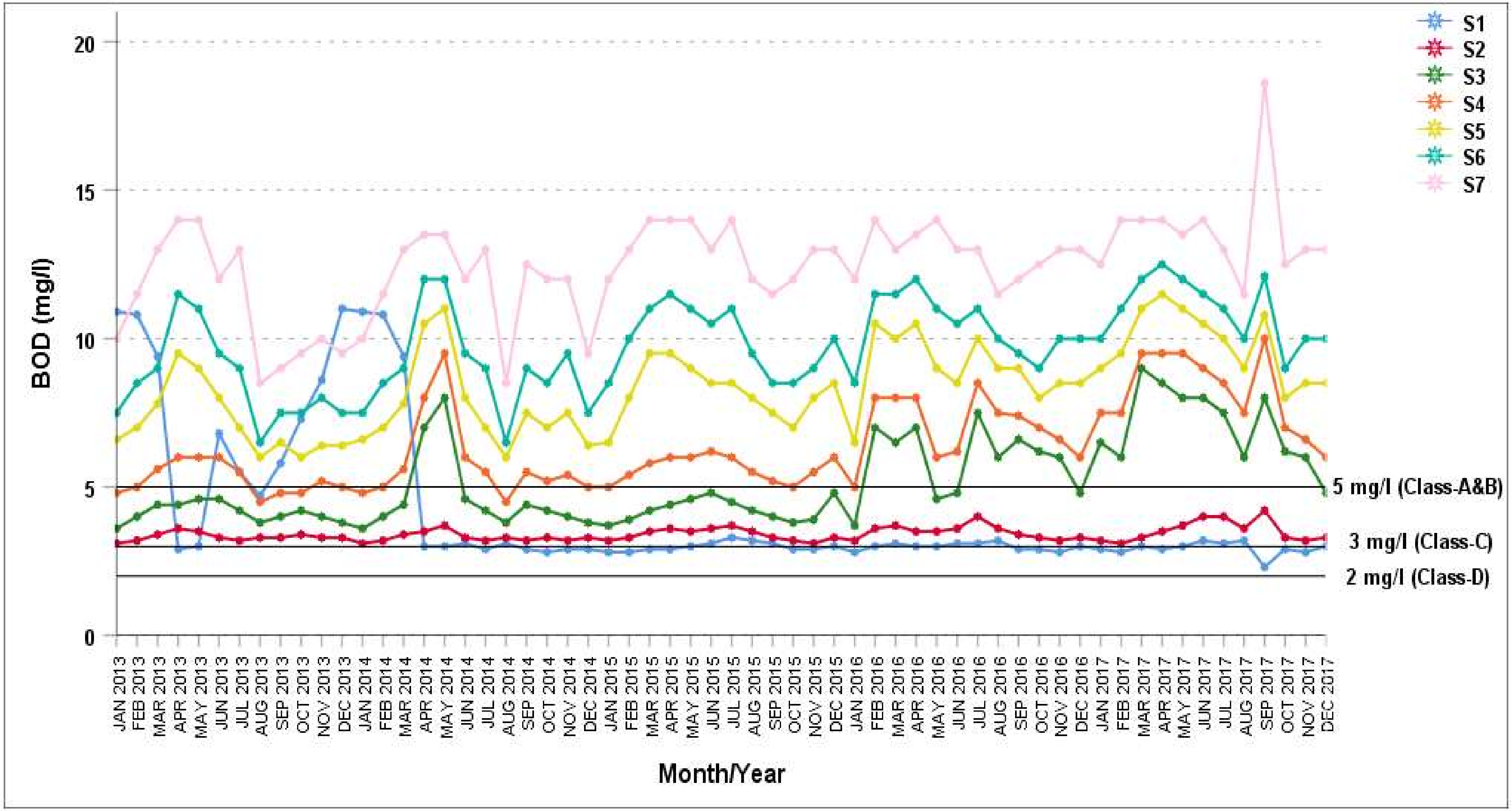


Figure 5.31: Variation of BOD during 2013-17 along river Gomti

As indicated above, for each scenario, concentrations are higher during the dry season than the wet season because of the lower flows during the dry season, which results in higher concentrations of pollutant loads, lower DO, and raised BOD owing to decomposition processes (Liu et al., 2020). It's crucial to realize that rivers' ability to assimilate pollutants is a complicated process that simultaneously incorporates physical, chemical, and biological processes. Most water pollutants are eliminated through biodegradation processes (Benjumea et al., 2018).

The relationship between DO and BOD variability and distance was also studied by Zubaidah et al. (2019). The diffuse combination of pollutant loads led the DO concentration to drop in downstream points while the BOD increased. However, the river's self-purification process was still possible, mainly between S1 and S2 of the studied section, as the distance between them is 32.5 km, but the total distance between S2 to S7 is only 26 km, which also receives 461.33 MLD of wastewater by 28 major and minor drains. This pollution load affects the assimilative capacity of the river and renders its self-purification process. The assimilative process was seen in the area with the highest effluent concentration, and DO decreased before trending upward. Results are also justified by Torres-Bejarano et al. (2022) research on how a decline in river flow during the dry season also affects the ability of pollutants in domestic wastewater to be diluted, which has an impact on assimilative capacity.

5.9.2 Simulated scenarios and assimilative capacity (2018-2027)

A comparison between the concentrations in the time series and the defined reference limits was made to assess the assimilation capacity. The statistical analysis for DO and BOD is detailed in Table 5.1 and includes mean, median, mode, range, standard deviation, kurtosis, skewness, and coefficient of variation. For DO and BOD, Ljung-Box Q(18) analysis, stationary R-squared, R-squared, RMSE, MAPE, MaxAPE, MAE, MaxAE, and Normalised BIC are shown in Table 5.14.

Dissolved oxygen: Mean, median, and mode values are not the same; thus, the curve is not normal at all sampling stations. At all sites, SD and kurtosis values are low; hence, the curve is symmetrical and platykurtic, respectively. Skewness values are close to zero, which shows that the curve is symmetrical. Time series models outperform baseline models for all locations because stationary R-squared and R-squared values behave similarly. Because the RMSE values are small, the dependent series is closed at the level predicted by the model. From the Ljung-Box model, for all sites, the value of statistics lies between 5.35 to 33.16, the significance level between 0.00 and 0.15, the degree of freedom ranged between 3 to 15, and Winters' Additive ARIMA model was used for prediction. Using plot of residual ACF, residual PACF, forecast, observed, best fit, LCL, UCL, residual ACF, residual PACF values for next 10 years (2018-2027) for DO and BOD (ANNEXURE – X, and XI), it is observed that value of DO lies between 6.51-10.71 mg/l for S1, 2.52-9.28 mg/l for S2, 0.21-4.84 mg/l for S3, 0.48-4.46 mg/l for S4, 0.46-2.95 mg/l for S5, 1.81-3.42 for S6 and 0.54-2.01 mg/l for S7 and the quality of river water gets affected at all sampling stations during the predicted period (2018-2027), which is calculated at 95 % confidence scale.

When DO concentrations fall below the standard limit of 4 mg/l, water is deemed to be of poor quality, which may be detrimental to some fish and macroinvertebrate populations and negatively affect the chemical processes in aquatic ecosystems. As shown in Figure 5.32a & b, DO does not remain at good levels over this limit throughout the predicted time (2018-2027) at S5, S6, and S7 in both dry and wet seasons. DO concentrations are higher than the reference limit at S1 during the predicted period, but in the case of S2, S3, and S4, DO concentration is higher in the wet season and lower in the dry season. It can be concluded that the river can effectively digest present discharges without materially changing this parameter. As a result, the river maintains its ability to assimilate pollutants that require oxygen without damaging the aquatic ecology (Chapra et al., 2021). At S5, S6, and S7, the DO decreased more during the dry season than it does now, which is related to low flow values and less medium aeration (Liu et al., 2020). It is consistent with what has been discovered in other studies that discharge causes a DO drop in water bodies (Torres-Bejarano et al., 2022).

Biochemical oxygen demand: At sampling stations S2, S4, S5, S6, and S7, mean, median, and mode values are equal; thus, data behave normally. BOD exhibits low SD values, and kurtosis lies below 3; hence, the curve is symmetrical and platykurtic for all sites. Since stationary R-squared and R-squared values display comparable behavior, the model performs better than the baseline model. Since the RMSE value is low, the dependent series is closed at the model's prediction level for all locations. From the Ljung-Box model, for all sites, statistics lie between 12.42 and 30.31, significance varies from 0.01 to 0.65, degree of freedom ranged is 15, and Winters' Additive ARIMA model was used for prediction.

Table 5.14: Trend and time series analysis of DO and BOD of river Gomti

	S1	S2	S3	S4	S5	S6	S7
Model Fit Statistics for DO							
Stationary R-squared	0.74	0.57	0.67	0.63	0.59	0.48	0.51
R-squared	0.74	0.90	0.48	0.67	0.49	0.48	0.22
RMSE	1.53	0.67	1.77	1.02	0.87	0.94	0.78
MAPE	17.05	7.81	41.18	20.45	23.43	32.93	49.64
MAE	0.95	0.50	1.39	0.76	0.67	0.63	0.57
MaxAPE	132.30	40.61	339.14	104.58	104.99	175.60	287.71
MaxAE	3.79	1.86	4.62	3.11	2.27	2.24	2.01
Normalized BIC	1.94	-0.59	1.35	0.24	-0.09	0.97	-0.30
Ljung-Box Q(18) for DO							
Statistics	11.26	24.73	25.77	27.30	33.16	5.35	29.57
df*	3	15	15	15	15	3	15
Sig.*	0.01	0.05	0.04	0.03	0.00	0.15	0.01
Model Fit Statistics for BOD							
Stationary R-squared	0.43	0.52	0.67	0.63	0.73	0.72	0.70
R-squared	0.88	0.50	0.66	0.67	0.81	0.83	0.60
RMSE	0.90	0.17	0.90	0.86	0.67	0.65	1.09

	S1	S2	S3	S4	S5	S6	S7
MAPE	13.69	3.65	12.92	10.23	6.20	5.48	6.23
MAE	0.54	0.13	0.67	0.66	0.52	0.53	0.76
MaxAPE	105.59	14.51	43.78	32.60	17.41	20.46	31.15
MaxAE	3.07	0.61	2.34	2.56	1.85	1.59	4.99
Normalized BIC	-0.00	-3.29	-0.03	-0.09	-0.60	-0.65	0.38
Ljung-Box Q(18) for BOD							
Statistics	17.03	22.93	22.85	25.45	19.76	30.31	12.42
df*	15	15	15	15	15	15	15
Sig.*	0.32	0.09	0.09	0.04	0.18	0.01	0.65

*df - degree of freedom, Sig. - significance level

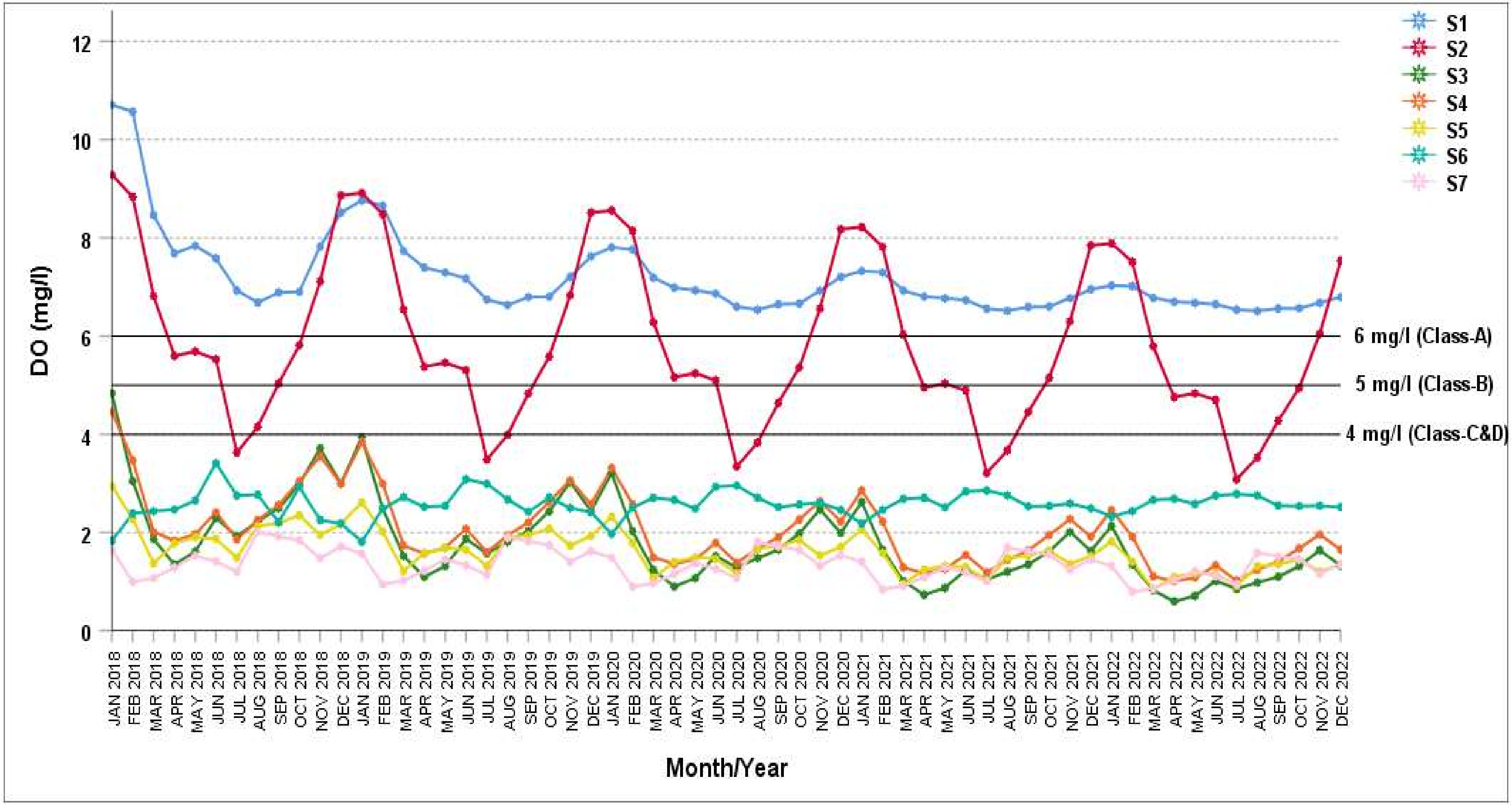


Figure 5.32a: Predicted variation of DO during 2018-2022 along river Gomti

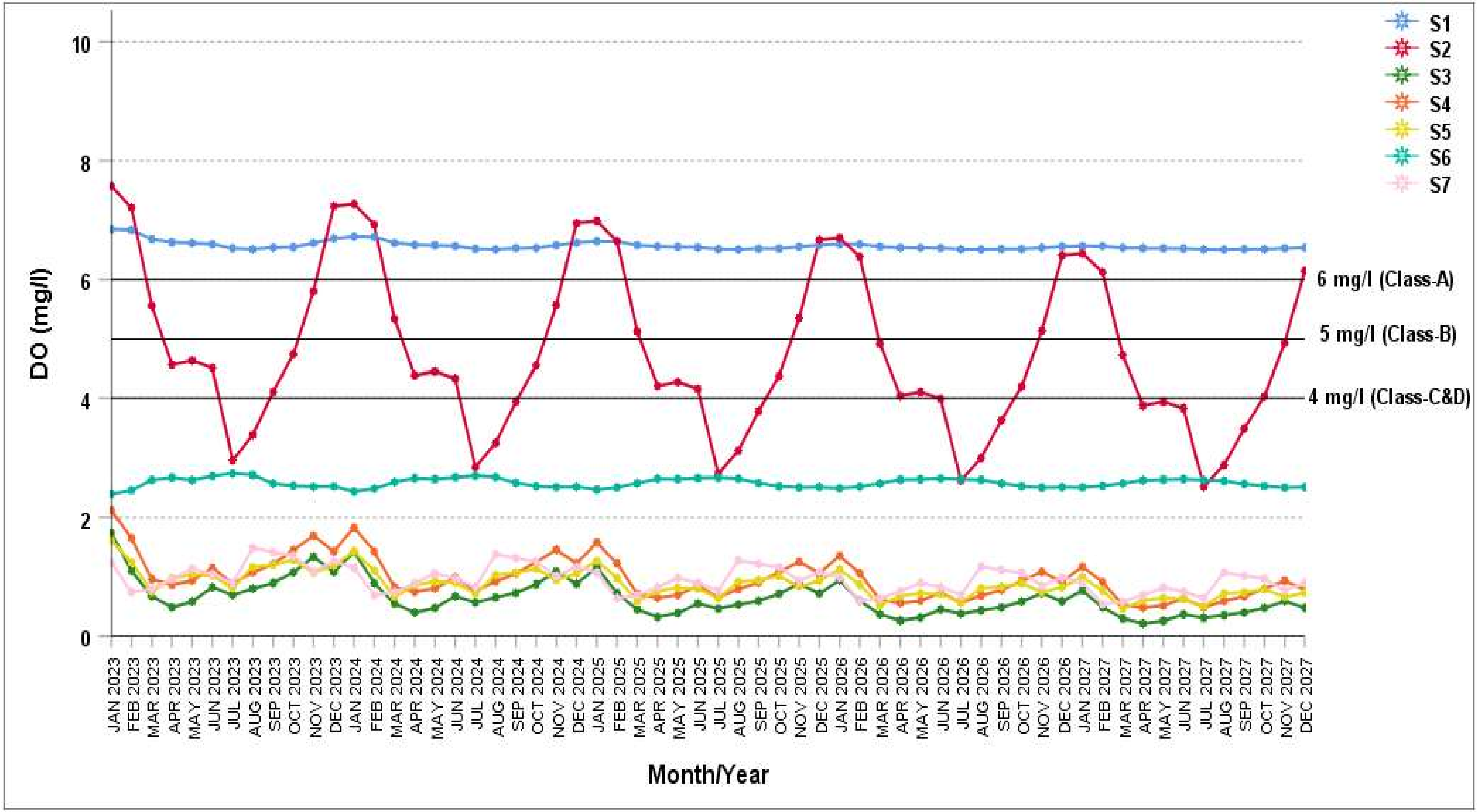


Figure 5.32b: Predicted variation of DO during 2023-2027 along river Gomti

Using plot of residual ACF, residual PACF, forecast, observed, best fit, LCL, UCL, residual ACF, residual PACF, and ARIMA prediction monthly values for the next 10 years (2018-2027) for DO and BOD (ANNEXURE – XII and XIII), explains that the value of BOD lies between 2.05-6.46 mg/l for S1, 3.34-4.34 mg/l for S2, 6.22-14.60 mg/l for S3, 7.57-15.94 mg/l for S4, 9.01-18.11 mg/l for S5, 10.19-19.11 mg/l for S6 and 12.26-21.12 mg/l for S7 and the quality of water gets affected at all sampling stations during the predicted period (2018-2027), which is calculated at 95 % confidence limits.

The graph (Figure 5.33a, b) shows that all sampling stations exceed the reference limit (2 mg/l), and this occurs during the whole predicted period (2018-2027), and water bodies that exceed the reference limit are considered polluted (Jingsheng et al., 2006). The highest concentration of this characteristic at S7 during the dry season is 21.12 mg/l. Due to the reduced river flow in this scenario, all sampling stations similarly indicate a significant increase in this parameter during the dry season. These findings demonstrate that river flow changes primarily affect the river's capacity to assimilate this parameter. Generally, the factor that has the greatest impact on absorption capacity is the variation in flow rates, both in the river and outflows (Torres-Bejarano et al., 2022). This tendency is consistent with the findings of Islam et al. (2015), who found that BOD decreased during the wet season and increased during the dry season. Liu et al. (2018) suggest that the reduction in water assimilative capacity during the dry season demonstrated that the pollution loads in this season were significantly more serious than wet season, and a reduction in pollutant loads must be done to achieve its water quality protective goal where there were higher concentrations of BOD in the dry season.

5.10 Impact of rising temperatures on water quality status

According to global climate models, future global AT has consistently been predicted to shift significantly. The change in AT directly affects the temperature of the water, which could, therefore, impact the water's quality. This study aims to create fabricated scenarios for AT and investigate how these scenarios might affect river water quality. It was utilized to extract WT data from the anticipated AT after a linear regression analysis of time series data of WT and AT was conducted to establish a link. The regression analysis simulates how the water quality index (BWQI) responds to various fabricated scenarios.

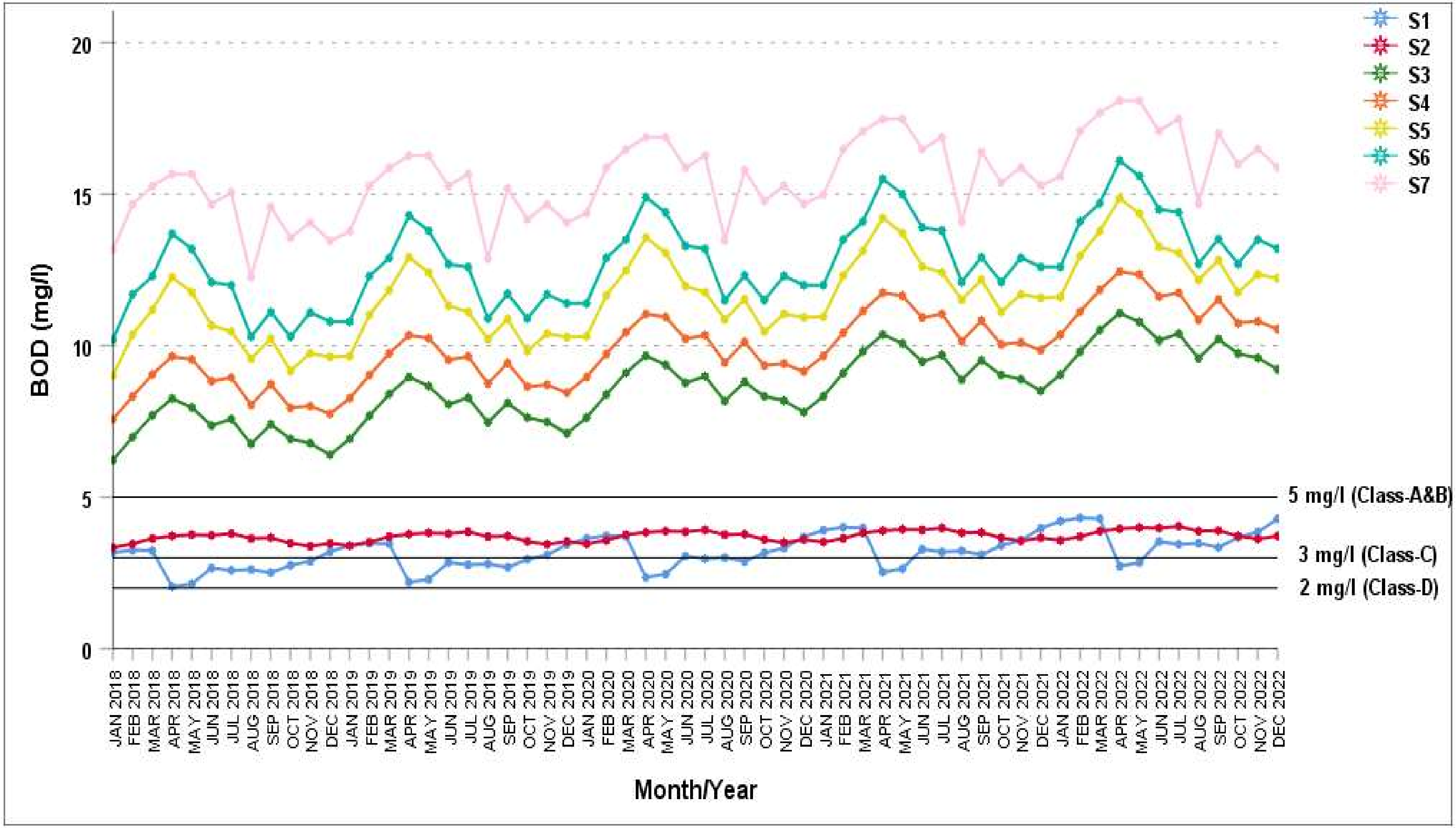


Figure 5.33a: Predicted variation of BOD during 2018-2022 along river Gomti

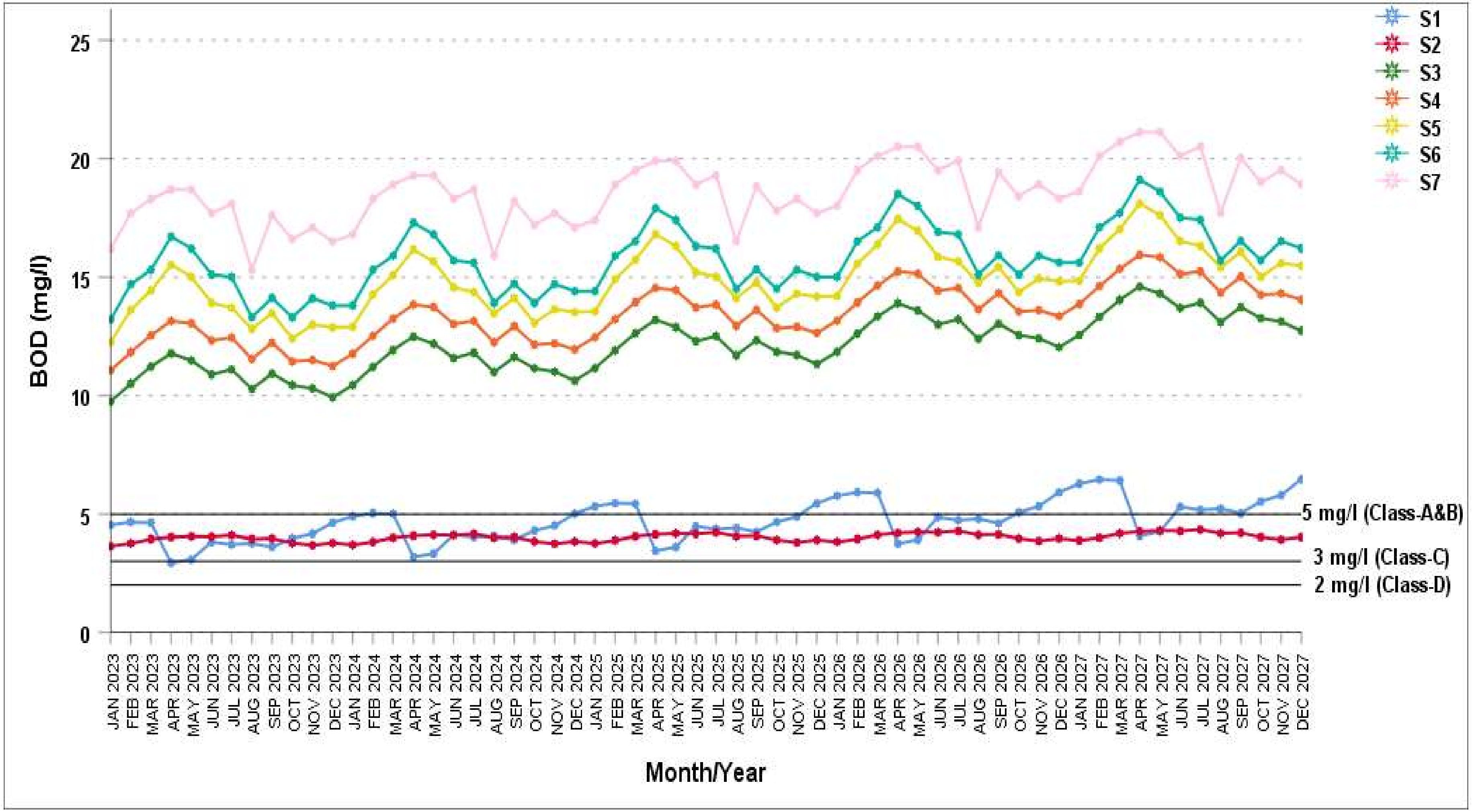


Figure 5.33b: Predicted variation of BOD during 2023-2027 along river Gomti

The Bascaron WQI (BWQI) was assessed and compared with the previous 20 years (1998-2017) data to check the impact of various simulated scenarios on water quality. The places along the stretch of water prone to degradation owing to changes in different scenarios are identified, and the changes in water quality for the various scenarios relative to the base scenario are quantified.

5.10.1 Relationship between air temperature, water temperature and BWQI

The regression equation with the best R^2 value obtained for WT with AT, and for WT with BWQI is given in Table 5.15.

Table 5.15: Regression equation with best R^2 value

Parameters	Regression equation	R^2
WT	Y= 0.6463X + 8.4916	0.5734
BWQI	Y = - 2.3009X + 117.18	0.5734

For the above-mentioned regression equation, the dependent variable is Y, and the independent variable is X. For WT, the dependent variable is WT, and the independent is AT; for BWQI, the dependent variable is BWQI, and WT is an independent variable. WT and BWQI were calculated for RCP 4.5 and RCP 8.5 scenarios by using regression equations with RCP 4.5 and RCP 8.5 fabricated scenarios of AT and WT, respectively (Table 5.16).

Table 5.16: Fabricated scenarios for air temperature

Variables	RCP 4.5		RCP 8.5	
Period	2040-2069	2070-2099	2040-2069	2070-2099
AT (^{0}C)	42.67	43.27	43.37	45.33

5.10.2 Impact on water quality

The collected data from CWC (Lucknow) at the sampling station (Hanuman Setu) has been used to calculate BWQI for the period of 1998 to 2017 as per the given methodology (ANNEXURE – XIV). The regression equation is used to calculate climate change scenario RCP 4.5 (2040-2069), RCP 4.5 (2070-2099), RCP 8.5 (2040-2069) and RCP 8.5 (2070-2099). The BWQI is predicted for future climate change scenarios and compared with the previous years (1998-2017).

BWQI value was evaluated at the sampling station (Hanuman Setu, Lucknow) using water quality parameters (WT, DO, and BOD) for the period between 1998 to 2017 according to the methodology for the classification of the overall water quality status of the river Gomti (Table 5.17). To assess the annual variability in water quality, the monthly BWQI data were organized, which were further used to calculate the mean BWQI of each year during the study period (Figure 5.34). The BWQI values for 20 years lie only in two water quality classifications, i.e., medium and bad, which are 42.92 to 70.00, respectively. The maximum value (70.00) of BWQI was found in 2004, and the minimum (42.92) in 2016 and 2017. Data reflects that the BWQI value keeps decreasing with time, which shows that river water quality is deteriorating. It occurs due to the rapid urbanization, industrialization, and encroachment of the river bed, which requires immediate remedial actions to retain and to maintain the water quality of river Gomti by concerned authorities.

Changes in stream WT can be linked to the effects of climate change. The evolution of AT in the future, together with other meteorological and physical characteristics, will significantly impact how climate change affects stream WT (Ficklin et al., 2013; Khani and Rajaee, 2017). These modifications will affect DO and BOD concentrations and instream biological activity, which will affect BWQI. This led to establishing a WT-BWQI relationship for the river to forecast future water quality index based on WT. As a result, future WT for the river was predicted, and matching BWQI was computed.

The BWQI was not highly different from the previous scenario (2014-2017) as it lies in the bad category in water quality classification; however, a slight decrease in BWQI is expected in the future under all scenarios. Based on predicted increases in air and river water temperatures under climate change scenarios, the BWQI does not generally indicate a significant decline in the near future. BWQI value was found to be 38.79 for scenario (RCP 4.5) 2040-2069, 37.90 for scenario (RCP 4.5) 2070-2099, 37.75 for scenario (RCP 8.5) 2040-2069, 34.83 for scenario (RCP 8.5) 2070-2099, which reflects a reduction in RCP 8.5 than RCP 4.5. A past study found a similar result of WQIs with climate change conditions for 15 rivers in New Brunswick, Canada's Atlantic coast (El-Jabi et al., 2014).

Low values for DO can result from the stream temperature increase since it decreases the solubility of oxygen in the water. The stream temperature rise may also accelerate the growth of algae and phytoplankton, further depleting DO in the water (Santy et al., 2022). The river's capacity to absorb pollution loads may be diminished by the rising stream temperature (Chapra et al., 2021); hence, with warming, a rise in BOD is predicted, and this is supported by other studies (Rehana and Mujumdar, 2012; Chapra et al., 2021) which also influences BWQI.

Table 5.17: Water quality status of the river Gomti during the study period as per BWQI

Years	**BWQI**	**Water quality classification**
1998	65.28	Medium
1999	66.39	Medium
2000	67.50	Medium
2001	69.44	Medium
2002	69.86	Medium
2003	68.89	Medium
2004	70.00	Medium
2005	60.97	Medium
2006	54.86	Medium
2007	56.94	Medium
2008	61.81	Medium
2009	58.19	Medium
2010	54.17	Medium
2011	53.33	Medium
2012	61.94	Medium
2013	55.56	Medium
2014	45.00	Bad
2015	50.00	Bad
2016	42.92	Bad
2017	42.92	Bad
(RCP 4.5) 2040-2069	***38.79***	***Bad***
(RCP 4.5) 2070-2099	***37.90***	***Bad***
(RCP 8.5) 2040-2069	***37.75***	***Bad***
(RCP 8.5) 2070-2099	***34.83***	***Bad***

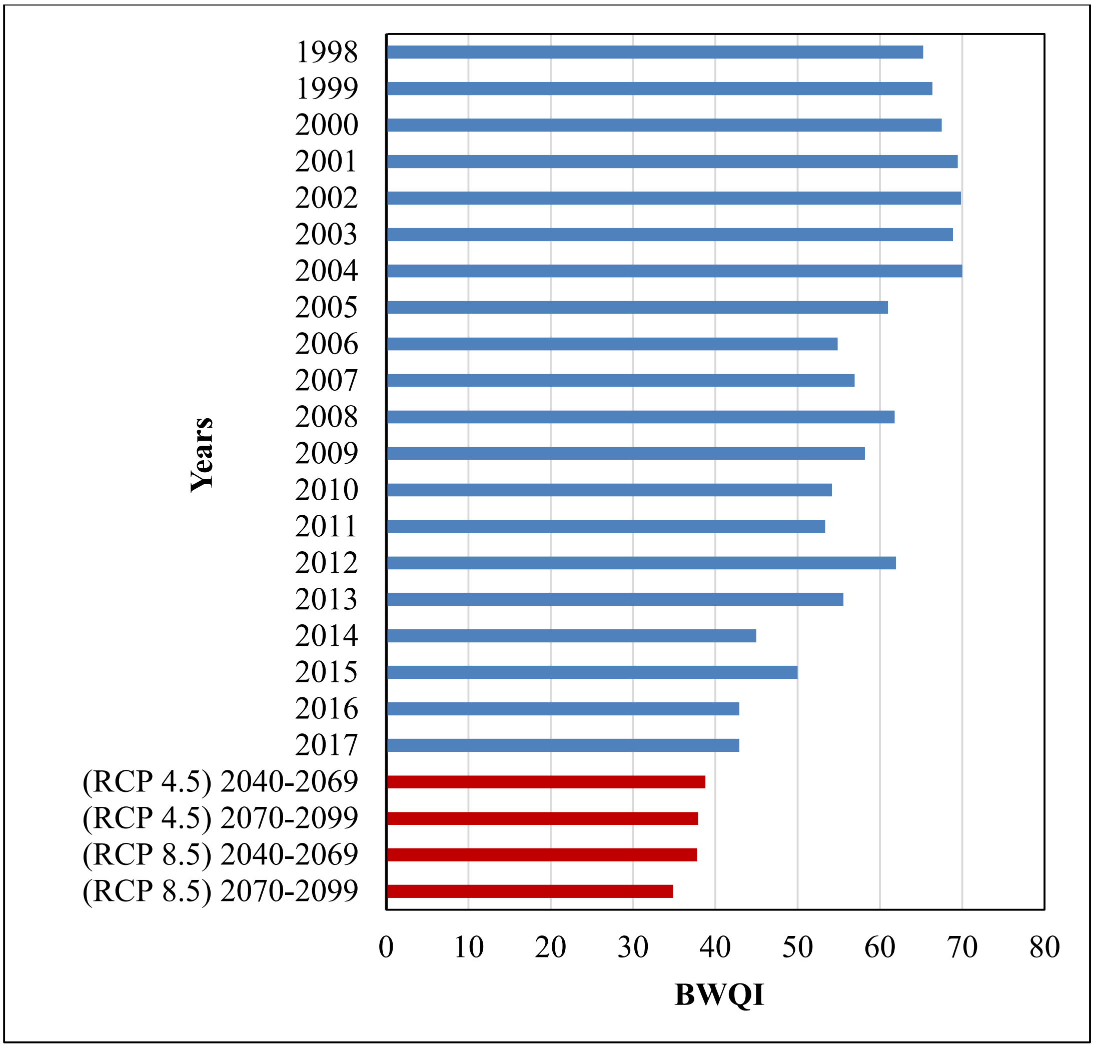


Figure 5.34: BWQI profile plots

5.11 River water quality management plan

Unchecked pollution disposal often results in various environmental problems, including the growth of hazardous algal blooms, eutrophication, the extinction of aquatic life, a reduction in biodiversity, and, eventually, adverse effects on human health. The current water pollution threatens the viability of the river environment and the urban area next to it. Therefore, it is necessary to regulate the concentration of water quality to an ideal level to preserve the water ecosystem. The best management scenarios must be created to launch credible water-quality management plans to conserve river water habitats. These plans must also be practical and affordable. Poor river water management has led to significant changes in water quantity and quality as well as altered ecosystems, which have reduced the advantages that can be obtained by the people who depend on them.

5.11.1 Status of the Gomti river water quality

According to the CPCB (2017), the most polluted rivers in India are some of the rivers in Uttar Pradesh. The Gomti, Hindon, Kali, and Yamuna rivers' water quality is considered to be gravely worrying. Gomti stretch from Sitapur to Varanasi is classified as Priority Class – I (Sitapur, Lucknow, Sultanpur) according to CPCB (2017).

According to UPPCB river water quality monitoring from 2017 to 2019, the river Gomti is not appropriate for drinking or outdoor bathing between Kudiaghat and Jagdishpur due to the detected polluted length of the river between Sitapur to Jaunpur. It can only be used for controlled waste disposal, industrial cooling, or irrigation (Class – E, specified as per IS: 2296:1992).

According to the current study, four WQIs were used to assess the status of the water quality of the river Gomti at seven sampling stations (S1 to S7). The result showed that according to Arithmetic WQI, water at all stations is unsuitable for drinking and fish culture. Out of all, S1 and S2 have comparatively better water quality. Similar results were found in the case of the other three WQIs. A gradual increase in the value of WQIs occurs after sampling station S2 due to the discharge of 28 drains between S2 to S7. The condition worsens at S7 due to the lack of self-purification capacity between S2 and S7. The river experiences more deterioration in water quality during the dry season and non-monsoon season due to the lack of sufficient flow. The predicted value of WQIs for future (2018- 2027) water quality shows the same deterioration rate.

5.11.2 Sources and causes of pollution

Surface runoff is a seasonal occurrence that is heavily influenced by the climate in the basin, whereas human discharges are a continuous polluting source. Domestic sewage from Class-I cities, Class-II cities, and many towns, as effluents from various industries, are discharged into the river Gomti throughout its length. About 78% of the pollution is caused by raw sewage, effluents, and sludge disposal. The major sources of river Gomti pollution are given below:

- The river Sarayan, a tributary of the river Gomti, confluences in the village of Kantaayan, district of Sitapur. Ten industries in the river's catchment discharge sewage and industrial waste into the river. About 4 MLD of treated effluent from these industries and nearly 20 MLD of sewage are dumped into the river Sarayan, which eventually merges with the river Gomti.

- The majority of the river's stretch has seen encroachment from urban areas, sewage discharge from Lucknow, and activities related to washing clothes (Dhobighat). From Lakhimpur to Barabanki, the river Gomti traverses 275 km, while in Lucknow city, it goes 20 km from upstream (Ghaila Ghat) to downstream (Pipra Ghat).
- There are 28 important drains in Lucknow; 14 are in the Cis-Gomti area, the southern half, and 14 are in the Trans-Gomti area, the northern section, with a total discharge of 461.33 MLD. Some large drains can discharge more than 100 MLD of wastewater, whereas the smaller drains can only discharge 0.5 MLD between sampling stations S2 to S7.
- Due to a lack of water, particularly during the summer, the quality of the river Gomti is affected by the daily withdrawal of raw water (270 MLD) from the river.
- On the banks of this polluted section of the river, there are 132 villages (50 on the left bank and 82 on the right bank). According to the 2011 census, these settlements have a combined population of 3,25,844 producing trash that contributes to river pollution.
- Total sewage and industrial effluent discharge through 68 drains that discharge directly or partially into the river is estimated to be 865 MLD in the polluted section of the Gomti River. According to a desk inventory, several drains are currently discharging 835 MLD of sewage and 30 MLD of industrial effluent into the river Gomti. Since only 443 MLD of the estimated 835 MLD total sewage discharge gets treated, this is a significant area of concern.
- Fourteen drains come from Jaunpur and have a combined discharge of roughly 16 MLD. They are all small drains, and most convey domestic wastewater that is less than 1 MLD. Only Turtipur and Ahyapur drains transport sewage, which is around 5 MLD. At Jaunpur, raw sewage is dumped directly into the Gomti River. In the Kerakat (Jaunpur) area, seven minor drains with a combined flow of about 8.7 MLD dumped directly into the Gomti River.
- The river's catchment region has seven major towns—Sitapur, Sandila, Lucknow, Barabanki, Jagdishpur, Sultanpur, and Jaunpur—as well as one town area, Kerakat (Jaunpur). The sewage and other effluent these cities produce add to the river's organic burden. As previously indicated, sewage treatment is a

severe cause for worry as the installed capacity of the sewage treatment plants is 443 MLD, and they are operating at 100% of their installed capacity. About 422 MLD of untreated sewage enters the river, Gomti. This suggests that the available treatment facility is insufficient. The river Gomti and the 345 MLD Bharwara STP's treated sewage meet just downstream of Lucknow city, close to Khaledeoria. Upstream of Lucknow city, close to Kudiyaghat, the river Gomti is where the 56 MLD treated sewage from Daulatganj STP meets.

- Existing STPs have an installed capacity of 443 MLD, and 373 MLD capacity STPs are planned for installation in Jaunpur, Sultanpur, and Lucknow; however, there is a need for more STPs to be built in Sitapur, Barabanki, Amethi (Jagdishpur), and Kerakat (Jaunpur).
- In the catchment basin of the Gomti River's polluted section, there are 30 water-polluting enterprises. These businesses have wastewater treatment facilities, and the processed wastewater is released through 10 drains, all combined drains where the treated industrial wastewater is mixed with sewage. The industries related to sugar, distilleries, textiles, electroplating, slaughterhouses, and other unrelated industries are highly polluting. The quantified consented discharge from the units is the basis for the estimates of industrial effluent; however, actual industrial effluent may exceed the estimates due to over-discharge by consented industries and discharge from illegal units operating in nonconforming regions.
- As a result of several anthropogenic activities, the water quality of river Gomti is currently witnessing an alarming loss. The overall water quality has been significantly impacted by destructive habitat change, water diversion, insufficient plant cover along riverbanks, siltation, water abstraction, and low water velocity. In the research region, dredging, artificial barriers, and river fragmentation caused by riverfront development projects pose a serious threat to the deterioration of water quality brought on by sewage pollution between sampling stations S4 to S6.

5.11.3 Gomti River stretch rejuvenation action plan

The research and site visits have revealed that the degradation of river water quality can be attributed to two primary factors: pollution and low discharge (mainly during the dry season). The following are mitigation measures for improving river water quality:

- The riverfront project has significantly impeded the natural flow of the Gomti River, causing detrimental effects on its water quality. Particularly, the 8.2 km stretch between Kuriyaghat (S3) and Laamart Rubber Dam has experienced water stagnation due to numerous barriers constructed as part of the project. This interruption goes against the inherent nature of a flowing water body and has faced severe degradation. The Gomti River heavily relies on groundwater as its primary source of replenishment, but the riverfront project has disrupted the vital connection between the river and the groundwater. To address this issue, implementing rainwater harvesting and creating ponds upstream of Kuriyaghat (S3), i.e., between S1 to S3, can play a crucial role in recharging groundwater and replenishing the Gomti River.
- Cultivating Satha Dhaan (garmi wala dhaan/ chaini dhaan), a water-intensive variety of rice poses a significant challenge as it consumes around ten times more water than other varieties. This high water demand puts added pressure on the already limited groundwater. Since the Gomti River relies heavily on groundwater, the diminishing water levels directly impact the river's health. Continuously cultivating Satha Dhaan can have detrimental effects on the river. Therefore, it is essential to consider making Satha Dhaan farming illegal between S1 to S2. Raising awareness among farmers through various campaigns and promoting alternative crops like pulses can help discourage Satha Dhaan cultivation. Additionally, encouraging afforestation, especially of Neem tree, Ashok tree, Tamarind/Imli tree, and Jamun tree, along the riverbanks between S1 to S2 would aid in replenishing the groundwater levels and prevent encroachments.
- The excessive presence of water hyacinths on the river between S2 to S4 creates dense mats that block sunlight, reducing oxygen levels and promoting the growth of harmful organisms. Decomposition leads to increased organic matter and stagnant water, posing risks to aquatic life and human health. Effective measures should be taken to control and manage the spread of water hyacinths. This may involve mechanical removal, such as manually harvesting the plants or using biological controls like introducing natural predators or herbivorous species that feed on water hyacinths. Regular monitoring and maintenance

should also be enforced to prevent its regrowth.

- The presence of algae over the water, mainly at S3, depletes oxygen levels, produces harmful toxins, disrupts the ecosystem balance, and diminishes aesthetics and odor. Algal blooms can occur due to excessive nutrient levels in the water, such as nitrogen and phosphorus. Key measures to improve water quality and address algae overgrowth include responsible nutrient management, establishing riparian buffer zones, upgrading wastewater treatment, implementing stormwater management, raising public awareness, and conducting regular monitoring for early detection and intervention.
- Despite being Asia's biggest STP (Bharwara Sewage Treatment Plant, Bharwara, Gomtinagar, Lucknow), its operation was short-lived, and currently, it is running at only one-fourth of its capacity. The primary issue lies in the lack of interlinking drains, which prevents the diversion of all the sewage to the treatment plant as intended. Mitigation measures for this challenge include interlinking drains, upgrading and maintenance, increasing capacity utilization, monitoring and enforcement, public awareness, and stakeholder engagement. An alternative approach to maximizing efficiency and optimizing resource allocation would have been establishing multiple smaller plants along the stretch between S2 and S7 rather than relying on a single large plant.
- The presence of foam, mainly at S7, can indicate excessive organic matter, detergents, or industrial waste entering the river. These substances can contribute to the depletion of oxygen levels, harm aquatic life, and degrade water quality. Key measures to mitigate foam presence in the river include identifying and controlling pollution sources, upgrading wastewater treatment, raising public awareness, managing nutrient pollution, implementing regular monitoring, and fostering collaboration and regulation.
- Pollution from dhobi ghats and chikankari work significantly impacts water quality between S2 to S6. The pollution of water with chemicals, detergents, solid wastes, and dyes from these sources introduces pollutants that degrade water ecosystems. The excessive nutrient levels from these activities contribute to eutrophication, leading to algal blooms and oxygen depletion. Mitigation measures include proper wastewater treatment, promoting eco-friendly materials, responsible waste management, raising awareness, and enforcing

regulations. Implementation of separate designated areas can help mitigate the impact on river water caused by dhobi ghats and chikankari work in Lucknow. By this, it becomes easier to manage and control the discharge of pollutants into the river. This segregation helps prevent direct pollution and allows for the implementation of proper wastewater treatment systems tailored to handle effluents.

- The major urban habitation between S2 to S6 results in significant solid waste disposal challenges. The high population density and urban activities generate substantial waste that needs proper management. Mitigation measures should focus on implementing efficient waste management practices, such as establishing proper waste collection and segregation systems, promoting recycling and composting, raising public awareness about waste reduction and responsible disposal, and enforcing regulations for waste management compliance.

In order to enhance the water quality of the Gomti River in Lucknow (UP) between S1 and S7, it is crucial to implement the aforementioned suggestions along with additional mitigation measures to achieve this goal, which are as follows:

- Declare the river as the “State River” of Uttar Pradesh; since the river originates in the state (Pilibhit) and joins with the Ganga there (Ghazipur), there is no interstate dispute or controversy with this designation. To restore the beauty and holiness of this river, this will be a fantastic project to resuscitate the river culture of the Awadh. Declare all 24 major tributaries' points of origin and confluence as "Eco-fragile regions."
- The Sharda Canal System occasionally adds extra flow to the Gomti through escapes of up to 2.83 m^3/s through the Kheri branch on the left and the Lucknow branch on the right. According to the roaster, the branches in Lucknow and Kheri operate concurrently and alternately. Sharda flows can be pumped in Gomti's upper reaches. However, Sharda will not have sufficient flows since all flows are directed into the Sharda Canal at Banbasa during the dry season. A canal should be planned with a well-fed Sharda River, designed to provide surplus water, connected to the Gomti River. The chronic issue of a fast-drying Gomti may be resolved by a steady supply of water from the Sharda, which

receives abundant water from its Himalayan source.

- Restoring the drainage of the Gomti River, particularly in the upper watershed, is also advised. A series of minor check-dams can be built in the head region of the tributaries to ensure the flow of water to the river.
- Define the boundaries of the entire floodplain, from its source to Ganga's confluence, and clear any unauthorized encroachments. Stop using the land, and the land-use change should not be violated by using a barrier.
- Declare a no-construction zone 500 m from the middle of the river. Clean up the silt that has accumulated in the riverbed near the main settlements of Sultanpur, Jaunpur, and Lucknow.
- Estimating the total amount of sewage produced by cities and towns without sewage treatment facilities and preparing a Detailed Project Report (DPR) for sewage treatment. Construction of sewage treatment facilities with sufficient capacity. Completion and commissioning of the STP being built at Lucknow's Ghiyasuddin Haider (G.H.) Canal.
- Installing a secondary or tertiary treatment system in STPs that are currently in operation but cannot meet discharge standards under the current system. Treatment of wastewater entering rivers from rural regions using bioremediation, phytoremediation, oxidation ponds, etc.
- The re-invention and monitoring of water-polluting industries in the drainage system's catchment region and their current condition concerning permission, ETP installation, ETP sufficiency, and final discharge point and enforcing their closure if they are operating without permission or in compliance.
- Modernization and operation of currently existing Solid Waste Treatment facilities that are not in operation or compliant with regulations. Strict enforcement of the ban on solid and other trash disposals within 500 m of riverbanks.
- Ensuring idol immersion is eco-friendly by constructing artificial ponds with suitable lining and efficient sludge and wastewater disposal, as well as building water harvesting structures, rainwater recharge structures, water ponds, and rainwater wells on river banks.

CHAPTER - 6

CONCLUSIONS AND FUTURE PROSPECTS

6.1 Conclusions

The physical, chemical, and biological properties of the river water samples from Gomti clearly show that the water is unfit for human consumption. Ranges of important parameters, including DO, BOD, COD, EC, TA, TC, and FC, exceeded the prescribed standards. The entire river stretch was found to be extremely polluted, and the amount of pollution increased from upstream to downstream (S1 to S7), demonstrating the effects of Lucknow's (UP) rapid industrialization and urbanization. Water quality parameter spatial variability maps demonstrated the rise in pollutant concentration along a river's course.

This study uses an integrated method to assess the river Gomti's surface water quality. By comparing the measured water quality to the national and international standards, data analysis has helped to identify the early warning indications of water quality decline. The concentration of water quality parameters in the river Gomti is above acceptable levels due to several anthropogenic activities, including the inflow of untreated sewage from residential and commercial establishments, the lack of adequate sanitation systems, agricultural runoff, direct disposal of untreated outflow from industries, and unabated dumping of solid waste by the communities living alongside the river, among others.

In the present study, fourteen water quality parameters have been considered for water quality management. Out of 14 water quality parameters, the mean values of WT, pH, TDS, TH, Ca, Mg, and Cl are well within the prescribed range of BIS (2012)/WHO (2011), whereas EC, TA, COD, TC, and FC were higher than the prescribed limit. DO, and BOD falls under the prescribed limit of BIS (2012)/WHO (2011) at station S1, S2, and S3 but not at other stations.

As per Designated Best Uses of Water (CPCB, IS: 2296:1992), the mean value of pH falls under Class – A at all sampling stations, DO falls under Class – A at S1 and S2, Class – B at S3, Class – C & D at S4 but S5, S6 and S7 falls under Class – E. In the case of BOD, values fall under Class – D. According to the mean value of TC sampling stations S1 and S2 fall under Class – C, whereas S3, S4, S5, S6, and S7 fall under Class - D.

One-way ANOVA analysis concluded that pH and DO gradually decrease from S1 to S7, whereas other parameters (EC, TDS, TA, TC, Ca, Mg, Cl, BOD, COD, TC, and FC) increase from S1 to S7. pH, TA, TH, DO, BOD, COD, TC, FC exhibit only temporal and spatial variation, whereas EC, TDS, Ca, Mg, and Cl show not only temporal and spatial variation but also annual variation.

To identify the sources of river pollution, PCA is utilized. The experimental results show that in the whole study period, the major PCs responsible for water quality deterioration are pH, Cl, DO, BOD, COD, TC, and FC, with a total variation of 54.65% within the dataset. These components represented organic pollution from domestic wastewater and sewage pollution. Thus, the PCA assisted in locating the study area's point and nonpoint sources of pollution. This fundamentally helps to prioritize control efforts concerning various pollution sources.

The CA helped in the categorization of similar stations for the river Gomti. CA resulted in three Clusters (moderate, high, and very high pollution sites) for river Gomti in all seasons. Cluster 1 (S1, S2, S3, and S4) represents a moderate pollution site because it is on the upstream side of Lucknow city. In contrast, Cluster 2 (S5 and S6) represents a high-pollution site because it is located in the middle of the route. The Cluster 3 (S7) represents the most polluted site because it is located in the downstream zone of Lucknow city.

The number of monitoring stations could be decreased with the help of this categorization. Each cluster will be represented by one monitoring station for sampling per cluster. This will undoubtedly lower the cost of river sampling in nations like India, where resources and specialized human skills are scarce.

WQIs can be used by policymakers to determine how different policy initiatives affect the water quality of a water body. It simplifies complex data so that stakeholders and decision-makers can easily understand it.

The present study assessed the Arithmetic WQI for five years (2013-2017). The results revealed that all the water samples fall into category E (>100), which is unsuitable for drinking and fish culture and requires proper treatment before use except at S1, S2, and S3 during monsoon season which falls under category D (75-100). These stations recorded the highest Arithmetic WQI values during 2017, ranging from 175.61 at Station S1 to 249.39 at Station S7. The Arithmetic WQI of the water samples collected at stations S1 and S2 were found to be better than other sampling stations.

The mean values of SPI are 1.112, 1.151, 1.250, 1.367, 1.532, 1.662 and 1.927 at S1, S2, S3, S4, S5, S6 and S7, respectively, which indicates “very poor” (1.0-3.0) status at all sampling sites during the study period. The water quality is severely polluted and can be used only for irrigation purposes.

The CPI value of the river Gomti water was found only in three categories: qualified (0.41-0.8), basically qualified (0.81-1.0), and polluted (1.01-2.0) during the study period at different locations and months. Moreover, the river water quality during the years 2013–2017 was found to be in the polluted category. CPI values increased from sampling stations S1 to S7, indicating increased pollution load due to extreme human activities in recent years.

The mean values of CPCB-WQI at S1 and S2 lie under the category medium to good, Class -B (50-63), S3 and S4 under the category bad, Class -C (38-50), S5, S6, and S7 under category bad to very bad, Class – D & E (<38). It was also noticed that the river Gomti water was found in all categories classified by CPCB-WQI for different sampling stations during the study period.

The maximum value was observed at station S7 for all four estimated WQIs. Thus, we can correlate the high WQIs of the station with anthropogenic activities, i.e., agricultural runoff and disposal of wastewater from urban and industrial areas nearby. This is further supported by the statistic that the WQIs were lower in the case of S1, where anthropogenic activities were low, and it increases as it goes from S1 to S7. PCA study further establishes that anthropogenic activities are the leading causes of the decline in water quality in this area. As a result, it can be said that WQIs are high at all sampling stations except at S1 and S2.

Statistical modeling for the period of 10 years (2018-2027) based on calculated data of WQIs (Arithmetic WQI, SPI, CPI, and CPCB-WQI) reveals similar results as the baseline period (2013-2017). The maximum value was observed at station S7, while minimum values at S1 and increase as it goes from S1 to S7 in the case of all four predicted WQIs. Model performance indicators or metrics were used to monitor the model's performance, i.e., RMSE, MAPE, MAE, MaxAPE, and MaxAE. Based on model performance indicators or metrics values, it was found that out of all four WQIs, SPI and CPI were the most suitable.

Statistical modeling results may help to plan the water quality management strategies for this water body. This study will be of great use to policymakers, managers of water quality, and scientists in the future. The model's effectiveness lies in the user's ability to evaluate the water quality at several sites using a small dataset.

During the study period (2013-2017), the minimum DO concentration at all sampling stations lay below 4 mg/l while the maximum DO concentration was well above the reference limit (4 mg/l), but the scenario at S7 shows a lower concentration than the reference limit (4 mg/l) for both minimum and maximum concentrations. For BOD, the river water quality at selected sampling stations is unfit for all purposes according to the designated best-use criteria of CPCB (IS: 2296:1992) for surface water.

DO does not remain at reasonable levels over this limit throughout the predicted time (2018-2027) at S5, S6, and S7 in both dry and wet seasons. DO concentrations are higher than the reference limit at S1 during the predicted period, but in the case of S2, S3, and S4, DO concentration is higher in the wet season and lower in the dry season. At all sampling stations, BOD exceeds the reference limit (2 mg/l), which occurs during the predicted period (2018-2027), so the water bodies that exceed the reference limit are considered polluted.

Conclusions for each scenario show that BOD concentrations are higher in the dry season than in the wet season due to the decline in flows during the dry season, and vice versa for DO. The Gomti River has an average daily flow of 1,500 MLD, and it rises to 55,000 MLD after rains and drops to 500 MLD during the summer. It is crucial to realize that rivers' ability to assimilate pollutants is a complicated process that simultaneously combines physical, chemical, and biological processes, with the majority of water pollutants being reduced through biodegradation processes.

The water quality profile of BWQI for climate change scenarios RCP 4.5 (2040-2069), RCP 4.5 (2070-2099), RCP 8.5 (2040-2069), and RCP 8.5 (2070-2099) has been done and concluded as the BWQI was not highly different from previous scenario (2014-2017) as it lies in bad category in water quality classification; however, a slight decrease in BWQI is expected in the future under all scenarios. BWQI value was found to be 38.79 for scenario (RCP 4.5) 2040-2069, 37.90 for scenario (RCP 4.5) 2070-2099, 37.75 for scenario (RCP 8.5) 2040-2069, 34.83 for scenario (RCP 8.5) 2070-2099 which reflects a reduction in RCP 8.5 than RCP 4.5.

The selected WQIs have been studied by adopting the GIS method and the Inverse Distance Weighted (IDW) Interpolation. The maps of WQIs showed that the study area was highly polluted by 28 drains discharges approximately 461.33 MLD wastewater. As a result, the water from the Gomti River should not be directly reused due to its high physicochemical and biological load. Prior treatment should be taken into account to enhance its quality to meet water quality regulations, live up to public expectations, and safeguard the environment and public health. The Gomti River, which flows through the main city of the province of the most populous state in India, has an issue with its surface water quality. The leading cause of the current extremely polluted water quality is the direct discharge of industrial and domestic wastewater into rivers through a system of drains. The river habitat is unfavorable for aquatic life and the surrounding environment because of the poor quality of the water.

As a result, management alternatives are suggested to lessen pollution. Between sampling stations S2 and S7, a sufficient sewage treatment facility ought to be set up. In order to facilitate the river's natural processes of self-purification and self-cleansing, adequate discharge must be maintained at all times, particularly during the dry or non-monsoon seasons. The removal of solid waste such as plastic, paper, dead animals, and other debris is necessary to keep the flow in the river body. The implementation of these initiatives will contribute to an improvement in water quality in the foreseeable future.

6.2 Scope for further work

The control of water quality is essential, given the steadily rising trends in water pollution. It is crucial to have a scientific method for identifying locations with a high potential for pollution in developing nations like India, where the economic structure of the nation is still being developed. An integrated strategy involving WQIs, GIS, and modeling makes it easier to conduct vulnerability analyses that will aid in classifying a region into zones with varied degrees of pollution so that appropriate interventions can be started well in advance. The project can be expanded to include additional rivers and bodies of water.

- Since water quality indices are created in various parts of the world with various goals or applications, it is imperative to develop a new water quality index for the river Gomti based on the study's goals, and it may be undertaken as a future project.
- The influence of pollution caused by agricultural fields could not be considered in WQMs due to a lack of data on agricultural runoff. The model may need to be updated in the future with data on agricultural runoff, which would shed light on the contribution of diffuse sources of pollution in the Gomti River.
- River water interacts with the sediment and is affected by the sediment's quality. Modeling sediment and water quality may be a grey area in the future. The

influence of the river's declining water quality on the basin's groundwater can be investigated further using a study based on the interactions between surface and subsurface water.

6.3 Significant contributions

The Gomti River's water quality was evaluated in this study using an integrated methodology (MSTs, WQIs, GIS, and statistical modeling), and the results were utilized to help develop the strategies for a surface water quality management plan. The following list includes the present study's major contributions:

- The river sampling stations have been categorized using the CA method. The results of CA enable the clustering of related sample stations, which facilitates the design of the optimal number of sampling stations, hence lowering the number of stations and the cost of sampling.
- In the current study, source apportionment was carried out using PCA, and the actual causes of river water quality decline were also evaluated. The policymakers and scientists will be benefitted from the source apportionment studies as they carefully create and implement surface water quality control programs.
- The usage of WQIs aids in understanding the condition of the entire study river stretch. The current study provides the overall appropriateness status of the water quality. The study also emphasizes the vital aspects of water quality. The Gomti River's water quality was predicted with statistical modeling of various WQIs. The interception and diversion (I&D) of sewage before it reaches rivers, as well as the installation of treatment facilities to treat the intercepted sewage, are some recommendations made based on both outcomes to preserve the river water quality.
- The results of this study show that employing an integrated strategy of MSTs, WQIs, GIS, and statistical modeling makes it possible to construct more reliable surface water quality management plans in a developing nation like India. The combined use of these scientific tools would not only aid in managing surface water quality but also result in time and cost savings.

REFERENCES

Abbasi, T., & Abbasi, S. A. (2012). *Water quality indices*. Elsevier. https://doi.org/10.1016/B978-0-444-54304-2.01001-0

Abbasnia, A., Yousefi, N., Mahvi, A. H., Nabizadeh, R., Radfard, M., Yousefi, M., & Alimohammadi, M. (2019). Evaluation of groundwater quality using water quality index and its suitability for assessing water for drinking and irrigation purposes: Case study of Sistan and Baluchistan Province (Iran). *Human and Ecological Risk Assessment: An International Journal*, *25*(4), 988–1005. https://doi.org/10.1080/10807039.2018.1458596

Abdel-Gawad, S., & Khalil, B. M. (2003). Site registry for the Nile River water quality monitoring network. Report no. : wq-te-0307-011-fn. *National water quality and availability management project, national water quality monitoring component*.

Abeysingha, N. S., Islam, A., & Singh, M. (2020). Assessment of climate change impact on flow regimes over the Gomti River basin under IPCC AR5 climate change scenarios. *Journal of Water and Climate Change*, *11*(1), 303–326, Ar.5. https://doi.org/10.2166/wcc.2018.039

Abeysingha, N. S., Singh, M., Sehgal, V. K., Khanna, M., & Pathak, H. (2016). Analysis of trends in streamflow and its linkages with rainfall and anthropogenic factors in Gomti River basin of North India. *Theoretical and Applied Climatology*, *123*(3–4), 785–799. https://doi.org/10.1007/s00704-015-1390-5

Abeysingha, N. S., Singh, M., Sehgal, V. K., Khanna, M., Pathak, H., Jayakody, P., & Srinivasan, R. (2015). Assessment of water yield and evapotranspiration over 1985 to 2010 in the Gomti River basin in India using the SWAT model. *Current Science*, *108*(12), 2202–2212.

Abrahao, R., Carvalho, M., da Silva, Jr., W. R., Machado, T., Gadelha, C., & Hernandez, M. (2007). Use of index analysis to evaluate the water quality of a stream receiving industrial effluents. *Water SA*, *33*(4). https://doi.org/10.4314/wsa.v33i4.52940

Ahmad, S., Khan, I. H., & Parida, B. P. (2001). Performance of stochastic approaches for forecasting river water quality. *Water Research*, *35*(18), 4261–4266. https://doi.org/10.1016/s0043-1354(01)00167-1

Ahmed, M., Mumtaz, R., & Hassan Zaidi, S. M. H. (2021). Analysis of water quality indices and machine learning techniques for rating water pollution: A case study of Rawal Dam, Pakistan. *Water Supply*, *21*(6), 3225–3250. https://doi.org/10.2166/ws.2021.082

Ahmed, W., Vieritz, A., Goonetilleke, A., & Gardner, T. (2010). Health risk from the use of roof-harvested rainwater in SouthEast Queensland, Australia, as potable or nonpotable water, determined using quantitative microbial risk assessment. *Applied and Environmental Microbiology*, *76*(22), 7382–7391. http://doi.org/10.1128/AEM.00944-10

Ali, S. Y., Sunar, S., Saha, P., Mukherjee, P., Saha, S., & Dutta, S. (2021). Drinking water quality assessment of river Ganga in West Bengal, India through integrated statistical and GIS techniques. *Water Science and Technology*, *84*(10–11), 2997–3017. https://doi.org/10.2166/wst.2021.293

Alsaqqar, A. S., Hashim, A., & Ali, A. M. (2015). Water quality index assessment using GIS case study: Tigris River in Baghdad city. *International Journal of Current Engineering and Technology*, *5*(4), 2515–2520.

Amadi, A. N. (2011). Assessing the effects of Aladimma dumpsite on soil and groundwater using water quality index and factor analysis. *Australian Journal of Basic and Applied Sciences*, *5*(11), 763–770.

Antonopoulos, V. Z., Papamichail, D. M., & Mitsiou, K. A. (2001). Statistical and trend analysis of water quality and quantity data for the Strymon River in Greece. *Hydrology and Earth System Sciences*, *5*(4), 679–692. https://doi.org/10.5194/hess-5-679-2001

Arora, S., & Keshari, A. K. (2021). Pattern recognition of water quality variance in Yamuna River (India) using hierarchical agglomerative cluster and principal component analyses. *Environmental Monitoring and Assessment*, *193*(8), 494. https://doi.org/10.1007/s10661-021-09318-1

Arslan, I. (2001). Treatability of a simulated disperse dye-bath by ferrous iron coagulation, ozonation, and ferrous iron-catalyzed ozonation. *Journal of Hazardous Materials*, *85*(3), 229–241. http://doi.org/10.1016/S0304-3894(01)00232-1

Arslan, O. (2009). A GIS-based spatial-multivariate statistical analysis of water quality data in the Porsuk River, Turkey. *Water Quality Research Journal*, *44*(3), 279–293. https://doi.org/10.2166/wqrj.2009.029

Arya, F. K., & Zhang, L. (2015). Time series analysis of water quality parameters at Stillaguamish River using order series method. *Stochastic Environmental Research and Risk Assessment*, *29*(1), 227–239. https://doi.org/10.1007/s00477-014-0907-2

Ayeni, O., & Soneye, A. S. O. (2013). Interpretation of surface water quality using principal components analysis and cluster analysis. *Journal of Geography and Regional Planning*, *6*(4), 132–141. https://doi.org/10.5897/ JGRP12.087

Azhar, S. C., Aris, A. Z., Yusoff, M. K., Ramli, M. F., & Juahir, H. (2015). Classification of river water quality using multivariate analysis. *Procedia Environmental Sciences*, *30*,79–84. https://doi.org/10.1016/j.proenv.2015.10.014

Baker-Austin, C., Wright, M. S., Stepanauskas, R., & McArthur, J. V. (2006). Co-selection of antibiotic and metal resistance. *Trends in Microbiology*, *14*(4), 176–182. https://doi.org/10.1016/j.tim.2006.02.006

Banerjee, M., Mukherjee, J., Banerjee, A., Roy, M., Bandyopdhyay, G., & Ray, S. (2015). Impact of environmental factors on maintaining water quality of Bakreswar reservoir, India. *Computational Ecology and Software*, *5*(3), 239–253.

Barakat, A., El Baghdadi, M., Rais, J., Aghezzaf, B., & Slassi, M. (2016). Assessment of spatial and seasonal water quality variation of Oum Er Rbia River (Morocco) using multivariate statistical techniques. *International Soil and Water Conservation Research*, *4*(4), 284–292. https://doi.org/10.1016/j.iswcr.2016.11.002

Bascaron, M. (1979). Establishment of a methodology for the determination of water quality. Bol Inf Medio Ambient, 9, 30-51.

Basu, S., & Lokesh, K. S. (2014). Application of Multiple Linear Regression and MANOVA to evaluate health impacts due to changing river water quality. *Applied Mathematics*, *05*(5), 799–807. https://doi.org/10.4236/am.2014.55076

Bellos, D., & Sawidis, T. (2005). Chemical pollution monitoring of the river Pinios (Thessalia-Greece). *Journal of Environmental Management*, *76*(4), 282–292. https://doi.org/10.1016/j.jenvman.2005.01.027

Benjumea Hoyos, C. A., Suárez-Segura, M. A., & Villabona-González, S. L. (2018). Temporary and spatial variation of nutrients and total suspended solids in the basin of a high mountain tropical river. *Revista de la Academia Colombiana de Ciencias Exactas, Físicas y Naturales*, *42*(165), 353–363. https://doi.org/10.18257/raccefyn.777

Bhandari, N. S., & Nayal, K. (2008). Correlation study on physico-chemical parameters and quality assessment of Kosi River water, Uttarakhand. *E-Journal of Chemistry*, *5*(2), 342–346. https://doi.org/10.1155/2008/140986

Bhargava, D. S. (1983). Use of water quality index for river classification and zoning of Ganga River. *Environmental Pollution Series B, Chemical and Physical, 6*(1), 51-67. https://doi.org/10.1016/0143-148X(83)90029-0

Bhargava, D. S. (2006). Revival of Mathura's ailing Yamuna River. *Environmentalist*, *26*(2), 111–122. https://doi.org/10.1007/s10669-006-7481-1

Bhat, S. A., & Pandit, A. K. (2014). Surface water quality assessment of Wular Lake, a Ramsar site in Kashmir Himalaya, using discriminant analysis and WQI. *Journal of Ecosystems*, *2014*, 1–18. https://doi.org/10.1155/2014/ 724728

Bhateria, R., & Jain, D. (2016). Water quality assessment of lake water: A review. *Sustainable Water Resources Management*, *2*(2), 161–173. https://doi.org/10.1007/s40899-015-0014-7

Bhatti, N., Siyal, A., & Qureshi, A. (2018). Groundwater quality assessment using water quality index: A case study of Nagarparkar, Sindh, Pakistan. *Sindh University Research Journal-SURJ (Science Series)*, *50*(2), 227–234.

Bhutiani, R., Khanna, D. R., Kulkarni, D. B., & Ruhela, M. (2016). Assessment of Ganga River ecosystem at Haridwar, Uttarakhand, India with reference to water quality indices. *Applied Water Science*, *6*(2), 107–113. https://doi.org/10.1007/s13201-014-0206-6

Birol, E., & Das, S. (2010). Estimating the value of improved wastewater treatment: The case of River Ganga, India. *Journal of Environmental Management*, *91*(11), 2163–2171. https://doi.org/10.1016/j.jenvman.2010. 05.008

Bisht, D. S., Chatterjee, C., Raghuwanshi, N. S., & Sridhar, V. (2018). Spatio-temporal trends of rainfall across Indian River basins. *Theoretical and Applied Climatology*, *132*(1–2), 419–436. https://doi.org/10.1007/s00704-017-2095-8

Bodrud-Doza, M., Islam, A. R. M. T., Ahmed, F., Das, S., Saha, N., & Rahman, M. S. (2016). Characterization of groundwater quality using water evaluation indices, multivariate statistics and geostatistics in Central Bangladesh. *Water Science*, *30*(1), 19–40. https://doi.org/10.1016/j.wsj.2016. 05.001

Bonansea, M., Bazán, R., Ferrero, S., Rodríguez, C., Ledesma, C., & Pinotti, L. (2018). Multivariate statistical analysis for estimating surface water quality in reservoirs.

International Journal of Hydrology Science and Technology, *8*(1), 52–68. https://doi.org/10.1504/IJHST.2018.088675

Bora, M., & Goswami, D. C. (2017). Water quality assessment in terms of water quality index (WQI): Case study of the Kolong River, Assam, India. *Applied Water Science*, *7*(6), 3125–3135. https://doi.org/10.1007/s13201-016-0451-y

Bouaziz, M., Leidig, M., & Gloaguen, R. (2011). Optimal parameter selection for qualitative regional Erosion risk monitoring: A remote sensing study of SE Ethiopia. *Geoscience Frontiers*, *2*(2), 237–245. https://doi.org/10.1016/j.gsf.2011.03.004

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2008). *Time series analysis: Forecasting and control* (4th ed). John Wiley & Sons, Inc.

Boyacioglu, H. (2007). Development of a water quality index based on a European classification scheme. *Water SA*, *33*(1), 101–106. https://doi.org/10.4314/wsa.v33i1.47882

Boyacioglu, H., & Boyacioglu, H. (2010). Detection of seasonal variations in surface water quality using discriminant analysis. *Environmental Monitoring and Assessment*, *162*(1–4), 15–20. https://doi.org/10.1007/s10661-009-0772-5

Brandt, M. J., Johnson, K. M., J., E. A., & Ratnayaka, D. D. (2017). *Twort's water supply*. Elsevier. https://doi.org/10.1016/c2012-0-06331-4

Brierley, G., Reid, H., Fryirs, K., & Trahan, N. (2010). What are we monitoring and why? Using geomorphic principles to frame eco-hydrological assessments of river condition. *Science of the Total Environment*, *408*(9), 2025–2033. https://doi.org/10.1016/j.scitotenv.2010.01.038

Brown, R. M., Mc-Clelland, N. I., Deininger, R. A., & Landwehr, J. M. (1973). Validating the WQI. In. The paper presented at national meeting of American society of civil engineers on water resources engineering. Washington, DC.

Brown, R. M., Mc-Clelland, N. I., Deininger, R. A., & O'Connor, M. F. (1972). A water quality index—Crashing the psychological barrier. In *Indicators of Environmental Quality*, 1, 173–182.

Brown, R. M., Mc-Clleland, N. I., Deininger, R. A., & Tozer, R. G. (1970). A water quality index – Do we dare? *Water and Sewage Works*, *117*(10), 339–343.

Bu, H., Meng, W., & Zhang, Y. (2014). Spatial and seasonal characteristics of river water chemistry in the Taizi River in Northeast China. *Environmental Monitoring and Assessment*, *186*(6), 3619–3632. https://doi.org/10.1007/s10661-014-3644-6

Bureau of Indian Standards (BIS). (2012). Indian standard (2nd revision), IS 10500: Drinking Water - Specification. New Delhi, India.

Cadraku, H. S. (2021). Groundwater quality assessment for irrigation: Case study in the blinaja river basin, Kosovo. *Civil Engineering Journal*, *7*(9), 1515–1528. https://doi.org/10.28991/cej-2021-03091740

Canadian Council of Ministers of the Environment. (2001). Canadian environmental quality guidelines for the protection of aquatic life, CCME water quality index [Technical report], 1.0. Ottawa.

Cely-Calixto, N. J., Bonilla-Granados, C. A., & Carrillo Soto, G. A. (2021). A mathematical model for the simulation of the Magdalena River in the city of Barrancabermeja, Colombia. *Journal of Physics: Conference Series*, *1981*(1), 012016. https://doi.org/10.1088/1742-6596/1981/1/012016

Census 2011. *common/censusdata2011.html*. https://censusindia.gov.in/2011-3, Accessed September 20, 2021.

Central Water Commission (CWC) (2019). Effect of time and temperature on DO levels in river waters. http://cwc.gov.in/sites/default/files/effect-time-and-temperature-do-levels-river-water-*.pdf (2019)*.

Chabuk, A., Al-Madhlom, Q., Al-Maliki, A., Al-Ansari, N., Hussain, H. M., & Laue, J. (2020). Water quality assessment along Tigris River (Iraq) using water quality index (WQI) and GIS software. *Arabian Journal of Geosciences*, *13*(14), 654. https://doi.org/10.1007/s12517-020-05575-5

Chakraborty, B., Bera, B., Adhikary, P. P., Bhattacharjee, S., Roy, S., Saha, S., Ghosh, A., Sengupta, D., & Shit, P. K. (2021). Positive effects of COVID-19 lockdown on river water quality: Evidence from River Damodar, India. *Scientific Reports*, *11*(1), 20140. https://doi.org/10.1038/s41598-021-99689-9

Chakravarty, T., & Gupta, S. (2021). Assessment of water quality of a hilly river of south Assam, north East India using water quality index and multivariate statistical analysis. *Environmental Challenges*, *5*, 100392. https://doi.org/10.1016/j.envc.2021.100392

Chan, M. C., Lou, I. C., Ung, W. K., & Mok, K. M. (2013). Integrating principle component analysis and canonical correlation analysis for monitoring water quality in storage reservoir. In. *Applied Mechanics and Materials*, 284–287, 1458–1462. https://doi.org/10.4028/www.scientific.net/ AMM.284-287.1458

Chandra, R., Singh, S., & Raj, A. (2006). Seasonal bacteriological analysis of Gola river water contaminated with pulp paper mill waste in Uttaranchal, India. *Environmental Monitoring and Assessment*, *118*(1–3), 393–406. https://doi.org/10.1007/s10661-006-1508-4

Chang, T. J. (1988). Stochastic forecast of water losses. *Journal of Irrigation and Drainage Engineering, 114(3)*, 558–558. https://doi.org/10.1061/(ASCE)0733-9437(1988) 114:3(547)

Chapra, S. C., Camacho, L. A., & McBride, G. B. (2021). Impact of global warming on dissolved oxygen and BOD assimilative capacity of the world's rivers: Modeling analysis. *Water*, *13*(17), 2408. https://doi.org/10.3390/w 13172408

Chaturvedi, R., Banerjee, S., Das, B., Chattopadhyay, P., Bhattacharjee, C. R., & Veer, V. (2016). High nitrate content in the surface water of Balipara, North Brahmaputra River basin, Sonitpur district, Assam, India: A multivariate approach. *Current Science*, *110*(7), 1350.

Chaudhary, M., Mishra, S., & Kumar, A. (2017). Estimation of water pollution and probability of health risk due to imbalanced nutrients in River Ganga, India. *International Journal of River Basin Management*, *15*(1), 53–60. https://doi.org/10.1080/15715124.2016.1205078

Chaudhary, S., Kuniyal, J. C., Vaidya, N., & Puri, S. (2019). Water quality assessment in headwater of the Satluj Basin, northwestern Himalaya, India. *Journal of Himalayan Ecology and Sustainable Development, 14*, 19–33.

Chen, P., Li, L., & Zhang, H. (2015). Spatio-temporal variations and source apportionment of water pollution in Danjiangkou Reservoir Basin, Central China. *Water*, *7*(12), 2591–2611. https://doi.org/10.3390/w7062591

Chen, Q., Wu, W., Blanckaert, K., Ma, J., & Huang, G. (2012). Optimization of water quality monitoring network in a large river by combining measurements, a numerical model and matter-element analyses. *Journal of Environmental Management*, *110*, 116–124. https://doi.org/10.1016/j.jenvman. 2012.05.024

Ching, L., & Mukherjee, M. (2015). Managing the socio-ecology of very large rivers: Collective choice rules in IWRM narratives. *Global Environmental Change*, *34*, 172–184. https://doi.org/10.1016/j.gloenvcha.2015.06.012

Chow, V. T., & Kareliotis, S. J. (1970). Analysis of Stochastic Hydrologic Systems. *Water Resources Research*, 6(6), 1569–1582. https://doi.org/10.1029/WR006i 006p01569

Colman, J. A., Massey, A. J., & Levin, S. B. (2011). *Determination of dilution factors for discharge of aluminum containing wastes. Public water supply treatment facilities into lakes and reservoirs in Massachusetts. Prepared in cooperation with the Massachusetts Department of Environmental Protection Scientific, Reston*.

Comber, A., Fisher, P., & Wadsworth, R. (2005). Comparing statistical and semantic approaches for identifying change from land cover datasets. *Journal of Environmental Management*, *77*(1), 47–55. https://doi.org/10.1016/j.jenvman.2005.02.009

Council, N. R. (2002). *Privatization of water services in the United States: An assessment of issues and experience*. The National Academies Press.

CPCB ENVIS. (2008). http://cpcb.nic.in/upload/AnnualReports/Annual_Report_37_ANNUAL_REPORT-08-09.pdf, Retrieved September 20, 2021

CPCB. (2000). Available online. http://www.cpcbenvis.nic.in/cpcb_newsletter /sewage pollution.pdf, Retrieved September 20, 2021

CPCB. (2015). *Inventorization of sewage treatment plants* (pp. 1–81).

CPCB. (2017). *Restoration of polluted river stretches, concept and plan. Central pollution control Board, Delhi, India*.

CPCB. (2019). *National inventory report. Available online*. https://cpcb.nic.in/uploads/hwmd/Annual_Inventory2019-20.pdf, Retrieved September 20, 2021

CPCB. (2021). http://cpcb.nic.in/effluent-emission/, Retrieved September 20, 2021

Crowther, J., Kay, D., & Wyer, M. D. (2001). Relationships between microbial water quality and environmental conditions in coastal recreational waters: The Fylde coast, UK. *Water Research*, *35*(17), 4029–4038. https://doi.org/10.1016/s0043-1354(01)00123-3

Cude, C. G. (2001). Oregon water quality index a tool for evaluating water quality management effectiveness. *Journal of the American Water Resources Association*, *37*(1), 125–137. https://doi.org/10.1111/j.17521688.2001.tb05480.x

Cun, C., & Vilagines, R. (1997). Time series analysis on chlorides, nitrates, ammonium and dissolved oxygen concentrations in the Seine river near Paris. *Science of the Total Environment*, *208*(1–2), 59–69. https://doi.org/10.1016/s0048-9697(97)00277-5

Damle, C., & Yalcin, A. (2007). Flood prediction using Time Series Data Mining. *Journal of Hydrology*, *333*(2–4), 305–316. https://doi.org/10.1016/j.jhydrol.2006.09.001

Danladi Bello, A.-A., Hashim, N. B., & Mohd Haniffah, M. R. (2017). Predicting impact of climate change on water temperature and dissolved oxygen in tropical rivers. *Climate*, *5*(3), 58. https://doi.org/10.3390/cli5030058

Darvishi, G., Kootenaei, F. G., Ramezani, M., Lotfi, E., & Asgharnia, H. (2016). Comparative investigation of river water quality by OWQI, NSFWQI and Wilcox indexes (case study: the talar River - Iran). *Archives of Environmental Protection*, *42*(1), 41–48. https://doi.org/10.1515/aep-2016-0005

Das, B., Jain, S. K., Thakur, P. K., & Singh, S. (2021). Assessment of climate change impact on the Gomti River basin in India under different RCP scenarios. *Arabian Journal of Geosciences*, *14*(2), 120. https://doi.org/10.1007/s12517-020-06359-7

Das, B., Jain, S., Singh, S., & Thakur, P. (2019). Evaluation of multisite performance of SWAT model in the Gomti River basin, India. *Applied Water Science*, *9*(5), 134. https://doi.org/10.1007/s13201-019-1013-x

Das, P., & Tamminga, K. R. (2012). The Ganges and the GAP: An assessment of efforts to clean a sacred river. *Sustainability*, *4*(8), 1647–1668. https://doi.org/ 10.3390/su4081647

De Andrade, E. M., Palácio, H. A., Souza, I. H., de Oliveira Leão, R. A., & Guerreiro, M. J. (2008). Land use effects in groundwater composition of an alluvial aquifer (Trussu river, Brazil) by multivariate Techniques. *Environmental Research*, *106*(2), 170–177. https://doi.org/10.1016/j.envres. 2007.10.008

De Andrade, L. N., Mauri, G. R., & Mendonça, A. S. F. (2013). General multiobjective model and simulated annealing algorithm for waste-load allocation. *Journal of Water Resources Planning and Management*, *139*(3), 339–344. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000257

De Smedt, F., Brevis, W., & Debels, P. (2005). Analytical solution for solute transport resulting from instantaneous injection in streams with transient storage. *Journal of Hydrology*, *315*(1–4), 25–39. https://doi.org/10.1016/ j.jhydrol.2005.04.002

De Stefano, L., Petersen-Perlman, J. D., Sproles, E. A., Eynard, J., & Wolf, A. T. (2017). Assessment of transboundary river basins for potential hydro-political tensions. *Global Environmental Change*, *45*, 35–46. https://doi.org/10.1016/j.gloenvcha.2017.04.008

Debels, P., Figueroa, R., Urrutia, R., Barra, R., & Niell, X. (2005). Evaluation of water quality in the Chillán river (Central Chile) using physicochemical parameters and a modified water quality index. *Environmental Monitoring and Assessment*, *110*(1–3), 301–322. https://doi.org/10.1007/s10661-005-8064-1

Dehghani Darmian, M., Khodabandeh, F., Azizyan, G., Giesy, J. P., & Hashemi Monfared, S. A. (2020). Analysis of assimilation capacity for conservation of water quality: Controllable discharges of pollutants. *Arabian Journal of Geosciences*, *13*(17), 888. https://doi.org/10.1007/s12517-020-05907-5

Deshmukh, K. K. (2013). Impact of human activities on the quality of groundwater from Sangamner area, Ahmednagar District, Maharashtra, India. *International Research Journal of Environmental Sciences*, *2*(8), 66–74.

Dewata, I. (2019). Water quality assessment of rivers in Padang using water pollution index and NSF-WQI method. *International Journal of GEOMATE*, *17*(64), 192–200. https://doi.org/10.21660/2019.64.16793

Dojlido, J., Raniszewski, J., & Woyciechowska, J. (1994). Water quality index - Application for rivers in Vistula River basin in Poland. *Water Science and Technology*, *30*(10), 57–64. https://doi.org/10.2166/wst.1994.0511

Dong, J. D., Zhang, Y. Y., Zhang, S., Wang, Y. S., Yang, Z. H., & Wu, M. L. (2010). Identification of temporal and spatial variations of water quality in Sanya Bay, China by three-way principal component analysis. *Environmental Earth Sciences*, *60*(8), 1673–1682. https://doi.org/10.1007/s12665-009-0301-4

Du, X., Shrestha, N. K., & Wang, J. (2019). Assessing climate change impacts on stream temperature in the Athabasca River Basin using SWAT equilibrium temperature model and its potential impacts on stream ecosystem. *Science of the Total Environment*, *650*(2), 1872–1881. https://doi.org/10.1016/j.scitotenv.2018.09.344

Dunnette, D. A. (1979). A geographically variable water quality index used in Oregon. *Water Pollution Control Federation*, 53–61.

Dutta, S., Dwivedi, A., & Suresh K. M. (2018b). Use of water quality index and multivariate statistical techniques for the assessment of spatial variations in water quality of a small river. *Environmental Monitoring and Assessment*, *190*(12), 718. https://doi.org/10.1007/s10661-018-7100-x

Dutta, V., Kumar, R., & Sharma, U. (2015). Assessment of human-induced impacts on hydrological regime of Gomti river basin, India. *Management of Environmental Quality*, *26*(5), 631–649. https://doi.org/10.1108/MEQ-11-2014-0160

Dutta, V., Sharma, U., Iqbal, K., Adeeba, Kumar, R., & Pathak, A. K. (2018a). Impact of river channelization and river front development on fluvial habitat: Evidence from Gomti River, a tributary of Ganges, India. *Environmental Sustainability*, *1*(2), 167–184. https://doi.org/10.1007/s42398-018-0016-0

Dutta, V., Srivastava, R. K., Yunus, M., Ahmed, S., Pathak, V. V., Rai, A., & Prasad, N. (2011). Restoration plan of Gomti River with designated best use classification of surface water quality based on river expedition, monitoring and quality assessment. *Earth Sciences, (India)*, *4*(III), 80–104.

Edokpayi, J. N., Odiyo, J. O., Msagati, T. A. M., & Potgieter, N. (2015). Temporal variations in physico-chemical and microbiological characteristics of Mvudi River, South Africa. *International Journal of Environmental Research and Public Health*, *12*(4), 4128–4140. https://doi.org/10.3390/ijerph120404128

Effendi, H., Romanto, Y., & Wardiatno, Y. (2015). Water quality status of Ciambulawung River, Banten Province, based on pollution index and NSF-WQI. *Procedia Environmental Sciences*, *24*, 228–237. https://doi.org/10.1016/ j.proenv .2015.03.030

Egbe, J. G., Agunwamba, J. C., & Okon, E. E. (2018). Modeling and modification of the effect of Self Purification of Kwa River pollution. *International Journal of Current Research and Academic Review*, *6*(9), 83–89. https://doi.org/10.20546/ ijcrar.2018.609.008

Egleston, E. S., Sabine, C. L., & Morel, F. M. M. (2010). Revelle revisited: Buffer factors that quantify the response of ocean chemistry to changes in DIC and alkalinity. *Global Biogeochemical Cycles*, *24*(1), n/a–n/a. https://doi.org/10. 1029/2008GB003407

El Osta, M., Masoud, M., & Ezzeldin, H. (2020). Assessment of the geochemical evolution of groundwater quality near the El Kharga Oasis, Egypt using NETPATH and water quality indices. *Environmental Earth Sciences*, *79*(2), 1–18. http://doi.org/10.1007/s12665-019-8793-z

El-Jabi, N., Caissie, D., & Turkkan, N. (2014). Water quality index assessment under climate change. *Journal of Water Resource and Protection*, *06*(6), 533–542. http://doi.org/10.4236/jwarp.2014.66052

El-Shaarawi, A. H., Esterby, S. R., & Kuntz, K. W. (1983). A statistical evaluation of trends in the water quality of the Niagara River. *Journal of Great Lakes Research*, *9*(2), 234–240. https://doi.org/10.1016/S0380-1330(83) 71892-7

El-Zeiny, A. M., & Elbeih, S. F. (2019). GIS-based evaluation of groundwater quality and suitability in Dakhla Oases, Egypt. *Earth Systems and Environment*, *3*(3), 507–523. http://doi.org/10.1007/s41748-019-00112-1

ENVIS. (2021). National status of wastewater generation and treatment. http://www.sulabhenvis.nic.in/Database/STST_wastewater_2090.aspx, Retrieved September 20, 2021.

Ewaid, S. H. (2017). Water quality evaluation of Al-Gharraf river by two water quality indices. *Applied Water Science*, *7*(7), 3759–3765. https://doi.org/10.1007/s13201-016-0523-z

Farhadian, M., Haddad, O. B., Seifollahi-Aghmiuni, S., & Loáiciga, H. A. (2014). Assimilative capacity and flow dilution for water quality protection in rivers. *Journal of Hazardous, Toxic, and Radioactive Waste*, *19*(2), 04014027. https://doi.org/10.1061/(ASCE)HZ.2153-5515.0000234

Felipe-Sotelo, M., Andrade, J. M., Carlosena, A., & Tauler, R. (2007). Temporal characterisation of river waters in urban and semi-urban areas using physico-chemical parameters and chemometric methods. *Analytica Chimica Acta*, *583*(1), 128–137. https://doi.org/10.1016/j.aca.2006.10.011

Feria Diaz, J. J., Náder Salgado, D., & Meza Pérez, S. J. (2017). Deoxygenation and re-aeration rates of the Sinu river. *Ingeniería y Desarrollo*, *35*(1), 1–17. https://doi.org/10.14482/inde.35.1.8940

Ficklin, D. L., Stewart, I. T., & Maurer, E. P. (2013). Effects of climate change on stream temperature, dissolved oxygen, and sediment concentration in the Sierra Nevada in California. *Water Resources Research*, *49*(5), 2765–2782. https://doi.org/10.1002/wrcr.20248

Florea, A. M., & Busselberg, D. (2006). Occurrence, use and potential toxic effects of metals and metal compounds. *Biometals*, *19*(4), 419–427. https://doi.org/10.1007/s10534-005-4451-x

Fuller, M. R., Doyle, M. W., & Strayer, D. L. (2015). Causes and consequences of habitat fragmentation in river networks. *Annals of the New York Academy of Sciences*, *1355*, 31–51. https://doi.org/10.1111/nyas.12853

Gangyan, Z., Goel, N. K., & Bhatt, V. K. (2002). Stochastic modelling of the sediment load of the upper Yangtze River (China). *Hydrological Sciences Journal*, *47*(sup1), S93–S105. https://doi.org/10.1080/02626660209493025

Garizi, A. Z., Sheikh, V., & Sadoddin, A. (2011). Assessment of seasonal variations of chemical characteristics in surface water using multivariate statistical methods. *International Journal of Environmental Science and Technology*, *8*(3), 581–592. https://doi.org/10.1007/BF03326244

Gautam, S. K., Maharana, C., Sharma, D., Singh, A. K., Tripathi, J. K., & Singh, S. K. (2015). Evaluation of groundwater quality in the Chotanagpur plateau region of the Subarnarekha River basin, Jharkhand State, India. *Sustainability of Water Quality and Ecology*, *6*, 57–74. https://doi.org/ 10.1016/j.swaqe.2015.06.001

Gazzaz, N. M., Yusoff, M. K., Aris, A. Z., Juahir, H., & Ramli, M. F. (2012). Artificial neural network modeling of the water quality index for Kinta River (Malaysia) using water quality variables as predictors. *Marine Pollution Bulletin*, *64*(11), 2409–2420. https://doi.org/10.1016/j.marpolbul.2012.08.005

Ghashghaie, M., Ostad-Ali-Askari, K., Eslamian, S., & Singh, V. P. (2018). Application of time series modeling to study river water quality. *American Journal of Engineering and Applied Sciences*, *11*(2), 574–585. https://doi.org/10.3844/ajeassp.2018.574.585

Gholikandi, G. B., Orumieh, H. R., Haddadi, S., & Mojir, N. (2011). Application of multivariate statistical techniques for surface water quality assessment: Case study of Karaj River, Iran. *WIT Transactions on Ecology and the Environment*, 361–370. https://doi.org/10.2495/WRM110311

Gholizadeh, M., Melesse, A., & Reddi, L. (2016). Water quality assessment and apportionment of pollution sources using APCS-MLR and PMF receptor modeling techniques in three major rivers of South Florida. *Science of the Total Environment*, *566-567*, 1552-1567. https://doi.org/10.1016/j.scitotenv.2016.06.046

Ghosh, S., & Mistri, B. (2015). Geographic concerns on flood climate and flood hydrology in monsoon-dominated Damodar River Basin, eastern India. *Geography Journal*, *2015*, 1–16. https://doi.org/10.1155/2015/486740

Gillibrand, P. A. (2006). *Improving assimilative capacity modelling for Scottish Coastal Waters: II. A model of physical exchange for open water sites. Funded by the Scottish aquaculture research forum*. Marine Physics Report No. 168.

Giussani, B., Monticelli, D., Gambillara, R., Pozzi, A., & Dossi, C. (2008). Three-way principal component analysis of chemical data from Lake Como watershed. *Microchemical Journal*, *88*(2), 160–166. https://doi.org/10.1016/j.microc.2007.11.006

Goel, P., Saxena, A., Singh, D. S., & Verma, D. (2018). Impact of rapid urbanization on water quality index in groundwater fed Gomati River, Lucknow, India. *Current Science*, *114*(3), 650–654.https://doi.org/10.18520/cs/v114/i03/650-654

Golbaz, S., Nabizadeh, R., Zarinkolah, S., Mahvi, A. H., Alimohammadi, M., & Yousefi, M. (2019). An innovative swimming pool water quality index (SPWQI) to monitor and evaluate the pools: Design and compilation of computational model. *Environmental Monitoring and Assessment*, *191*(7), 448. https://doi.org/10.1007/s10661-019-7577-y

Gong, G., Mattevada, S., & O'Bryant, S. E. (2014). Comparison of the accuracy of kriging and IDW interpolations in estimating groundwater arsenic concentrations in Texas. *Environmental Research*, *130*, 59–69. http://doi.org/ 10.1016/j.envres.2013.12.005

Gowri, V. S., Ramachandran, S., Ramesh, R., Pramiladevi, I. R. R., & Krishnaveni, K. (2008). Application of GIS in the study of mass transport of pollutants by Adyar and Cooum Rivers in Chennai, TamilNadu. *Environmental Monitoring and Assessment*, *138*(1–3), 41–49. https://doi.org/ 10.1007/s10661-007-9789-9

Greenlee, L. F., Lawler, D. F., Freeman, B. D., Marrot, B., & Moulin, P. (2009). Reverse osmosis desalination: Water sources, technology, and today's challenges. *Water Research*, *43*(9), 2317–2348. https://doi.org/10.1016/ j.watres.2009.03.010

Gupta, D., Shukla, R., Barya, M. P., Singh, G., & Mishra, V. K. (2020). Water quality assessment of Narmada River along the different topographical regions of the central India. *Water Science*, *34*(1), 202–212. https://doi.org/10.1080/ 11104929.2020.1839345

Gupta, I., Dhage, S., & Kumar, R. (2009). Study of variations in water quality of Mumbai coast through multivariate analysis techniques. *Indian Journal of Marine Sciences*, *38*(2), 170–177.

Gupta, N., Nafees, S. M., Jain, M. K., & Kalpana, S. (2011). Physico-chemical assessment of water quality of river Chambal in Kota city area of Rajasthan state (India). *Rasayan Journal of Chemistry*, *4*, 686–692.

Gupta, N., Pandey, P., & Hussain, J. (2017). Effect of physicochemical and biological parameters on the quality of river water of Narmada, Madhya Pradesh, India. *Water Science*, *31*(1), 11–23. https://doi.org/10.1016/j.wsj. 2017.03.002

Gupta, R. C., Gupta, A. K., & Shrivastava, R. K. (2014). Water quality management of river Kshipra (India). *International Journal of Environmental Sciences*, *5*(2), 438–446.

Gupta, R., Singh, A. N., & Singhal, A. (2019). Application of ANN for water quality index. *International Journal of Machine Learning and Computing*, *9*(5), 688–693. https://doi.org/10.18178/ijmlc.2019.9.5.859

Gurjar, S. K., & Tare, V. (2019). Spatial-temporal assessment of water quality and assimilative capacity of river Ramganga, a tributary of Ganga using multivariate analysis and QUEL2K. *Journal of Cleaner Production*, *222*, 550–564. https://doi.org/10.1016/j.jclepro.2019.03.064

Gyawali, S., Techato, K., Monprapussorn, S., & Yuangyai, C. (2013). Integrating land use and water quality for environmental based land use planning for U-tapao River Basin, Thailand. *Procedia – Social and Behavioral Sciences*, *91*, 556–563. https://doi.org/10.1016/j.sbspro.2013.08.454

Gyimah, R. A. A., Gyamfi, C., Anornu, G. K., Karikari, A. Y., & Tsyawo, F. W. (2021). Multivariate statistical analysis of water quality of the Densu River, Ghana. *International Journal of River Basin Management*, 19(2), 189–199. https://doi.org/10.1080/15715124.2020.1803337

Haddad, O. B., Beygi, S., & Mariño, M. A. (2014). Reservoir water allocation under abrupt pollution condition. *Journal of Irrigation and Drainage Engineering*, *140*(3), 04013017. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000679

Hajigholizadeh, M., & Melesse, A. M. (2017). Assortment and spatiotemporal analysis of surface water quality using cluster and discriminant analyses. *CATENA*, *151*, 247–258. https://doi.org/10.1016/j.catena.2016.12.018

Halliday, S. J., Wade, A. J., Skeffington, R. A., Neal, C., Reynolds, B., Rowland, P., Neal, M., & Norris, D. (2012). An analysis of long-term trends, seasonality and short-term dynamics in water quality data from Plynlimon, Wales. *Science of the Total Environment*, *434*, 186–200. https://doi.org/10.1016/j.scitotenv.2011.10.052

Hamid, A., Bhat, S. U., & Jehangir, A. (2020). Local determinants influencing stream water quality. *Applied Water Science*, *10*(1), 24. https://doi.org/10.1007/ s13201-019-1043-4

Hanh, P. T. M., Anh, N. V., Ba, D. T., Sthiannopkao, S., & Kim, K. W. (2010). Analysis of variation and relation of climate, hydrology and water quality in the lower Mekong River. *Water Science and Technology*, *62*(7), 1587–1594. https://doi.org/10.2166/wst.2010.449

Haque, M. A., Jewel, M. A. S., & Sultana, M. P. (2019). Assessment of physicochemical and bacteriological parameters in surface water of Padma River, Bangladesh. *Applied Water Science*, *9*(1), 10. https://doi.org/10.1007/ s13201-018-0885-5

Haque, M. Z., Abd Rahim, S., Abdullah, M. P., Fuad Embi, A., Elfithri, R., Lihan, T., Mohd Khali, W. M. A. W., Firoz Khan, M., & Mokhtar, M. (2016). Multivariate chemometric approach on the surface water quality in langat upstream tributaries, peninsular Malaysia. *Journal of Environmental Science and Technology*, *9*(3), 277–284. https://doi.org/10.3923/jest.2016.277.284

Harkins, R. D. (1974). An Objective Water Quality Index. *Journal of Water Pollution Control Federation, 46*(5), 588-591.

Hashemi Monfared, S. A., & Dehghani Darmian, M. (2016). Evaluation of appropriate advective transport function for one-dimensional pollutant simulation in rivers. *International Journal of Environment and Resource*, *10*(1), 77–84.

Hashemi Monfared, S. A., Dehghani Darmian, M., Snyder, S. A., Azizyan, G., Pirzadeh, B., & Azhdary Moghaddam, M. A. (2017). Water quality planning in rivers: Assimilative capacity and dilution flow. *Bulletin of Environmental Contamination and Toxicology*, *99*(5), 531–541. https://doi.org/10.1007/ s00128-017-2182-7

Hebert, S. (2005). Comparison between the index of overall quality of water in Quebec (IQBP) the water quality index CCME (WQI) for the protection of aquatic life, Quebec. *Ministry of Sustainable Development, Environment and Parks Department in Monitoring the State of Environment,* Québec.

Helfield, J. M., Capon, S. J., Nilsson, C., Jansson, R., & Palm, D. (2007). Restoration of rivers used for timber floating: Effects on riparian plant diversity. *Ecological Applications*, *17*(3), 840–851. https://doi.org/10.1890/06-0343

Hema, S., Subramani, T., & Elango, L. (2014). Assessment of surface water quality using multivariate statistical techniques in a part of river Cauvery, Tamil Nadu, India. *Journal of Environmental Science and Engineering*, *56*(3), 277–282.

Herojeet, R., Rishi, M. S., Lata, R., & Dolma, K. (2017). Quality characterization and pollution source identification of surface water using multivariate statistical techniques, Nalagarh Valley, Himachal Pradesh, India. *Applied Water Science*, *7*(5), 2137–2156. https://doi.org/10.1007/s13201-017-0600-y

Hirsch, R. M., Slack, J. R., & Smith, R. A. (1982). Techniques of Trend analysis for monthly water quality data. *Water Resources Research*, *18*(1), 107–121. https://doi.org/10.1029/WR018i001p00107

Horton, R. K. (1965). An index number system for rating water quality. *Journal (Water Pollution Control Federation)*, *37*(3), 300–306.

Huang, C. B., Dian, Y. Y., Zhou, Z. X., Wang, D., Chen, R. D., & Remot, J. (2015). *Sensors*, *19*, 657–668.

Huang, X. B., Li, H. B., Zhu, Y. C., Wang, Y. X., Zheng, X. X., Wang, Y. G., & High. (2017). Volt. *Engineering*, *43*, 1943–1949.

Hui, T., Du, J., Sun, Q., Liu, Q., Kang, Z., & Jin, H. (2020). Using the water quality index (WQI), and the synthetic pollution index (SPI) to evaluate the groundwater quality for drinking purpose in Hailun, China. *Sains Malaysiana*, *49*(10), 2383–2401. http://doi.org/10.17576/jsm-2020-4910-05

Hussain, M. R., & Abed, B. S. (2019). Simulation and assessment of groundwater for domestic and irrigation uses. *Civil Engineering Journal*, *5*(9), 1877–1892. https://doi.org/10.28991/cej-2019-03091379

Hussain, M., Ahmed, S. M., & Abderrahman, W. (2008). Cluster analysis and quality assessment of logged water at an irrigation project, eastern Saudi Arabia. *Journal of Environmental Management*, *86*(1), 297–307. https://doi.org/10.1016/j.jenvman .2006.12.007

ICMR. (1975). *Manual of standards of quality for drinking water supplies (Special Report Series No. 44)*. Indian Council of Medical Research.

IPCC. (2013). *Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press.

Iqbal, K., Ahmad, S., & Dutta, V. (2019). Pollution mapping in the urban segment of a tropical river: Is water quality index (WQI) enough for a nutrient-polluted river? *Applied Water Science*, *9*(8), 197. https://doi.org/10.1007/s13201-019-1083-9

Irvine, K. N., Richey, J. E., Holtgrieve, G. W., Sarkkula, J., & Sampson, M. (2011). Spatial and temporal variability of turbidity, dissolved oxygen, conductivity, temperature, and fluorescence in the lower Mekong River–Tonle Sap system identified using continuous monitoring. *International Journal of River Basin Management*, *9*(2), 151–168. https://doi.org/10.1080/15715124. 2011.621430

Isaac, R., & Siddiqui, S. (2022). Application of water quality index and multivariate statistical techniques for assessment of water quality around Yamuna River in Agra Region, Uttar Pradesh, India. *Water Supply*, *22*(3), 3399–3418. https://doi.org/10.2166/ws.2021.395

Isiyaka, H. A., & Juahir, H. (2015). Analysis of surface water pollution in the Kinta river using multivariate technique. *Malaysian Journal of Analytical Sciences*, *19*(5), 1019–1031.

Islam, A., Sikka, A. K., Saha, B., & Singh, A. (2012). Streamflow response to climate change in the Brahmani River Basin, India. *Water Resources Management*, *26*(6), 1409–1424. https://doi.org/10.1007/s11269-011-9965-0

Islam, M. M. M., Iqbal, M. S., Leemans, R., & Hofstra, N. (2018). Modelling the impact of future socio-economic and climate change scenarios on river microbial water quality. *International Journal of Hygiene and Environmental Health*, *221*(2), 283–292. https://doi.org/10.1016/j.ijheh.2017.11.006

Islam, M. S., Uddin, M. K., Tareq, S. M., Shammi, M., Kamal, A. K. I., Sugano, T., Kurasaki, M., Saito, T., Tanaka, S., & Kuramitz, H. (2015). Alteration of water pollution level with the seasonal changes in mean daily discharge in three main rivers around Dhaka City, Bangladesh. *Environments*, *2*(4), 280–294. https://doi.org/10.3390/environments2030280

Ismail, A. H., & Robescu, D. (2019). Assessment of water quality of the Danube river using water quality indices technique. *Environmental Engineering and Management Journal*, *18*(8),1727–1737.https://doi.org/10.30638/eemj.2019. 163

Ismail, A. H., Abed, B. S., & Abdul-Qader, S. (2014). Application of multivariate statistical techniques in the surface water quality assessment of Tigris River at Baghdād stretch. *Journal of Babylon University*, *22*(2), 450–462.

Iyer, C. S., Sindhu, M., Kulkarni, S. G., Tambe, S. S., & Kulkarni, B. D. (2003). Statistical analysis of the physico–chemical data on the coastal waters of Cochin. *Journal of Environmental Monitoring*, *5*(2), 324–327. https://doi.org/ 10.1039/ b209219k

Jadeja, N. B., Banerji, T., Kapley, A., & Kumar, R. (2022). Water pollution in India – Current scenario, *Water Security*, *16*, 100119. https://doi.org/10.1016/j.wasec.100119.

Jain, C. K., & Singh, S. (2020). Impact of climate change on the hydrological dynamics of River Ganga, India. *Journal of Water and Climate Change*, *11*(1), 274–290. https://doi.org/10.2166/wcc.2018.029

Jaishankar, M., Tseten, T., Anbalagan, N., Mathew, B. B., & Beeregowda, K. N. (2014). Toxicity, mechanism and health effects of some heavy metals. *Interdisciplinary Toxicology*,*7*(2),60–72.https://doi.org/10.2478/intox-20140009

Jaiswal, M., Hussain, J., Gupta, S. K., Nasr, M., & Nema, A. K. (2019). Comprehensive evaluation of water quality status for entire stretch of Yamuna River, India. *Environmental Monitoring and Assessment*, *191*(4), 208. https://doi.org/10.1007/s10661-019-7312-8

Jassby, A. D. Reuter., J. E. & Goldman, C. R. (2003). Determining long term water quality change in the presence of climate variability. Lake Tahoe (USA). Canadian Journal of Fisheries and Aquatic Sciences, 60, 1452- 1461.

Javadinejad, S., Eslamian, S., & Askari, K. O. A. (2021). The analysis of the most important climatic parameters affecting performance of crop variability in a changing climate. *International Journal of Hydrology Science and Technology*, 11(1). https://doi.org/10.1504/IJHST.2021.112651

Jayalakshmi, S., & Velappan, E. (2015). Assessment of water quality index in the St. Thomas mount block using GIS and remote sensing. *Polish Journal of Environmental Studies*, *24*(4), 1611–1619.

Jin, L., Whitehead, P. G., Sarkar, S., Sinha, R., Futter, M. N., Butterfield, D., Caesar, J., & Crossman, J. (2015). Assessing the impacts of climate change and socio-economic changes on flow and phosphorus flux in the Ganga river system. *Environmental Science. Processes and Impacts*, *17*(6), 1098–1110. https://doi.org/10.1039/C5EM00092K

Jindal, R., & Sharma, C. (2011). Studies on water quality of Sutlej River around Ludhiana with reference to physicochemical parameters. *Environmental Monitoring and Assessment*, *174*(1–4), 417–425. https://doi.org/10.1007/s10661-010-1466-8

Jingsheng, C., Tao, Y., & Ongley, E. (2006). Influence of high levels of total suspended solids on measurement of COD and BOD in the Yellow River, China.

Environmental Monitoring and Assessment, *116*(1–3), 321–334. https://doi.org/10.1007/s10661-006-7374-2

Joseph, P. V., & Jacob, C. (2010). Physicochemical characteristics of Pennar River, a fresh water wetland in Kerala, India. *E-Journal of Chemistry*, *7*(4), 1266–1273. https://doi.org/10.1155/2010/297931

Juahir, H., Zain, S. M., Yusoff, M. K., Hanidza, T. I. T., Armi, A. S. M., Toriman, M. E., & Mokhtar, M. (2011). Spatial water quality assessment of Langat River Basin (Malaysia) using environmetric techniques. *Environmental Monitoring and Assessment*, *173*(1–4), 625–641.https://doi.org/10.1007/s10661-010-1411-x

Kamboj, N., & Choudhary, M. (2013). Impact of solid waste disposal on ground water quality near Gazipur dumping site, Delhi, India. *Journal of Applied and Natural Science*, *5*(2), 306–312. https://doi.org/10.31018/jans. v5i2.322

Kamboj, N., & Kamboj, V. (2019). Water quality assessment using overall index of pollution in riverbed-mining area of Ganga-River Haridwar, India. *Water Science*, *33*(1), 65–74. https://doi.org/10.1080/11104929.2019.1626631

Kamboj, V., & Kamboj, N. (2020). Spatial and temporal variation of zooplankton assemblage in the mining-impacted stretch of Ganga River, Uttarakhand, India. *Environmental Science and Pollution Research International*, *27*(21), 27135–27146. https://doi.org/10.1007/s11356-020-09089-1

Kamboj, V., Kamboj, N., & Sharma, A. K. (2020). A review on general characteristics, classification and degradation of river systems. In V. Kumar, J. Singh & P. Kumar (Eds.), *Environmental degradation: Causes and remediation strategies*, *1* (pp. 47–62). https://doi.org/10.26832/aesa-2020-edcrs-04

Kannel, P. R., Lee, S., Kanel, S. R., & Khan, S. P. (2007). Chemometric application in classification and assessment of monitoring locations of an urban river system. *Analytica Chimica Acta*, *582*(2), 390–399. https://doi.org/10.1016/j.aca.2006.09.006

Karamouz, M., Kerachian, R., & Mahmoodian, M. (2003). *Seasonal waste load allocation model for river water quality management: Application of sequential dynamic genetic algorithms*. World Water and Environmental Resources Congress, American Society of Civil Engineers. https://doi.org/10.1061/40685(2003)75

Karr, J. R. (1981). Assessment of biotic integrity using fish communities. *Fisheries*, *6*(6),21–27.https://doi.org/10.1577/1548-8446(1981)006<0021:AOBIUF>2.0.CO;2

Karunanidhi, D., Aravinthasamy, P., Subramani, T., & Muthusankar, G. (2021). Revealing drinking water quality issues and possible health risks based on water quality index (WQI) method in the Shanmuganadhi River basin of South India. *Environmental Geochemistry and Health*, 43(2), 931–948. https://doi.org/10.1007/s10653-020-00613-3

Katyal, D., Qader, A., Ismail, A. H., & Sarma, K. (2012). Water quality assessment of Yamuna River in Delhi region using index mapping. *Interdisciplinary Environmental Review*, *13*(2/3), 170–186. https://doi.org/10.1504/IER.2012.047796

Kauffman, G. J. (2018). The cost of clean water in the Delaware River Basin (USA). *Water*, *10*(2), 95. https://doi.org/10.3390/w10020095

Kaur, R., & Dua, A. (2012). Application of multivariate statistical analysis in assessing surface water quality of Chamera-I reservoir on river Ravi. *International Journal of Scientific Engineering and Technology*, *3*(10), 1966–1971.

Kaushik, A., Kansal, A., Santosh, Meena, Kumari, S., & Kaushik, C. P. (2009). Heavy metal contamination of river Yamuna, Haryana, India: Assessment by metal enrichment factor of the sediments. *Journal of Hazardous Materials*, *164*(1), 265–270. https://doi.org/10.1016/j.jhazmat. 2008.08.031

Kazi, T. G., Arain, M. B., Jamali, M. K., Jalbani, N., Afridi, H. I., Sarfraz, R. A., Baig, J. A., & Shah, A. Q. (2009). Assessment of water quality of polluted lake using multivariate statistical techniques: A case study. *Ecotoxicology and Environmental Safety*, *72*(2), 301–309. https://doi.org/10.1016/j.ecoenv.2008.02.024

Keeling, A. M. (2007). Charting marine pollution science: Oceanography on Canada's Pacific coast, 1938–1970. *Journal of Historical Geography*, *33*(2), 403–428. https://doi.org/10.1016/j.jhg.2006.05.004

Khadse, G. K., Patni, P. M., Kelkar, P. S., & Devotta, S. (2008). Qualitative evaluation of Kanhan river and its tributaries flowing over central Indian plateau. *Environmental Monitoring and Assessment*, *147*(1–3), 83–92. https://doi.org/10.1007/s10661-007-0100-x

Khan, A. S., Anavkar, A., Ali, A., Patel, N., & Alim, H. (2021d). A review on current status of riverine pollution in India. *Biosciences Biotechnology Research Asia*, *18*(1), 9–22. https://doi.org/10.13005/bbra/2893

Khan, M. Y. A., Gani, K. M., & Chakrapani, G. J. (2017). Spatial and temporal variations of physicochemical and heavy metal pollution in Ramganga River—A tributary of River Ganges, India. *Environmental Earth Sciences*, *76*(5), 231. https://doi.org/10.1007/s12665-017-6547-3

Khan, R., Saxena, A., & Shukla, S. (2020). Evaluation of heavy metal pollution for River Gomti, in parts of Ganga Alluvial Plain, India. *SN Applied Sciences*, *2*(8), 1451. https://doi.org/10.1007/s42452-020-03233-9

Khan, R., Saxena, A., Shukla, S., Goel, P., Bhattacharya, P., Li, P., Ali, E. F., & Shaheen, S. M. (2022). Appraisal of water quality and ecological sensitivity with reference to riverfront development along the River Gomti, India. *Applied Water Science*, *12*(1), 13. https://doi.org/10.1007/s13201-021-01560-9

Khan, R., Saxena, A., Shukla, S., Sekar, S., & Goel, P. (2021b). Effect of COVID-19 lockdown on the water quality index of River Gomti, India, with potential hazard of faecal-oral transmission. *Environmental Science and Pollution Research International*, *28*(25),33021–33029.https://doi.org/10.1007/s11356-021-13096-1

Khan, R., Saxena, A., Shukla, S., Sekar, S., Senapathi, V., & Wu, J. (2021c). Environmental contamination by heavy metals and associated human health risk assessment: A case study of surface water in Gomti River Basin, India. *Environmental Science and Pollution Research International*, *28*(40), 56105–56116. https://doi.org/10.1007/s11356-021-14592-0

Khan, R., Saxena, A., Shukla, S., Sekar, S., Senapathi, V., & Wu, J. (2021a). Environmental contamination by heavy metals and associated human health risk assessment: A case study of surface water in Gomti River Basin, India. *Environmental Science and Pollution Research International*, *28*(40), 56105–56116. https://doi.org/10.1007/s11356-021-14592-0

Khani, S., & Rajaee, T. (2017). Modeling of dissolved oxygen concentration and its hysteresis behavior in rivers using wavelet transform-based hybrid models. *CLEAN – Soil, Air, Water*, *45*(2). https://doi.org/10.1002/clen. 201500395

Kharake, A. C., & Raut, V. S. (2021). An assessment of water quality index of Godavari River water in Nashik city, Maharashtra. *Applied Water Science*, *11*(6), 101. https://doi.org/10.1007/s13201-021-01432-2

Khattiyavong, C., & Lee, H. S. (2019). Performance Simulation and assessment of an appropriate wastewater treatment technology in a densely populated growing City in a developing country: A case study in Vientiane, Laos. *Water*, *11*(5), 1012. https://doi.org/10.3390/w11051012

Khouni, I., Louhichi, G., & Ghrabi, A. (2021). Use of GIS based Inverse Distance Weighted interpolation to assess surface water quality: Case of Wadi El Bey, Tunisia. *Environmental Technology and Innovation*, *24*, 101892. https://doi.org/10.1016/j.eti.2021.101892

Kim, A. G., & Cardone, C. R. (2005). Scatterscore: A reconnaissance method to evaluate changes in water quality. *Environmental Monitoring and Assessment*, *111*(1–3), 277–295. https://doi.org/10.1007/s10661-005-8225-2

Kim, J. H., Lee, J., Cheong, T. J., Kim, R. H., Koh, D. C., Ryu, J., & Chang, H. (2005). Use of time series analysis for the identification of tidal effect on groundwater in the coastal area of Kimje, Korea. *Journal of Hydrology*, *300*(1–4), 188–198. https://doi.org/10.1016/j.jhydrol.2004.06.004

Komornık, J., Komornıkova, M., Mesiar, R., Szökeová, D., & Szolgay, J. (2006). Comparison of forecasting performance of nonlinear models of hydrological time series. *Physics and Chemistry of the Earth, Parts A/B/C*, *31*(18), 1127–1145. https://doi.org/10.1016/j.pce.2006.05.006

Krishan, A., Khursheed, A., & Mishra, R. K. (2022a). Evaluation of water quality using water quality index, synthetic pollution index, and GIS technique: A case study of the river Gomti, Lucknow, India. *Environmental Science and Pollution Research International*, 29(54), 81954–81969. https://doi.org/10.1007/s11356-022-21493-3

Krishan, A., Mishra, R. K., & Khursheed, A. (2022b). Assessment of water quality using water quality index: A case study of the River Gomti, Lucknow, Uttar Pradesh, India. *Urban Water Journal*, *19*(5), 520–530. https://doi.org/10.1080/1573062X .2022.2032210

Krishnan, R. et al. (2020). Introduction to climate change over the Indian region. In R. Krishnan et al. (Eds.), *Assessment of climate change over the Indian region*. Springer. https://doi.org/10.1007/978-981-15-4327-2_1

Kulikova, D., Kovrov, O., Buchavy, Y., & Fedotov, V. (2018). GIS-based Assessment of the Assimilative Capacity of Rivers in Dnipropetrovsk Region. *Journal of*

Geology, Geography and Geoecology, *27*(2), 274–285. https://doi.org/10.15421/111851

Kumar, A., & Bahadur, Y. (2013). Water quality of river kosi and rajera system at Rampur (India): Impact assessment. *Journal of Chemistry*, *2013*, 1–4. https://doi.org/10.1155/2013/618612

Kumar, A., & Dua, A. (2009). Water quality index for assessment of water quality of river Ravi at Madhopur (India). *Global Journal of Environmental Sciences*, *8*(1). https://doi.org/10.4314/gjes.v8i1.50824

Kumar, A., Bojjagani, S., Maurya, A., & Kisku, G. C. (2022a). Spatial distribution of physicochemical-bacteriological parametric quality and water quality index of Gomti River, India. *Environmental Monitoring and Assessment*, *194*(3), 159. https://doi.org/10.1007/s10661-022-09814-y

Kumar, A., Mishra, S., Taxak, A. K., Pandey, R., & Yu, Z. G. (2020a). Nature rejuvenation: Long-term (1989–2016) vs short-term memory approach based appraisal of water quality of the upper part of Ganga River, India. *Environmental Technology and Innovation*, 20, 101164. http://doi.org/10.1016/j.eti.2020.101164

Kumar, A., Taxak, A. K., Mishra, S., & Pandey, R. (2021a). Long term trend analysis and suitability of water quality of River Ganga at Himalayan hills of Uttarakhand, India. *Environmental Technology and Innovation*, *22*, 101405. https://doi.org/10.1016/j.eti.2021.101405

Kumar, C., Ghosh, A., Yash, Debnath, M., & Bhadury, P. (2021b). Seasonal dynamicity of environmental variables and water quality index in the lower stretch of the River Ganga. *Environmental Research Communications*, *3*(7), 075008. https://doi.org/10.1088/2515-7620/ac10fd

Kumar, M., & Padhy, P. K. (2014). Multivariate statistical techniques and water quality assessment: Discourse and review on some analytical models. *International Journal of Environmental Sciences*, *5*(3), 607–626.

Kumar, P. (2018). Simulation of Gomti River (Lucknow City, India) future water quality under different mitigation strategies. *Heliyon*, *4*(12), e01074. https://doi.org/10.1016/j.heliyon.2018.e01074

Kumar, P., Kaushal, R. K., & Nigam, A. K. (2015). Assessment and management of Ganga River Water quality using multivariate statistical techniques in India.

Asian Journal of Water, Environment and Pollution, *12*(4), 61–69. https://doi.org/10.3233/AJW-150018

Kumar, R., Singh, R. D., & Sharma, K. D. (2005). Water resources of India. *Current Science*, *89*, 794–811.

Kumar, V., Kumar, S., Srivastava, S., Singh, J., & Kumar, P. (2018). Water quality of River Ganga with reference to physico-chemical and microbiological characteristics during Kanwar Mela 2017, at Haridwar, India: A case study. *Archives of Agriculture and Environmental Science*, *3*(1), 58–63. https://doi.org/10.26832/24566632.2018.030108

Kumar, V., Sahu, P., & Markandeya. (2022b). Sequential extraction and risk assessment of pollutants from one major tributary of the Ganga. *Water Supply*, *22*(3), 2767–2781. https://doi.org/10.2166/ws.2021.437

Kumar, V., Sahu, P., Singh, K., P., Shukla, K., N., Mishra, D. P., & Markandeya. (2021c). Evaluation and quantification of anionic surfactant in the Gomti River at Lucknow City, India. *Promising Techniques for Wastewater Treatment and Water Quality Assessment*. https://doi.org/10.5772/intechopen.93517

Kumar, V., Sahu, P., Singh, P. K., & Markandeya (2020b). Multivariate Statistical Approach for the Analysis of Organic and Inorganic Pollutants Loads in Gomti River at Lucknow City. *International Journal of Environmental Research*, 14(6), 653–666. https://doi.org/10.1007/s41742-020-00290-1

Kumarasamy, P., Arthur James, R. A., Dahms, H. U., Byeon, C. W., & Ramesh, R. (2014). Multivariate water quality assessment from the Tamiraparani river basin, Southern India. *Environmental Earth Sciences*, *71*(5), 2441–2451. https://doi.org/10.1007/s12665-013-2644-0

Kurunc, A., Yürekli, K., & Çevik, O. Performance of two stochastic approaches for forecasting water quality and streamflow data from Yeşilırmak River, Turkey. (2005). *Environmental Modelling and Software*, *20*(9), 1195–1200. https://doi.org/10.1016/j.envsoft.2004.11.001

Kwon, H. G., & Jo, C. D. (2023). Water quality assessment of the Nam River, Korea, using multivariate statistical analysis and WQI. *International Journal of Environmental Science and Technology*. https://doi.org/10.1007/s13762-023-04756-5

Landis, W. G. (2008). Defining assimilative capacity application of assimilative capacity to the TMDL process. *USEPA (1999) protocol for developing nutrient TMDLs, Elsevier* B.V. pp 264–268.

Landner, L., Grahn, O., Härdig, J., Lehtinen, K. J., Monfelt, C., & Tana, J. (1994). A field study of environmental impacts at a bleached kraft pulp mill site on the Baltic Sea coast. *Ecotoxicology and Environmental Safety*, *27*(2), 128–157. https://doi.org/10.1006/eesa.1994.1012

LDA, Lucknow Master Plan 2031 (2016) Lucknow Development Authority, Uttar Pradesh, India.

Lee, I., Hwang, H., Lee, J., Yu, N., Yun, J., & Kim, H. (2017). Modeling approach to evaluation of environmental impacts on river water quality: A case study with Galing River, Kuantan, Pahang, Malaysia. *Ecological Modelling*, *353*, 167–173. https://doi.org/10.1016/j.ecolmodel.2017.01.021

Lee, J. Y., & Lee, K. K. (2003). Viability of natural attenuation in a petroleum-contaminated shallow sandy aquifer. *Environmental Pollution*, *126*(2), 201–212. https://doi.org/10.1016/S0269-7491(03)00187-8

Li, R., Dong, M., Zhao, Y., Zhang, L., Cui, Q., & He, W. (2007). Assessment of water quality and identification of pollution sources of plateau lakes in Yunnan (China). *Journal of Environmental Quality*, *36*(1), 291–297. https://doi.org/10. 2134/jeq 2006.0165

Li, X., Lee, S. L., Wong, S. C., Shi, W., & Thornton, I. (2004). The study of metal contamination in urban soils of Hong Kong using a GIS-based approach. *Environmental Pollution*, *129*(1), 113–124. https://doi.org/10.1016/j.envpol. 2003.09.030

Li, X., Li, P., Wang, D., & Wang, Y. (2014). Assessment of temporal and spatial variations in water quality using multivariate statistical methods: A case study of the Xin'anjiang River, China. *Frontiers of Environmental Science and Engineering*, *8*(6), 895–904. https://doi.org/10.1007/s11783-014-0736-z

Liao, S. W., Gau, H. S., Lai, W. L., Chen, J. J., & Lee, C. G. (2008). Identification of pollution of Tapeng Lagoon from neighbouring rivers using multivariate statistical method. *Journal of Environmental Management*, *88*(2), 286–292. https://doi.org/10.1016/j.jenvman.2007.02.010

Liebman, H. (1969). *Atlas of water quality, methods and practical conditions*. Oldenbourg.

Ling, T. Y., Soo, C. L., Liew, J. J., Nyanti, L., Sim, S. F., & Grinang, J. (2017). Application of multivariate statistical analysis in evaluation of surface river water quality of a tropical river. *Journal of Chemistry*, *2017*, 1–13. https://doi.org/10.1155/2017/5737452

Liou, S. M., Lo, S. L., & Wang, S. H. (2004). A generalized water quality index for Taiwan. *Environmental Monitoring and Assessment*, *96*(1–3), 35–52. https://doi.org/10.1023/b:emas.0000031715.83752.a1

Liu, G., He, W., & Cai, S. (2020). Seasonal variation of dissolved oxygen in the southeast of the Pearl River estuary. *Water*, *12*(9), 2475. https://doi.org/10.3390/w12092475

Liu, J., Zhang, D., Tang, Q., Xu, H., Huang, S., Shang, D., & Liu, R. (2021). Water quality assessment and source identification of the Shuangji River (China) using multivariate statistical methods. *PLOS ONE*, *16*(1), e0245525. https://doi.org/10.1371/journal.pone.0245525

Liu, Q., Jiang, J., Jing, C., & Qi, J. (2018). Spatial and seasonal dynamics of water environmental capacity in mountainous rivers of the Southeastern Coast, China. *International Journal of Environmental Research and Public Health*, *15*(1), 99. https://doi.org/10.3390/ijerph15010099

Lkr, A., Singh, M. R., & Puro, N. (2020) Assessment of water quality status of Doyang River, Nagaland, India, using Water Quality Index. *Applied Water Science*, *10*(1), 46. https://doi.org/10.1007/s13201-019-1133-3

Loftis, J. C. (1996). Trends in groundwater quality. *Hydrological Processes*, *10*(2), 335–355. https://doi.org/10.1002/(SICI)1099-1085(199602)10:2 <335:: AID-HYP359>3.0.CO;2-T

Loucks, D. P., & Van Beek, E. (2005). *Water resources systems planning and management*. UNESCO.

Love, D., Hallbauer, D., Amos, A., & Hranova, R. (2004). Factor analysis as a tool in groundwater quality management: Two southern African case studies. *Physics and Chemistry of the Earth, Parts A/B/C*, *29*(15–18), 1135–1143. https://doi.org/10.1016/j.pce.2004.09.027

Lu, W. X., Zhao, Y., Chu, H. B., & Yang, L. L. (2014). The analysis of groundwater levels influenced by dual factors in western Jilin Province by using time series analysis method. *Applied Water Science*, 4(3), 251–260. https://doi.org/10.1007/s13201-013-0111-4

Lunde, K. B., & Resh, V. H. (2012). Development and validation of a macroinvertebrate index of biotic integrity (IBI) for assessing urban impacts to Northern California freshwater wetlands. *Environmental Monitoring and Assessment*, *184*(6), 3653–3674. https://doi.org/10.1007/s10661-011-2214-4

Luo, Y., Chen, Q., & Liu, Y. (2019). Xiaohui Xie and Qianying Du Water quality prediction analysis of Qingyi River based on time series E3S Web conference, *118*. https://doi.org/10.1051/e3sconf/201911803005

Ma, J., Ding, Z., Wei, G., Zhao, H., & Huang, T. (2009). Sources of water pollution and evolution of water quality in the Wuwei basin of Shiyang river, Northwest China. *Journal of Environmental Management*, *90*(2), 1168–1177. https://doi.org/10.1016/j.jenvman.2008.05.007

Madhloom, H. M., & Alansari, N. (2018). Geographical information system and remote sensing for water resources management case study: The Diyālā River, Iraq. *International Journal of Civil Engineering and Technology, 9*, 971–984.

Mahmoudi, N., Orouji, H., & Fallah-Mehdipour, E. (2016). Integration of shuffled frog leaping algorithm and support vector regression for prediction of water quality parameters. *Water Resources Management*, *30*(7), 2195–2211. https://doi.org/10.1007/s11269-016-1280-3

Maity, S., Maiti, R., & Senapati, T. (2022). Evaluation of spatio-temporal variation of water quality and source identification of conducive parameters in Damodar River, India. *Environmental Monitoring and Assessment*, *194*(4), 308. https://doi.org/10.1007/s10661-022-09955-0

Malakootian, M., Mansoorian, H. J., & Moosazadeh, M. (2010). Performance evaluation of electrocoagulation process using iron-rod electrodes for removing hardness from drinking water. *Desalination*, *255*(1–3), 67–71. https://doi.org/10.1016/j.desal.2010.01.015

Malik, A., Verma, P., Singh, A. K., & Singh, K. P. (2011). Distribution of polycyclic aromatic hydrocarbons in water and bed sediments of the Gomti River, India. *Environmental Monitoring and Assessment*, *172*(1–4), 529–545. https://doi.org/10.1007/s10661-010-1352-4

Malik, R. N., & Hashmi, M. Z. (2017). Multivariate statistical techniques for the evaluation of surface water quality of the Himalayan foothills streams, Pakistan. *Applied Water Science*, *7*(6), 2817–2830. https://doi.org/10.1007/s13201-017-0532-6

Mall, R. K., Bhatla, R., & Pandey, S. N. (2007). Water resources in India and impact of climate change. *Jalvigyan Sameeksha*, *22*, 157–176.

Mallin, M. A., Williams, K. E., Esham, E. C., & Lowe, R. P. (2000). Effect of human development on bacteriological water quality in coastal watersheds. *Ecological Applications*, *10*(4), 1047–1056. https://doi.org/10.1890/1051-0761(2000)010[1047:EOHDOB]2.0.CO;2

Markandeya, M., Shukla, S. P., & Srivastav, A. L. (2021) Removal of Disperse Orange and Disperse Blue dyes present in textile mill effluent using zeolite synthesized from cenospheres. *Water Science and Technology*, 84(2), 445–457. https://doi.org/10.2166/wst.2021.216

Maruya, K. A., Schlenk, D., Anderson, P. D., Denslow, N. D., Drewes, J. E., Olivieri, A. W., Scott, G. I., & Snyder, S. A. (2014). An adaptive, comprehensive monitoring strategy for chemicals of emerging concern (CECs) in California's aquatic ecosystems. *Integrated Environmental Assessment and Management*, *10*(1), 69–77. https://doi.org/10.1002/ieam.1483

Massoud, M. A. (2012). Assessment of water quality along a recreational section of the Damour River in Lebanon using the water quality index. *Environmental Monitoring and Assessment*, *184*(7), 4151–4160. https://doi.org/10.1007/ s10661-011-2251-z

Matta, G., Naik, P. K., Machell, J., Kumar, A., Gjyli, L., Kumar Tiwari, A., & Kumar, A. (2018). Comparative study on seasonal variation in hydro-chemical parameters of Ganga river water using comprehensive pollution index (CPI) at Rishikesh, (Uttarakhand) India. *Desalination and Water Treatment*, *118*, 87–95. https://doi.org/10.5004/dwt.2018.22487

Matta, G., Nayak, A., Kumar, A., & Kumar, P. (2020). Water quality assessment using NSFWQI, OIP and multivariate techniques of Ganga River system, Uttarakhand, India. Applied Water Science, 10(9), 1–12. https://doi.org/10.1007/s13201-020-01288-y

Mazor, R. D., Stein, E. D., Ode, P. R., & Schiff, K. (2014). Integrating intermittent streams into watershed assessments: Applicability of an index of biotic integrity. *Freshwater Science*, *33*(2), 459–474. https://doi.org/10.1086/ 675683

McDuffie, B., & Haney, J. T. (1973). Proposed river pollution index. In abstracts of papers of the American Chemical Society, *1155 16th ST, NW, Washington, DC 20036*. American Chemical Society.

McKerchar, A. I., & Delleur, J. W. (1974). Application of seasonal parametric linear stochastic models to monthly flow data. *Water Resources Research*, *10*(2), 246–255. https://doi.org/10.1029/WR010i002p00246

McNeil, V. H., Cox, M. E., & Preda, M. (2005). Assessment of chemical water types and their spatial variation using multi-stage cluster analysis, Queensland, Australia. *Journal of Hydrology*, *310*(1), 181–200.

Meme, F. K., Arimoro, F. O., & Nwadukwe, F. O. (2014). Analyses of physical and chemical parameters in surface waters nearby a Cement Factory in North Central, Nigeria. *Journal of Environmental Protection*, *05*(10), 826–834. https://doi.org/10.4236/jep.2014.510085

Miller, S. L., Anderson, M. J., Daly, E. P., & Milford, J. B. (2002). Source apportionment of exposures to volatile organic compounds. Evaluation of receptor models using simulated exposure data. *Atmospheric Environment*, *36*(22), 3629–3641. https://doi.org/10.1016/S1352-2310(02)00279-0

Ministry of Water Resources. (2000). *Available online*, Accessed September 20, 2021.

Mirzaei, R., & Sakizadeh, M. (2016). Comparison of interpolation methods for the estimation of groundwater contamination in Andimeshk-Shush Plain, Southwest of Iran. *Environmental Science and Pollution Research International*, *23*(3), 2758–2769. http://doi.org/10.1007/s11356-015-5507-2

Misaghi, F., Delgosha, F., Razzaghmanesh, M., & Myers, B. (2017). Introducing a water quality index for assessing water for irrigation purposes: A case study of the Ghezel Ozan River. *Science of the Total Environment*, *589*, 107–116. https://doi.org/10.1016/j.scitotenv.2017.02.226

Mishra, A., & Tripathi, B. D. (2007). Seasonal and Temporal variations in physico-chemical and bacteriological characteristic's of river Ganga in Varanasi. *Current World Environment*, *2*(2), 149–154. https://doi.org/10.12944/ CWE.2.2.08

MoEF&CC. (2020). Available online. http://moef.gov.in/wp-content/uploads/2020/01/finalization.pdf, Retrieved September 20, 2021

Mohan, S. V., Nithila, P., & Reddy, S. J. (1996). Estimation of heavy metals in drinking water and development of heavy metal pollution index. *Journal of Environmental Science and Health. Part A*, *31*(2), 283–289. https://doi.org/10.1080/10934529609376357

Morshed, M. M., Islam, M. T., & Jamil, R. (2016). Soil salinity detection from satellite image analysis: An integrated approach of salinity indices and field data.

Environmental Monitoring and Assessment, *188*(2), 119. https://doi.org/10.1007/s10661-015-5045-x

Mostafaei, A. (2014). Application of multivariate statistical methods and water-quality index to evaluation of water quality in the Kashkan River. *Environmental Management*, *53*(4), 865–881. https://doi.org/10.1007/s00267-014-0238-6

Mtetwa, S., Kusangaya, S., & Schutte, C. F. (2003). The application of geographic information systems (GIS) in the analysis of nutrient loadings from an agro-rural catchment. *Water SA*, *29*(2), 189–194. http://doi.org/10.4314/wsa. v29i2.4855

Munfarida, I., Auvaria, Shinfi W., Munir, M., & Rezagama, A. (2020). Analysis of pollution load carrying capacity of Cibatarua River in Pamulihan District, Garut Regency, west Java. *AIP Conference Proceedings*, *2231*, 040044. https://doi.org/10.1063/5.0002732

Mustapha, A., & Abdu, A. (2012). Application of principal component analysis and multiple regression models in surface water quality assessment. *Environmental Earth Sciences*, *2*(2), 16–23.

Mustapha, A., Aris, A. Z., Juahir, H., Ramli, M. F., & Kura, N. U. (2013). River water quality assessment using environmentric techniques: Case study of Jakara River Basin. *Environmental Science and Pollution Research International*, *20*(8), 5630–5644. https://doi.org/10.1007/s11356-013-1542-z

Namugize, J. N., Jewitt, G., & Graham, M. (2018). Effects of land use and land cover changes on water quality in the uMngeni river catchment, South Africa. *Physics and Chemistry of the Earth, Parts A/B/C*, *105*, 247–264. https://doi.org/10. 1016/j.pce.2018.03.013

Nandi, I., Tewari, A., & Shah, K. (2016). Evolving human dimensions and the need for continuous health assessment of Indian rivers. *Current Science*, *111*(2), 263–271. https://doi.org/10.18520/cs/v111/i2/263-271

Nasir, M. F. M., Samsudin, M. F., Mohamad, I., Awaluddin, M. R. A., Mansor, M. A., Juahir, H. et al. (2011). River water quality modeling using combined principal component analysis (PCA) and multiple linear regressions (MLR): A case study at Klang River, Malaysia. *World Applied Sciences Journal*, *14*, 73–82.

Naubi, I., Zardari, N. H., Shirazi, S. M., Ibrahim, F., & Baloo, L. (2016). Effectiveness of water quality index for monitoring Malaysian river water quality. *Polish Journal of Environmental Studies*, *25*(1), 231–239. https://doi.org/10.15244/pjoes/60109

Newson, M. (2010). Understanding "hot-spot" problems in catchments: The need for scale-sensitive measures and mechanisms to secure effective solutions for river management and conservation. *Aquatic Conservation: Marine and Freshwater Ecosystems*, *20*, S62–S72. https://doi.org/10.1002/aqc.1091

Nigel, W. T., & Quinn, P. E. (2005). *Advancing the concept of real-time water quality management in the San Joaquin Basin Hydro Ecological Engineering Advanced Decision Support Berkeley National Laboratory. Berkeley, CA CWEMF annual meeting asilomar, California*.

Nikoo, M. R., Kerachian, R., Malakpour-Estalaki, S., Bashi-Azghadi, S. N., & Azimi-Ghadikolaee, M. M. (2011). A probabilistic water quality index for river water quality assessment: A case study. *Environmental Monitoring and Assessment*, *181*(1–4), 465–478. https://doi.org/10.1007/s10661-010-1842-4

NOAA. National Oceanic and Atmospheric Administration. (2019). Carbon dioxide levels in atmosphere hit record high in May. https://www.noaa.gov/news/ carbon-dioxide-levels-in-atmosphere-hit-record-high-inmay. United States Department of Commerce.

Noori, R., Sabahi, M. S., Karbassi, A. R., Baghvand, A., & Taati Zadeh, H. T. (2010). Multivariate statistical analysis of surface water quality based on correlations and variations in the data set. *Desalination*, *260*(1–3), 129–136. https://doi.org/10.1016/j.desal.2010.04.053

Norah, M., Shumirai, Z., Zelma, M. L., & Upenyu, M. (2015). Impacts of untreated sewage discharge on water quality of middle Manyame River: A case of Chinhoyi town, Zimbabwe. *International Journal of Environmental Monitoring and Analysis*, *3*(3), 133–138. https://doi.org/10.11648/j.ijema. 20150303.14

Novo, P. (2017). Accounting for the assimilative capacity of water systems in Scotland. *Water*, *9*(8), 559. https://doi.org/10.3390/w9080559

Nurseitova, A. T., Jamalov, J. K., Azimov, A. A., Nurseitov, D. B., & Tursunov, E. A.. (2021). Comparison of methods for assessing the assimilation capacity of the Kazakhstani sector of the Ili River. *Modelling and Simulation in Engineering*, *2021*. https://doi.org/10.1155/2021/9387827

Obin, N., Tao, H., Ge, F., & Liu, X. (2021). Research on water quality simulation and water environmental capacity in Lushui river based on WASP model. *Water*, *13*(20), 2819. https://doi.org/10.3390/w13202819

Omer, N. H. (2019). Water quality parameters. In (Ed.), Water Quality - Science, *Assessments and policy. intech open*. https://doi.org/10.5772/ intechopen.89657

Onojake, M. C., Sikoki, F. D., Omokheyeke, O., & Akpiri, R. U. (2017). Surface water characteristics and trace metals level of the Bonny/New Calabar River Estuary, Niger Delta, Nigeria. *Applied Water Science*, *7*(2), 951–959. https://doi.org/ 10.1007/s13201-015-0306-y

Oseke, F. I., Anornu, G. K., Adjei, K. A., & Eduvie, M. O. (2021). Assessment of water quality using GIS techniques and water quality index in reservoirs affected by water diversion. *Water-Energy Nexus*, *4*, 25–34. https://doi.org/10.1016/j.wen. 2020.12.002

Ostad-Ali-Askari, K. (2022). Management of risks substances and sustainable development. *Applied Water Science*, *12*(4), 65. https://doi.org/10.1007/s1 3201-021-01562-7

Ostad-Ali-Askari, K., Shayannejad, M., & Ghorbanizadeh-Kharazi, H. (2017). Artificial neural network for modeling nitrate pollution of groundwater in marginal area of Zayandeh-rood River, Isfahan, Iran. *KSCE Journal of Civil Engineering*, *21*(1), 134–140. https://doi.org/10.1007/s12205-016-0572-8

Palmer, M. A., Reidy Liermann, C. A., Nilsson, C., Flörke, M., Alcamo, J., Lake, P. S., & Bond, N. (2008). Climate change and the world's river basins: Anticipating management options. *Frontiers in Ecology and the Environment*, *6*(2), 81–89. https://doi.org/10.1890/060148

Panda, D. K., Kumar, A., & Mohanty, S. (2011). Recent trends in sediment load of the tropical (Peninsular) river basins of India. *Global and Planetary Change*, *75*(3–4), 108–118. https://doi.org/10.1016/j.gloplacha.2010.10.012

Pandey, R., & Dikshit, A. (2016). Assessment of water quality of River Ganga using multivariate statistical technique: Principal component analysis. *Advances in Applied Research*, *8*(1), 60–63. https://doi.org/10.5958/2349-2104.2016. 00012.7

Pandey, S. S., Barwa, M. S., Gautam, Y. P., Markandeya, , & Pani, B. (2021). Spatial dependency of the groundwater uranium in the alluvial soil region of Gunnaur, India. *Journal of Radioanalytical and Nuclear Chemistry*, *329*(1), 35–43. https://doi.org/10.1007/s10967-021-07756-2

Panhalkar, S. S., & Jarag, A. P. (2015). Assessment of spatial interpolation techniques for river bathymetry generation of Panchganga River basin using Geoinformatic techniques. *Asian Journal of Geoinformatics, 15*, 10–15.

Papamichail, D. M., Antonopoulos, V. Z., & Georgiou, P. E. (2000). Stochastic models for Strymon river flow and water quality parameters. In *Proceedings of the of International Conference "Protection and Restoration of Environment V," I* (pp. 219–226).

Pardo, R., Vega, M., Debán, L., Cazurro, C., & Carretero, C. (2008). Modelling of chemical fractionation patterns of metals in soils by two-way and three-way principal component analysis. *Analytica Chimica Acta*, *606*(1), 26–36. https://doi.org/10.1016/j.aca.2007.11.004

Parmar, K. S., & Bhardwaj, R. (2013). Water quality index and fractal dimension analysis of water parameters. *International Journal of Environmental Science and Technology*, *10*(1), 151–164. https://doi.org/ 10.1007/s13762-012-0086-y

Parmar, K. S., & Bhardwaj, R. (2014). Water quality management using statistical analysis and time-series prediction model. *Applied Water Science*, *4*(4), 425–434. https://doi.org/10.1007/s13201-014-0159-9

Parmar, K. S., & Bhardwaj, R. (2015). Statistical, time series, and fractal analysis of full stretch of river Yamuna (India) for water quality management. *Environmental Science and Pollution Research International*, *22*(1), 397–414. https://doi.org/10.1007/s11356-014-3346-1

Pati, S., Dash, M. K., Mukherjee, C. K., Dash, B., & Pokhrel, S. (2014). Assessment of water quality using multivariate statistical techniques in the coastal region of Visakhapatnam, India. *Environmental Monitoring and Assessment*, *186*(10), 6385–6402. https://doi.org/10.1007/s10661-014-3862-y

Paul, R., Brindha, K., Gowrisankar, G., Tan, M. L., & Singh, M. K. (2019). Identification of hydrogeochemical processes controlling groundwater quality in Tripura, Northeast India using evaluation indices, GIS, and multivariate statistical methods. *Environmental Earth Sciences*, *78*(15), 470. http://doi.org/10.1007/ s12665-019-8479-6

Pekel, J. F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, *540*(7633), 418–422. https://doi.org/10.1038/nature20584

Pekey, H., Karakaş, D., & Bakoğlu, M. (2004). Source apportionment of trace metals in surface waters of a polluted stream using multivariate statistical analyses. *Marine Pollution Bulletin*, *49*(9–10), 809–818. https://doi.org/10.1016/ j.marpolbul.2004.06.029

Pesce, S. F., & Wunderlin, D. A. (2000). Use of water quality indices to verify the impact of Cordoba City (Argentina) on Suquia River. *Water Research*, *34*(11), 2915–2926. https://doi.org/10.1016/S0043-1354(00)00036-1

Philip, B., & Paul, R. (2012). *River conservation and management*. Wiley.

Phiri, O., Mumba, P., Moyo, B. H. Z., & Kadewa, W. (2005). Assessment of the impact of industrial effluents on water quality of receiving rivers in urban areas of Malawi. *International Journal of Environmental Science and Technology*, *2*(3), 237–244. https://doi.org/10.1007/BF03325882

Pramanik, A. K., Majumdar, D., & Chatterjee, A. (2020). Factors affecting lean, wet-season water quality of Tilaiya reservoir in Koderma district, India during 2013–2017. *Water Science*, *34*(1), 85–97. https://doi.org/10.1080/11104929.2020.1765451

Prasad, B., Kumari, P., Bano, S., & Kumari, S. (2014). Ground water quality evaluation near mining area and development of heavy metal pollution index. *Applied Water Science*, *4*(1),11-17.https://doi.org/10.1007/s13201-013-0126-x

Prati, L., Pavanello, R., & Pesarin, F. (1971). Assessment of surface water quality by a single index of pollution. *Water Research*, *5*(9), 741–751. https://doi.org/10.1016/0043-1354(71)90097-2

Praus, P. (2005). SVD-based principal component analysis of geochemical data. *Open Chemistry*, *3*(4), 731–741. https://doi.org/10.2478/BF02475200

Pujar, P. M., Kenchannavar, H. H., Kulkarni, R. M., & Kulkarni, U. P. (2020). Real-time water quality monitoring through internet of things and ANOVA-based analysis: A case study on river Krishna. *Applied Water Science*, *10*(1), 1–16. https://doi.org/10.1007/s13201-019-1111-9

Qiao, P., Lei, M., Yang, S., Yang, J., Guo, G., & Zhou, X. (2018). Comparing ordinary kriging and inverse distance weighting for soil as pollution in Beijing. *Environmental Science and Pollution Research International*, *25*(16), 15597–15608. http://doi.org/10.1007/s11356-018-1552-y

Qu, L., Xiao, H., Zheng, N., Zhang, Z., & Xu, Y. (2017). Comparison of four methods for spatial interpolation of estimated atmospheric nitrogen deposition in South China. *Environmental Science and Pollution Research International*, *24*(3), 2578–2588. http://doi.org/10.1007/s11356-016-7995-0

Quinn, N. W. T., Tansey, M. K., & Lu, J. (2021). Comparison of deterministic and statistical models for water quality compliance forecasting in the San Joaquin River basin, California. *Water*, *13*(19), 2661. https://doi.org/10.3390/ w13192661

Rajesh, M., & Rehana, S. (2022). Impact of climate change on river water temperature and dissolved oxygen: Indian riverine thermal regimes. *Scientific Reports*, *12*(1), 9222. https://doi.org/10.1038/s41598-022-12996-7

Rajesh, S., Kanchan, B., Prasanjeet, M., & Satendra, S. (2015). Water quality assessment of river Ganga health hazard identification and control. *International Journal of Scientific and Research Publications, 5*(5).

Rajkumar, B., & Sharma, G. D. (2013). Seasonal bacteriological analysis of Barak River, Assam, India. *Applied Water Science*, *3*(3), 625–630. https://doi.org/10.1007/s13201-013-0120-3

Rakhecha, P. R. (2020). Water environment pollution with its impact on human diseases in India. *International Journal of Hydrology*, 4(4), 152–158. https://doi.org/10.15406/ijh.2020.04.00240'

Rasmussen, K. E., Svenstrup Petersen, O., Thompson, J. R., Flower, R. J., & Ahmed, M. H. (2009). Hydrodynamic-ecological model analyses of the water quality of Lake Manzala (Nile Delta, Northern Egypt). *Hydrobiologia*, *622*(1), 195–220. https://doi.org/10.1007/s10750-008-9683-7

Raven, P. J., Holmes, N. T. H., Vaughan, I. P., Dawson, F. H., & Scarlett, P. (2010). Benchmarking habitat quality: Observations using River Habitat Survey on near-natural streams and rivers in northern and Western Europe. *Aquatic Conservation: Marine and Freshwater Ecosystems*, *20*(S1)(Suppl. 1), S13–S30. https://doi.org/10.1002/aqc.1103

Ravikumar, P., Aneesul Mehmood, M. A., & Somashekar, R. K. (2013). Water quality index to determine the surface water quality of Sankey tank and Mallathahalli lake, Bangalore urban district, Karnataka, India. *Applied Water Science*, *3*(1), 247–261. https://doi.org/10.1007/s13201-013-0077-2

Rawat, K. S., & Singh, S. K. (2018). Water Quality Indices and GIS-based evaluation of a decadal groundwater quality. *Geology, Ecology, and Landscapes*, *2*(4), 240–255. https://doi.org/10.1080/24749508.2018.1452462

Rawat, K. S., Singh, S. K., Jacintha, T. G. A., Nemčić-Jurec, J., & Tripathi, V. K. (2017). Appraisal of long term groundwater quality of peninsular India using water quality index and fractal dimension. *Journal of Earth System Science*, *126*(8), 122. https://doi.org/10.1007/s12040-017-0895-y

Rehana, S., & Mujumdar, P. P. (2011). River water quality response under hypothetical climate change scenarios in Tunga-Bhadra river, India. *Hydrological Processes*, *25*(22), 3373–3386. https://doi.org/10.1002/hyp.8057

Rehana, S., & Mujumdar, P. P. (2012). Climate change induced risk in water quality control problems. *Journal of Hydrology*, 444–445, 63–77. https://doi.org/10.1016/j.jhydrol.2012.03.042

Rezaei, A., & Sayadi, M. H. (2015). Long-term evolution of the composition of surface water from the River Gharasoo, Iran: a case study using multivariate statistical techniques. *Environmental Geochemistry and Health,* 37, 251–261. https://doi.org/10.1007/s10653-014-9643-2

Rickwood, C. J., & Carr, G. M. (2009). Development and sensitivity analysis of a global drinking water quality index. *Environmental Monitoring and Assessment*, *156*(1–4), 73–90. https://doi.org/10.1007/s10661-008-0464-6

Rizvi, N., Katyal, D., & Joshi, V. (2015). A multivariate statistical approach for water quality assessment of river Hindon, India. *International Journal of Environmental and Ecological Engineering*, *10*(1), 6–11.

Rizvi, N., Katyal, D., & Joshi, V. (2016). Seasonal and spatial variation in the water quality of river Hindon at NCR, India. *International Journal of Current Research*, *8*(05), 31282–31289.

Robson, A. J., & Neal, C. (1996). Water quality trends at an upland site in Wales, UK, (1983–1993). *Hydrological Processes*, *10*(2), 183–203. https://doi.org/10.1002/(SICI)1099-1085(199602)10:2<183::AID-HYP356> 3.0.CO;2-8

Ross, S. L. (1977). An index system for classifying river water quality. *Water Pollution Control*, *76*(1), 113–122.

Roy, M., Shamim, F., & Chatterjee, S. (2021). Evaluation of Physicochemical and Biological Parameters on the Water Quality of Shilabati River, West Bengal, India'. *Water Science*, *35*(1), 71–81. https://doi.org/10.1080/23570008.2021.1928902

Saha, A., & Ghosh, S. (2020). Relative impacts of projected climate and land use changes on terrestrial water balance: A case study on ganga river Basin. *Frontiers in Water*, *2*, 12. https://doi.org/10.3389/frwa.2020.00012

Saha, N., Rahman, M. S., Ahmed, M. B., Zhou, J. L., Ngo, H. H., & Guo, W. (2017). Industrial metal pollution in water and probabilistic assessment of human health risk. *Journal of Environmental Management*, *185*, 70–78. https://doi.org/10.1016/j.jenvman.2016.10.023

Saha, P., & Paul, B. (2019). Assessment of heavy metal toxicity related with human health risk in the surface water of an industrialized area by a novel technique. *Human and Ecological Risk Assessment: An International Journal*, *25*(4), 966–987. https://doi.org/10.1080/10807039.2018.1458595

Sakelarieva, L., & Varadinova, E. (2013). Water quality and ecological state assessment of the Blagoevgradska Bistritsa River (South-West Bulgaria) based on macrozoobenthos collected by two sampling standards. *Biotechnology and Biotechnological Equipment*, *27*(3), 3787–3790. https://doi.org/10.5504/BBEQ.2013.0019

Salih, S. S., Alkarkhi, A. F., Lalung, J. B., & Ismail, N. (2013). Water quality of river, lake and drinking water supply in Penang state by means of multivariate analysis. *World Applied Sciences Journal*, *26*, 75–82.

Sallam, G. A. H., & Elsayed, E. A. (2018). Estimating relations between temperature, relative humidity as independed variables and selected water quality parameters in Lake Manzala, Egypt. *Ain Shams Engineering Journal*, *9*(1), 1–14. https://doi.org/10.1016/j.asej.2015.10.002

Sanchez, E., Colmenarejo, M. F., Vicente, J., Rubio, A., Garcıa, M. G., Travieso, L., & Borja, R. (2007). Use of the water quality index and dissolved oxygen deficit as simple indicators of watersheds pollution. *Ecological Indicators*, 7(2), 315–328. https://doi.org/10.1016/j.ecolind.2006.02.005

Santy, S., Mujumdar, P., & Bala, G. (2020). Potential impacts of climate and land use change on the water quality of ganga river around the industrialized Kanpur region. *Scientific Reports*, *10*(1), 9107. https://doi.org/10.1038/ s41598-020-66171-x

Santy, S., Mujumdar, P., & Bala, G. (2022). Increased risk of water quality deterioration under climate change in Ganga River. *Frontiers in Water*, *4*, 971623. https://doi.org/10.3389/frwa.2022.971623

Sargaonkar, A., & Deshpande, V. (2003). Development of an overall index of pollution for surface water based on a general classification scheme in Indian context.

Environmental Monitoring and Assessment, *89*(1), 43–67. https://doi.org/10.1023/a:1025886025137

Sarkar, C., & Abbasi, S. A. (2006). Qualidex – a new software for generating water quality indices. *Environmental Monitoring and Assessment*, *119*(1–3), 201–231. https://doi.org/10.1007/s10661-005-9023-6

Schmalle, G. F., & Rehmann, C. R. (2014). Analytical solution of a model of contaminant transport in the advective zone of a river. *Journal of Hydraulic Engineering*, *140*(7), 04014029. https://doi.org/10.1061/(ASCE)HY.1943-7900.0000885

Seifi, A., Dehghani, M., & Singh, V. P. (2020). Uncertainty analysis of water quality index (WQI) for groundwater quality evaluation: Application of Monte-Carlo method for weight allocation. *Ecological Indicators*, *117*, 106653. https://doi.org/10.1016/j.ecolind.2020.106653

Semy, K., & Singh, M. R. (2021). Quality assessment of Tsurang River water affected by coal mining along the Tsurangkong Range, Nagaland, India. *Applied Water Science*, *11*(7), 115. https://doi.org/10.1007/s13201-021-01444-y

Sener, S., Sener, E., & Davraz, A. (2017). Evaluation of water quality using water quality index (WQI) method and GIS in Aksu River (SW-Turkey). *Science of the Total Environment*, *584–585*, 131–144. https://doi.org/10.1016/j.scitotenv.2017.01.102

Seth, R., Singh, P., Mohan, M., Singh, R., & Aswal, R. S. (2013). Monitoring of phenolic compounds and surfactants in water of Ganga Canal, Haridwar (India). *Applied Water Science*, 3(4), 717–720. https://doi.org/10.1007/s13201 -013-0116-z

Shah, A. B., Rai, U. N., & Singh, R. P. (2015). Correlations between some hazardous inorganic pollutants in the Gomti River and their accumulation in selected macrophytes under aquatic ecosystem. *Bulletin of Environmental Contamination and Toxicology*, *94*(6), 783–790. https://doi.org/10.1007/ s00128-015-1546-0

Shah, K. A., & Joshi, G. S. (2017). Evaluation of water quality index for River Sabarmati, Gujarat, India. *Applied Water Science*, *7*(3), 1349–1358. https://doi.org/10.1007/s13201-015-0318-7

Sharma, D., & Kansal, A. (2011). Water quality analysis of River Yamuna using water quality index in the national capital territory, India (2000–2009). *Applied Water Science*, *1*(3–4), 147–157. https://doi.org/10.1007/s13201-011-0011-4

Sharma, G., Lata, R., Thakur, N., Bajala, V., Kuniyal, J. C., & Kumar, K. (2021b). Application of multivariate statistical analysis and water quality index for quality characterization of Parbati River, Northwestern Himalaya, India. *Discover Water*, *1*(1), 5. https://doi.org/10.1007/s43832-021-00005-3

Sharma, M., Kansal, A., Jain, S., & Sharma, P. (2015). Application of multivariate statistical techniques in determining the spatial temporal water quality variation of Ganga and Y. Rivers Present in Uttarakhand State, India. *Water Quality, Exposure and Health*, *7*(4),567–581.https://doi.org/10.1007/s12403-015- 0173-7

Sharma, R., Kumar, R., Satapathy, S. C., Al-Ansari, N., Singh, K. K., Mahapatra, R. P., Agarwal, A. K., Le, H. V., & Pham, B. T. (2020). Analysis of water pollution using different physicochemical parameters: A study of Yamuna River. *Frontiers in Environmental Science*, *8*, 581591. https://doi.org/10.3389/fenvs.2020.581591

Sharma, T. R., & Ravichandran, C. (2021). Appraisal of seasonal variations in water quality of river Cauvery using multivariate analysis. *Water Science*, *35*(1), 49–62. https://doi.org/10.1080/23570008.2021.1897741

Sharma, U., Khan, A., & Dutta, V. (2021a). Long-term sustainability of groundwater resources in the central Ganga Alluvial Plain, India: Study from Gomti River Basin. *Environment, Development and Sustainability*, *23*(11), 16015–16037. https://doi.org/10.1007/s10668-021-01325-z

Sheng, H., & Chen, Y. Q. (2011). FARIMA with stable innovations model of Great Salt Lake elevation time series. *Signal Processing*, *91*(3), 553–561. https://doi.org/10.1016/j.sigpro.2010.01.023

Shil, S., Singh, U. K., & Mehta, P. (2019). Water quality assessment of a tropical river using water quality index (WQI), multivariate statistical techniques and GIS. *Applied Water Science*,*9*(7),168. https://doi.org/10.1007/s13201-0191045-2

Shivayogimath, C. B., Kalburgi, P. B., Deshannavar, U. B., & Virupakshaiah, D. B. M. (2012). Water quality evaluation of river Ghataprabha, India. *Research Journal of Environmental Sciences*, *1*(1), 12–18.

Shrestha, S., & Kazama, F. (2007). Assessment of surface water quality using multivariate statistical techniques: A case study of the Fuji river basin, Japan. *Environmental Modelling and Software*, *22*(4), 464–475. https://doi.org/10.1016/j.envsoft.2006.02.001

Sidabutar, N. V., Hartono, D. M., Soesilo, T. E. B., & Hutapea, R. C. (2017). The quality of raw water for drinking water unit in Jakarta-Indonesia. *AIP Conference Proceedings*, *1823*, 020067. https://doi.org/10.1063/1.4978140

Sikder, M., Tanaka, S., Saito, T., Hosokawa, T., Gumiri, S., Ardianor, A., & Kurasaki, M. (2015). Vulnerability assessment of surface water quality with an innovative integrated multi-parameter water quality index (IMWQI). *Pollution*, *1*(3), 333–346.

Simeonov, V., Stratis, J. A., Samara, C., Zachariadis, G., Voutsa, D., Anthemidis, A., Sofoniou, M., & Kouimtzis, T. (2003). Assessment of the surface water quality in Northern Greece. *Water Research*, *37*(17), 4119–4124. https://doi.org/10.1016/S0043-1354(03)00398-1

Singare, U. P., Mishra, R. M., Trivedi, M. P., & Dagli, D. V. (2012). Aquatic pollution in Mithi River of Mumbai: Assessment of physio-chemical parameters. Interdiscip. *Environmental Reviews*, *13*(4), 245–268.

Singh, A. N., Shivastava, R., Mohan, D., & Kumar, P. (2018). Assessment of spatial and temporal variations in water quality dynamics of river Ganga in Varanasi. *Pollution*, *4*:239-250. https://doi.org/10.22059/POLL

Singh, D. S., & Awasthi, A. (2011a). Natural hazards in the Ghaghara River Area, Ganga Plain, India. *Natural Hazards*, *57*(2), 213–225. https://doi.org/10.1007/s11069-010-9605-7

Singh, D. S., & Awasthi, A. (2011b). Implication of drainage basin parameters of Chhoti Gandak River, Ganga Plain, India. *Journal of the Geological Society of India*, *78*(4), 370–378. https://doi.org/10.1007/s12594-011-0102-8

Singh, K. P., Malik, A., & Sinha, S. (2005). Water quality assessment and apportionment of pollution sources of Gomti river (India) using multivariate statistical techniques—A case study. *Analytica Chimica Acta*, *538*(1–2), 355–374. https://doi.org/10.1016/j.aca.2005.02.006

Singh, K. P., Malik, A., Mohan, D., & Sinha, S. (2004). Multivariate statistical techniques for the evaluation of spatial and temporal variations in water quality of Gomti River (India)—A case study. *Water Research*, *38*(18), 3980–3992. https://doi.org/10.1016/j.watres.2004.06.011

Singh, M., Kumar, S., Kumar, B., Singh, S., & Singh, I. B. (2013). Investigation on the hydrodynamics of Ganga alluvial plain using environmental isotopes: A case study of the Gomati river basin, Northern India. *Hydrogeology Journal*, *21*(3), 687–700. https://doi.org/10.1007/s10040-013-0958-3

Singh, P. K., & Singh, A. K. (2014). Assessment of the microbiological quality of the river Gomati at Jaunpur (UP) India. *International Journal of Life Science and Pharma Research*, *4*(4), 11–16.

Singh, R. K., & Singh, K. N. (2007). Physico-chemical and biological analysis of Gomati river water affected by urban wastes. *Current World Environment*, *2*(2), 233–236. https://doi.org/10.12944/CWE.2.2.23

Singh, R., Upreti, P., Allemailem, K. S., Almatroudi, A., Rahmani, A. H., & Albalawi, G. M. (2022). Geospatial assessment of ground water quality and associated health problems in the western region of India. *Water*, *14*(3), 296. https://doi.org/10.3390/w14030296

Singh, V., Nagpoore, N. K., Jaichand, & Lehri, A. (2020) Monitoring and assessment of pollution load in surface water of River Ganga around Kanpur, India: A study for suitability of this water for different uses. *Environmental Technology and Innovation*, *18*, 100676. http://doi.org/10.1016/j.eti. 2020.100676

Singh, V., Sharma, M. P., Sharma, S., & Mishra, S. (2019). Bio-assessment of River Ujh using benthic macro-invertebrates as bioindicators, India. *International Journal of River Basin Management*, *17*(1), 79–87. https://doi.org/10.1080/15715124.2017.1394318

Smeti, E. M., & Golfinopoulos, S. K. (2016). Characterization of the quality of a surface water resource by multivariate statistical analysis. *Analytical Letters*, *49*(7), 1032–1039. https://doi.org/10.1080/00032719.2015.1045585

Smith, D. G. (1990). A better water quality indexing system for rivers and streams. *Water Research*, *24*(10), 1237–1244. https://doi.org/10.1016/0043-354(90)90047-A

Solangi, G. S., Siyal, A. A., Babar, M. M., & Siyal, P. (2018). Evaluation of surface water quality using the water quality index (WQI) and the synthetic pollution index (SPI): A case study of Indus Delta region of Pakistan. *Desalination and Water Treatment*, *118*, 39–48. https://doi.org/10.5004/ dwt.2018.22407

Solangi, G. S., Siyal, A. A., Babar, M. M., & Siyal, P. (2020). Groundwater quality evaluation using the water quality index (WQI), the synthetic pollution index (SPI), and geospatial tools: A case study of Sujawal district, Pakistan. *Human and*

Ecological Risk Assessment: An International Journal, *26*(6), 1529–1549. https://doi.org/10.1080/10807039.2019.1588099

Somura, H., Takeda, I., Arnold, J. G., Mori, Y., Jeong, J., Kannan, N., & Hoffman, D. (2012). Impact of suspended sediment and nutrient loading from land uses against water quality in the Hii River basin, Japan. *Journal of Hydrology*, *450–451*, 25–35. https://doi.org/10.1016/j.jhydrol.2012.05.032

Sophia, S., Milton, M. C. J., & Prakash, M. (2017). Analysis and seasonal variation of heavy metals in water and sediment from Adyar estuary. *Environmental Risk Assessment and Remediation, 1*(2), 2-7. DOI: 10.4066/2529-8046.100013

Srivastava, P. K., Mukherjee, S., Gupta, M., & Singh, S. K. (2011). Characterizing monsoonal variation on water quality index of River Mahi in India using geographical information system. *Water Quality, Exposure and Health*, *2*(3–4), 193–203. https://doi.org/10.1007/s12403-011-0038-7

Stambuk-Giljanovic, N. (1999). Water quality evaluation by index in Dalmatia. *Water Research*, *33*(16), 3423–3440. https://doi.org/10.1016/S0043-1354(99)00063-9

Stansfield, B. (2001). Effects of sampling frequency and laboratory detection limits on the determination of time series water quality trends. *New Zealand Journal of Marine and Freshwater Research*, *35*(5), 1071–1075. https://doi.org/10.1080/00288330.2001.9517064

Strehmel, A., Schmalz, B., & Fohrer, N. (2016). Evaluation of Land Use, Land Management and Soil Conservation Strategies to Reduce Non-Point Source Pollution Loads in the Three Gorges Region, China. *Environmental Management*, 58(5), 906–921. https://doi.org/10.1007/s00267-016-0758-3

Su, S., Li, D., Zhang, Q., Xiao, R., Huang, F., & Wu, J. (2011). Temporal trend and source apportionment of water pollution in different functional zones of Qiantang River, China. *Water Research*, *45*(4), 1781–1795. https://doi.org/10.1016/j.watres.2010.11.030

Sunar, S., Tripathi, O. P., & Mishra, B. P. (2020). Water quality and pollution indices application in monitoring water quality of Serlui river impacted by Serlui-B dam, Mizoram, North East India. *Current Science*, *119*(10), 1685–1689. https://doi.org/10.18520/cs/v119/i10/1685-1689

Sutadian, A. D., Muttil, N., Yilmaz, A. G., & Perera, B. J. C. (2016). Development of river water quality indices-a review. *Environmental Monitoring and Assessment*, *188*(1), 58. https://doi.org/10.1007/s10661-015-5050-0

Suthar, S., Sharma, J., Chabukdhara, M., & Nema, A. K. (2010). Water quality assessment of river Hindon at Ghaziabad, India: Impact of industrial and urban wastewater. *Environmental Monitoring and Assessment*, *165*(1–4), 103–112. https://doi.org/10.1007/s10661-009-0930-9

Svendsen, M. B. S., Bushnell, P. G., Christensen, E. A. F., & Steffensen, J. F. (2016). Sources of variation in oxygen consumption of aquatic animals demonstrated by simulated constant oxygen consumption and respirometers of different sizes. *Journal of Fish Biology*, *88*(1), 51–64. https://doi.org/10.1111/ jfb.12851

Taheri Tizro, A., Ghashghaie, M., Georgiou, P., & Voudouris, K. (2014). Time series analysis of water quality parameters. *Journal of Applied Research in Water and Wastewater*, *1*(1), 43–52.

Tajmunnaher, T., & Chowdhury, M. A. I. (2017). Correlation study for assessment of water quality and its parameters of Kushiyara River, Sylhet, Bangladesh. *International Journal of New Technology and Research*, *3*.

Tangri, A. K., Kumar, D., Singh, D. S., & Dubey, C. A. (2018). *The Gomati River: Lifeline of central Ganga plain. Springer, Singapore* (pp. 135–150). https://doi.org/10.1007/978-981-10-2984-4_11

Taniwaki, R. H., Piggott, J. J., Ferraz, S. F. B., & Matthaei, C. D. (2017). Climate change and multiple stressors in small tropical streams. *Hydrobiologia*, *793*(1), 41–53. https://doi.org/10.1007/s10750-016-2907-3

Tanty, H., Bekti, R. D., Herlina, T., & Nurlelasari, . (2014). MANOVA statistical analysis of inorganic compounds in groundwater Indonesia. In *AIP Conference Proceedings*. Australian Institute of Physics, *1621*(1), 492–497. https://doi.org/ 10.1063/1.4898511

Thomas, H. A., & Fiering, M. B. (1962). *Mathematical synthesis of stream flow sequences for the analysis of river basin by simulation*. Harward University Press.

Tiwari, M., & Kisku, G. C. (2016). Impact assessment of Gomti river water quality after immersion of idols during Durga Utsav. *Biochemistry and Analytical Biochemistry*, *5*(287), 2161–1009. https://doi.org/10.4172/2161-1009.10002

Torres-Bejarano, F., Verbel-Escobar, M., & Atencia-Osorio, M. C. (2022). Water quality model-based methodology to assess assimilative capacity of wastewater discharges in rivers. *Global Journal of Environmental Science and Management*, *8*(4), 449–472. https://doi.org/10.22034/gjesm.2022.04.01

Tripathi, M., & Singal, S. K. (2019). Use of principal component analysis for parameter selection for development of a novel water quality index: A case study of river Ganga India. *Ecological Indicators*, *96*(1), 430–436. https://doi.org/10.1016/j.ecolind.2018.09.025

Trombadore, O., Nandi, I., & Shah, K. (2020). Effective data convergence, mapping, and pollution categorization of ghats at Ganga River Front in Varanasi. *Environmental Science and Pollution Research International*, 27(13), 15912–15924. http://doi.org/10.1007/s11356-019-06526-8

Tsegaye, T., Sheppard, D., Islam, K. R., Tadesse, W., Atalay, A., & Marzen, L. (2006). Development of chemical index as a measure of in-stream water quality in response to land-use and land cover changes. *Water, Air and Soil Pollution, 174*(1), 161-179. https://doi.org/10.1007/s11270-006-9090-5

Turner, B. F., Gardner, L. R., & Sharp, W. E. (1996). The hydrology of Lake Bosumtwi, a climate-sensitive lake in Ghana, West Africa. *Journal of Hydrology*, *183*(3–4), 243–261. https://doi.org/10.1016/0022-1694(95)02982-6

Tyagi, V. K., Bhatia, A., Gaur, R. Z., Khan, A. A., Ali, M., Khursheed, A., Kazmi, A. A., & Lo, S. (2013). Impairment in water quality of Ganges River and consequential health risks on account of mass ritualistic bathing. *Desalination and Water Treatment*, *51*(10–12), 2121–2129. http://doi.org/10.1080/19443994.2013.734677

UN Environmental Program, & GEMS. (2007). Global drinking water quality index. Development and sensitivity analysis report. http://www.gemswater.org/publications/pdfs/gwqi.pdf.

Unger-Shayesteh, K., Vorogushyn, S., Merz, B., & Frede, H. -G. (2013). Introduction to “Water in Central Asia—perspectives under global change”. *Global and Planetary Change*, *110*, 1–3. https://doi.org/10.1016/j.gloplacha. 2013.09.016

United Nations Children’s Fund. (2008). *UNICEF handbook on water quality*. United Nations.

UPPCB (Uttar Pradesh Pollution Control Board). (2019). *Action plan for restoration of polluted stretch of river Gomti from Sitapur to Kaithi (district Ghazipur) (UPPCB, Lucknow)*.

Usali, N., & Ismail, M. H. (2010). Use of remote sensing and GIS in monitoring water quality. *Journal of Sustainable Development*, *3*(3), 228. https://doi.org/10.5539/jsd.v3n3p228

Ustaoglu, F., Tepe, Y., & Taş, B. (2020). Assessment of stream quality and health risk in a subtropical Turkey river system: A combined approach using statistical analysis and water quality index. *Ecological Indicators*, *113*, 105815. https://doi.org/10.1016/j.ecolind.2019.105815

Valeriy, G., Olga, S., & Kristina, D., Sign. Imag. Anal. (2015). Biomed. *Life Science*, *823*, 107–126.

Van Vliet, M. T. H., Franssen, W. H. P., Yearsley, J. R., Ludwig, F., Haddeland, I., Lettenmaier, D. P., & Kabat, P. (2013). Global river discharge and water temperature under climate change. *Global Environmental Change*, *23*(2), 450–464. https://doi.org/10.1016/j.gloenvcha.2012.11.002

Varol, M. (2020). Use of water quality index and multivariate statistical methods for the evaluation of water quality of a stream affected by multiple stressors: A case study. *Environmental Pollution*, *266*(3), 115417. https://doi.org/10.1016/j.envpol.2020.115417

Varol, M., Gökot, B., Bekleyen, A., & Şen, B. (2012). Water quality assessment and apportionment of pollution sources of Tigris River (Turkey) using multivariate statistical techniques-A case study. *River Research and Applications*, *28*(9), 1428–1438. https://doi.org/10.1002/rra.1533

Venkatesharaju, K., Ravikumar, P., Somashekar, R. K., & Prakash, K. L. (2010). Physico-chemical and bacteriological investigation on the river Cauvery of Kollegal stretch in Karnataka. *Kathmandu University Journal of Science, Engineering and Technology*, *6*(1), 50–59. https://doi.org/10.3126/kuset.v6i1.3310

Venkatramanan, S., Chung, S. Y., Lee, S. Y., & Park, N. (2014). Assessment of river water quality via environmentric multivariate statistical tools and water quality index: A case study of Nakdong River basin, Korea. *Carpathian Journal of Earth and Environmental Sciences*, *9*(2), 125–132.

Villota-Lopez, C., Rodríguez-Cuevas, C., Torres-Bejarano, F., Cisneros-Pérez, R., Cisneros-Almazán, R., & Couder-Castañeda, C. (2021). Applying EFDC Explorer model in the Gallinas River, Mexico to estimate its assimilation capacity for water quality protection. *Scientific Reports*, *11*(1), 13023. https://doi.org/10.1038/s41598-021-92453-z

Vishnuradhan, R., Zainudin, Zaki, & Vethamony, P. (2012). Introduction to water quality modeling. *Jurutera*, *8*, 12–16.

Voza, D., Vukovic, M., Takic, L., Nikolic, D., & Mladenovic-Ranisavljevic, I. (2015). Application of multivariate statistical techniques in the water quality assessment of Danube River, Serbia. *Archives of Environmental Protection*, *41*(4), 96–103. https://doi.org/10.1515/aep-2015-0044

Walski, T. M., & Parker, F. L. (1974). Consumers water quality index. *Journal of the Environmental Engineering Division*, *100*(3), 593–611. https://doi.org/10.1061/JEEGAV.0000184

Wang, M., Yao, Y., Shen, Q., Gao, H., Li, J., Zhang, F., & Wu, Q. (2021). Time-series analysis of surface-water quality in Xiong'an new area, 2016–2019. *Journal of the Indian Society of Remote Sensing*, *49*(4), 857–872. https://doi.org/10.1007/s12524-020-01264-8

Wang, Q., Li, S., Jia, P., Qi, C., & Ding, F. (2013). A review of surface water quality models. *The Scientific World Journal*, *2013*, 31768. https://doi.org/10.1155/2013/231768

Wang, X. Q., Wen, J., Chen, P. H., & Liu, N. N. (2018). Monitoring and assessment of Youshui river water quality in Youyang. *IOP Conference Series: Earth and Environmental Science*, *113*, 012069. https://doi.org/10.1088/1755-1315/113/1/012069

Wang, Y., Teng, E., Liu, T., Lv, Y., Jin, X., Giesy, J. P., & Hollert, H. (2014). A national pilot scheme for monitoring and assessment of ecological integrity of surface waters in China. *Environmental Development*, 10, 104–107. https://doi.org/10.1016/j.envdev.2014.02.003

Webb, B. W., Clack, P. D., & Walling, D. E. (2003). Water-air temperature relationships in a Devon River system and the role of flow. *Hydrological Processes*, *17*(15), 3069–3084. https://doi.org/10.1002/hyp.1280

Wen, C. G., & Lee, C. S. (1998). A neural network approach to multi objective optimization for water quality management in a river basin. *Water Resources Research,* 34(3), 427–436. https://doi.org/10.1029/97WR02943

WHO (2011). Guidelines for drinking water quality, 4th edn. World Health Organization, Geneva, Switzerland

Wilson, T. M., Ogden, A. E., & Mills, H. H. (1992). *Time-Series analysis of groundwater chemistry in the west Tennessee sand aquifers*.

World Bank. (1998). Available online. https://www.ircwash.org/sites/default/ files/Worldbank-1998-Inter.pdf, Retrieved September 20, 2021

Yandamuri, S. R., Srinivasan, K., & Murty Bhallamudi, S. M. (2006). Multiobjective optimal waste load allocation models for rivers using nondominated sorting genetic algorithm-II. *Journal of Water Resources Planning and Management*, *132*(3), 133–143. https://doi.org/10.1061/(ASCE) 0733-9496(2006)132:3(133)

Yu, Y., Zou, S., & Whittemore, D. (1993). Non-parametric trend analysis of water quality data of rivers in Kansas. *Journal of Hydrology*, 150(1), 61–80. https://doi.org/10.1016/0022-1694(93)90156-4

Yuceer, M., & Coskun, M. A. (2016). Modeling water quality in rivers: A case study of Beylerderesi River in Turkey. *Applied Ecology and Environmental Research*, *14*(1), 383–395. https://doi.org/10.15666/aeer/1401_383395

Yurekli, K., & Kurunc, A. (2005). Performance of stochastic approaches in generating low streamflow data for drought analysis. *Journal of Spatial Hydrology*, *5*,20–32.

Zainudin, Z., Azmi, A., Norainijimat, D., & Jamal, P. (2015). Determination of waste assimilative capacity (WAC) of rivers located within the Desaru region, Johor. *Environmental Protection Engineering, 41(4), 49-60.* https://doi.org/10.5277cpe 150404

Zeinalzadeh, K., & Rezaei, E. (2017). Determining spatial and temporal changes of surface water quality using principal component analysis. *Journal of Hydrology: Regional Studies*, *13*, 1–10. https://doi.org/10.1016/j.ejrh.2017. 07.002

Zhang, G. P. (2003). Time series forecasting using a hybrid Arima and neural network model. *Neurocomputing*, *50*, 159–175. https://doi.org/10.1016/S0925-2312(01) 00702-0

Zhang, L. (2019). Big data, knowledge mapping for sustainable development: A water quality index case study. *Emerging Science Journal*, *3*(4), 249–254. https://doi.org/10.28991/esj-2019-01187

Zhang, Z., Tao, F., Du, J., Shi, P., Yu, D., Meng, Y., & Sun, Y. (2010). Surface water quality and its control in a river with intensive human impacts–a case study of the Xiangjiang River, China. *Journal of Environmental Management*, *91*(12), 2483–2490. https://doi.org/10.1016/j.jenvman. 2010.07.002

Zhao, J., Fu, G., Lei, K., & Li, Y. (2011). Multivariate analysis of surface water quality in the three Gorges area of China and implications for water management. *Journal of Environmental Sciences*, *23*(9), 1460–1471. https://doi.org/10.1016/ s1001-0742(10)60599-2

Zubaidah, T., Karnaningroem, N., & Slamet, A. (2019). The selfpurification ability in the rivers of Banjarmasin, Indonesia. *Journal of Ecological Engineering*, *20*(2), 177–182. https://doi.org/10.12911/22998993/97286

ANNEXURES

ANNEXURE – I

Sampling Stations Photographs

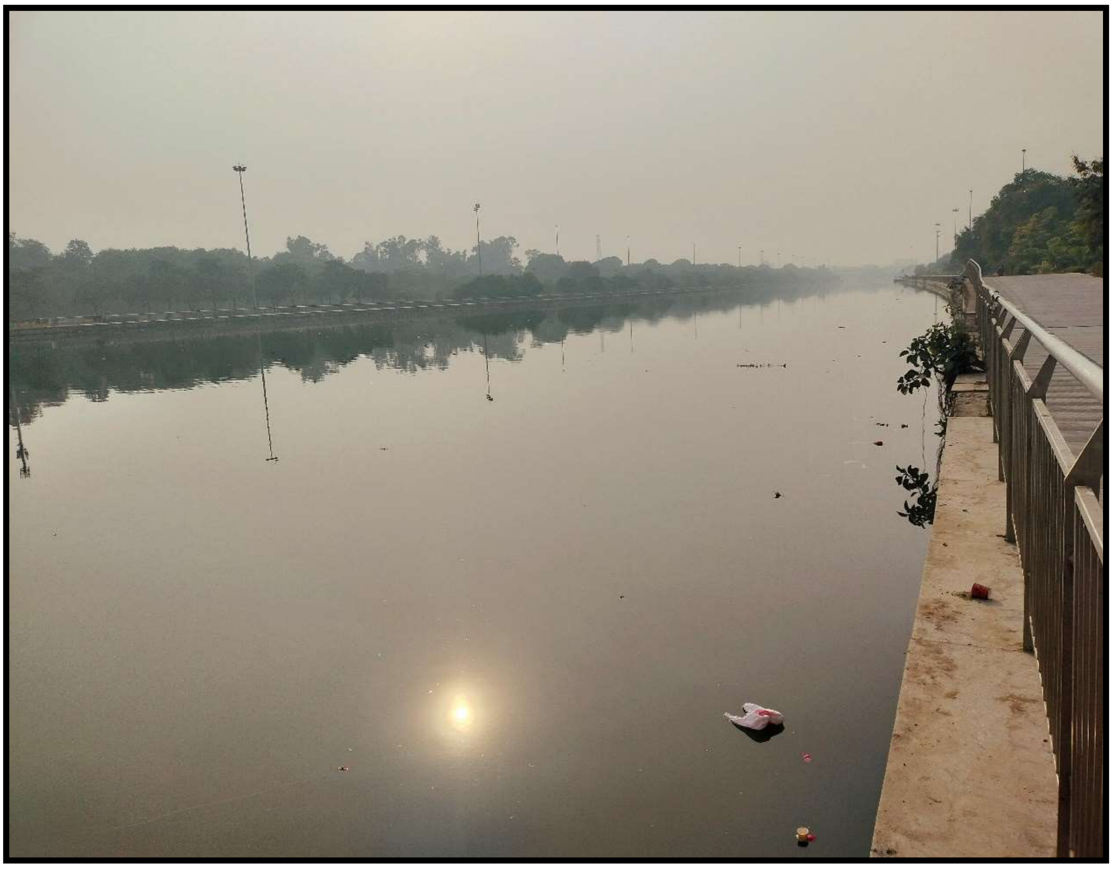
S1 - Manjhi Ghat

S2 - Up Stream water intake

S3 - Kuriyaghat

S4 - Downstream Mohan Meakins

S5 - Nishat Ganj Bridge



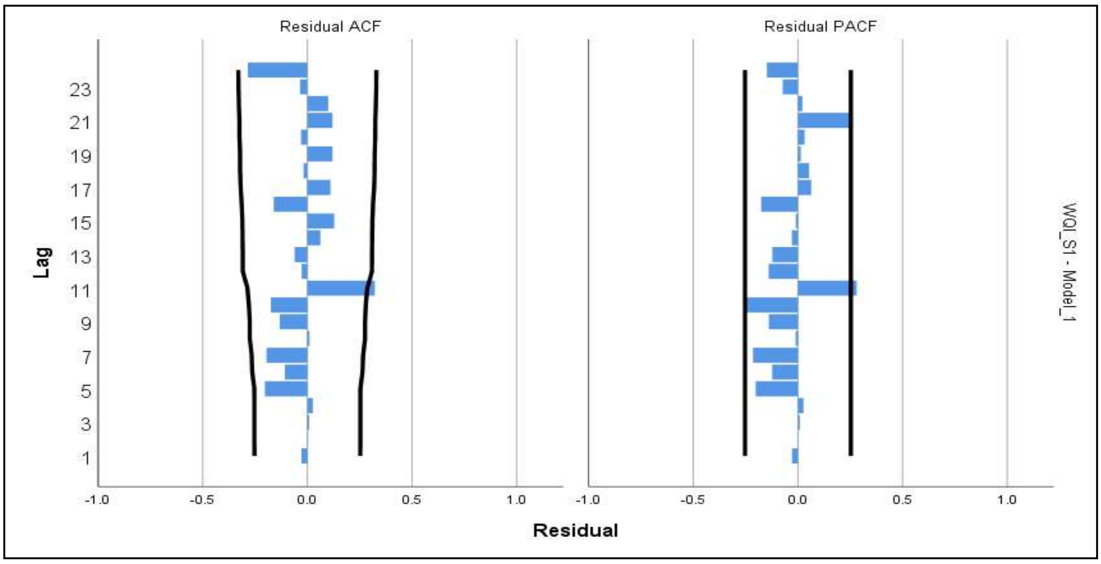
S6 - Upstream Barrage

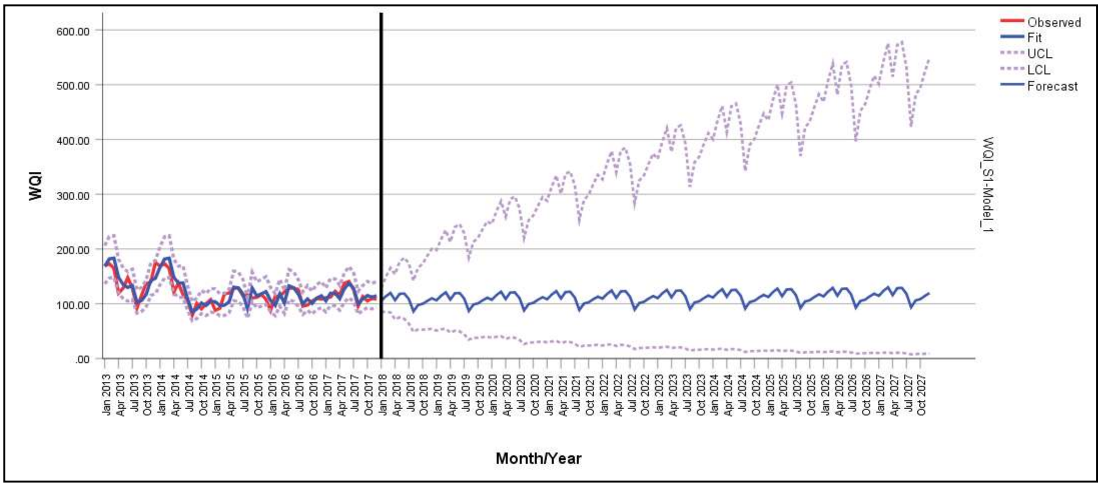
S7 - Downstream STP Nala Bharwara junction

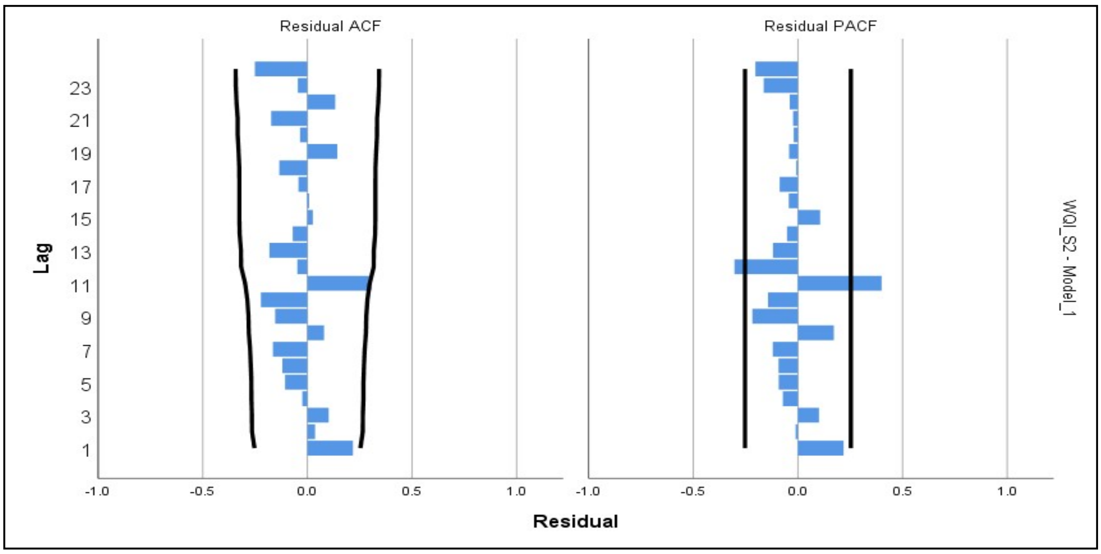
Hanuman Sethu (CWC)

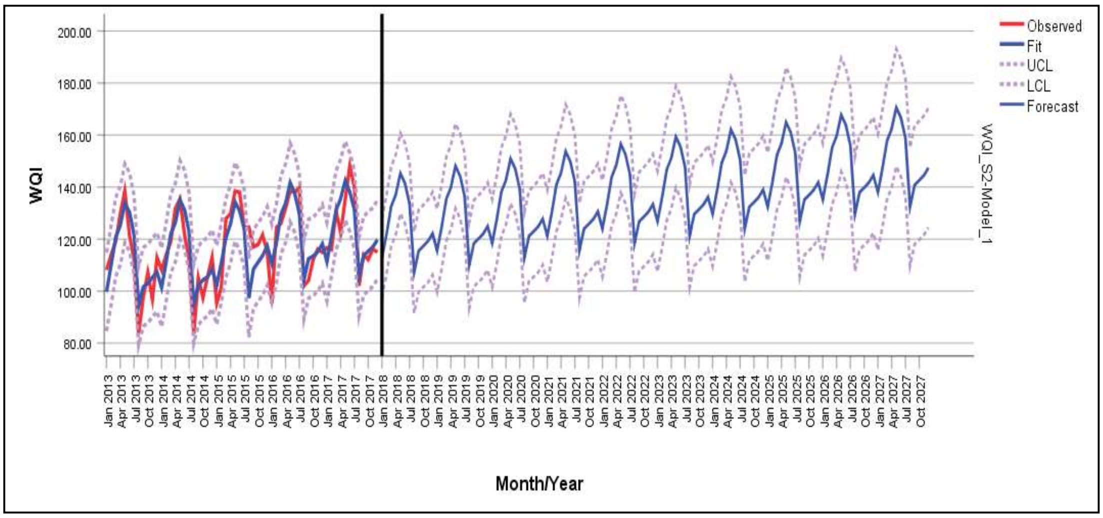
ANNEXURE – II

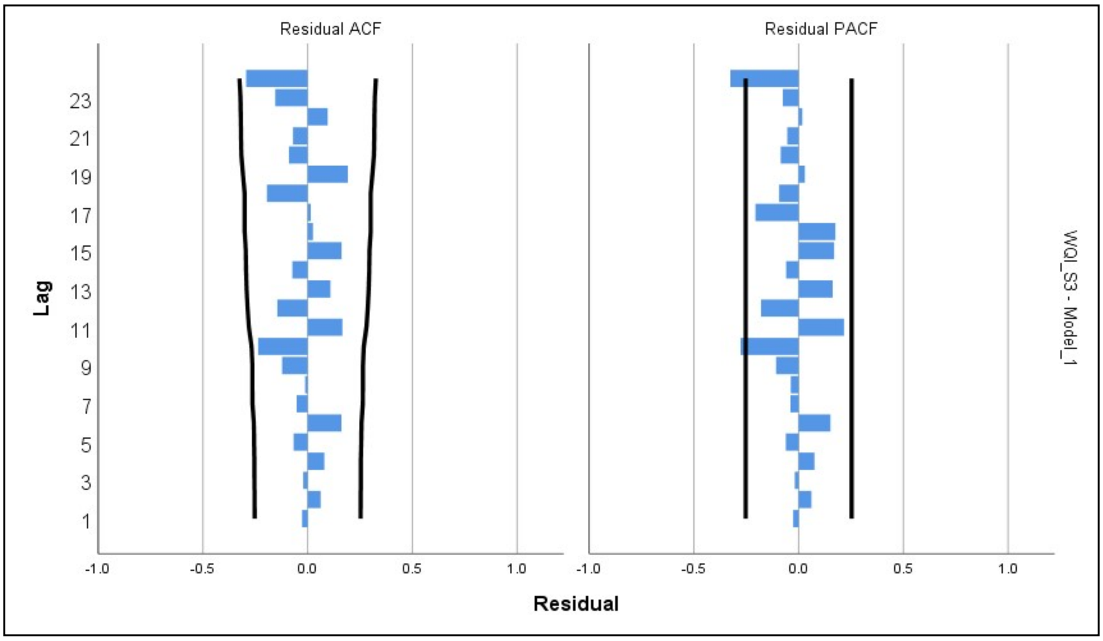
Graphical representation of trend, time series analysis (ACF, PACF, observed, best fit, LCL, UCL) of Arithmetic WQI (S1 – S7)

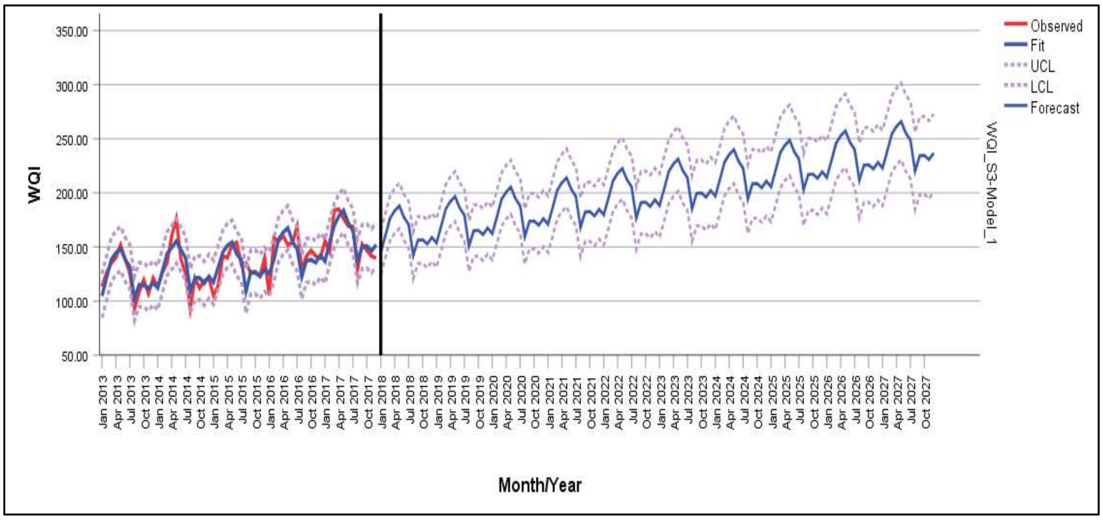


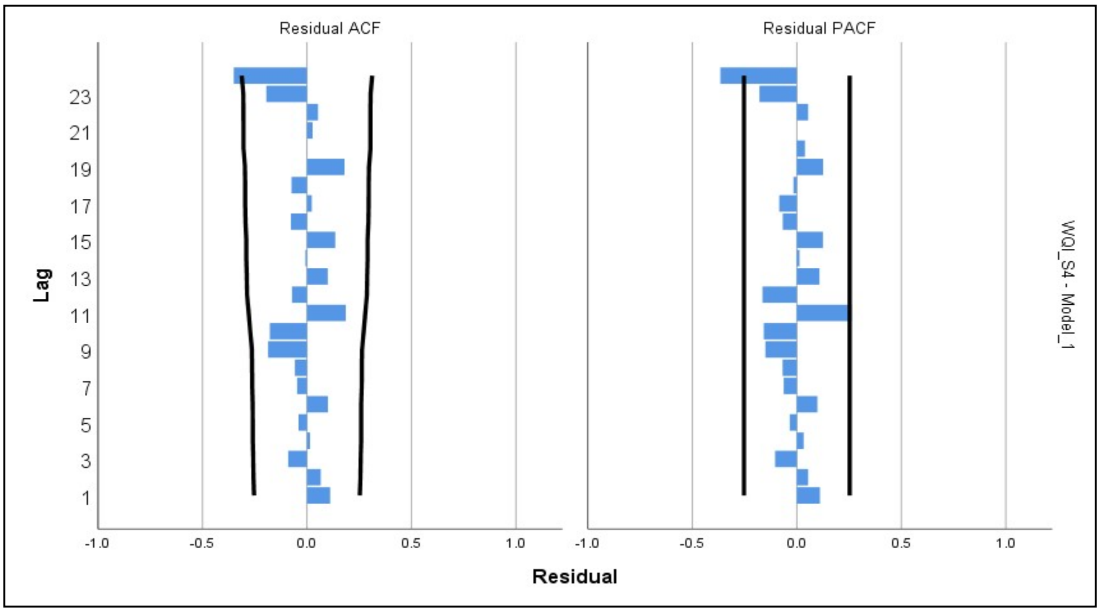




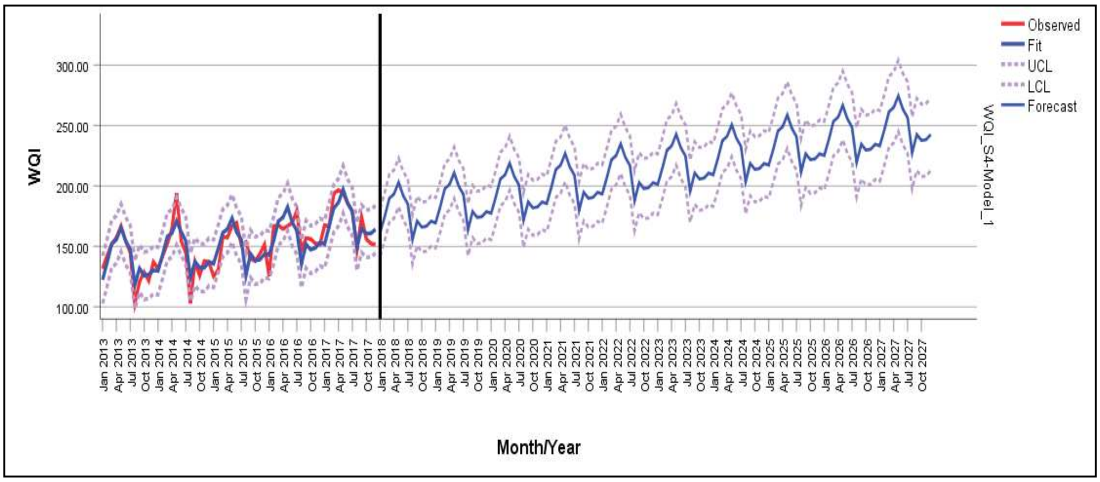

Observed
Fit
UCL
LCL
Forecast
WQI_S2-Model_1
WQI
Month/Year


Residual ACF
Residual PACF
Lag
Residual
WQI_S3 - Model_1

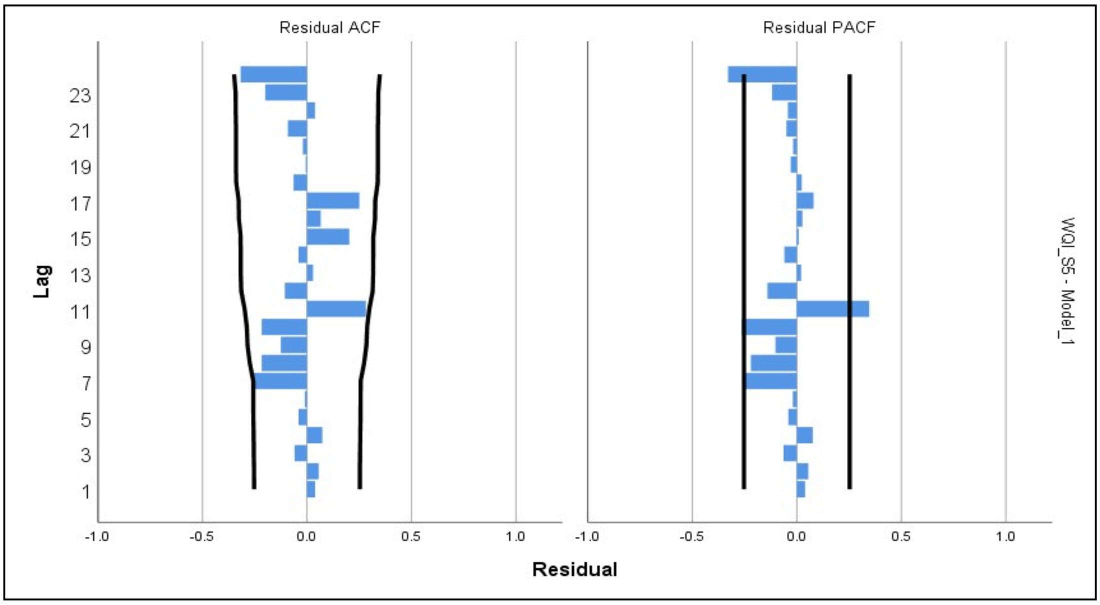

Observed
Fit
UCL
LCL
Forecast
WQI_S3-Model_1
WQI
Month/Year



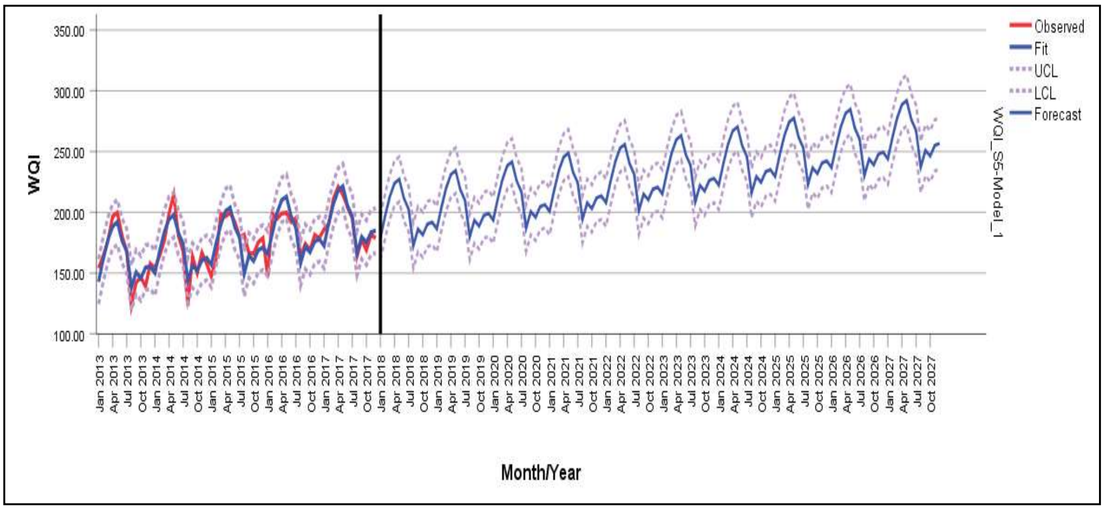
Residual ACF
Residual PACF
Lag
Residual
WQI_S4 - Model_1



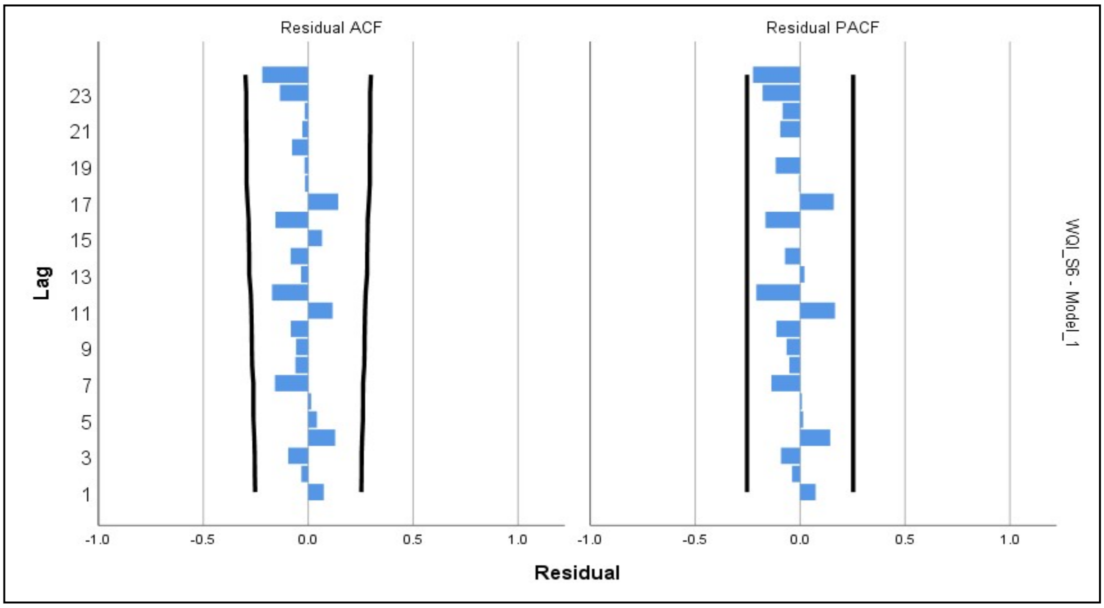
Observed
Fit
UCL
LCL
Forecast
WQI
Month/Year
WQI_S4-Model_1



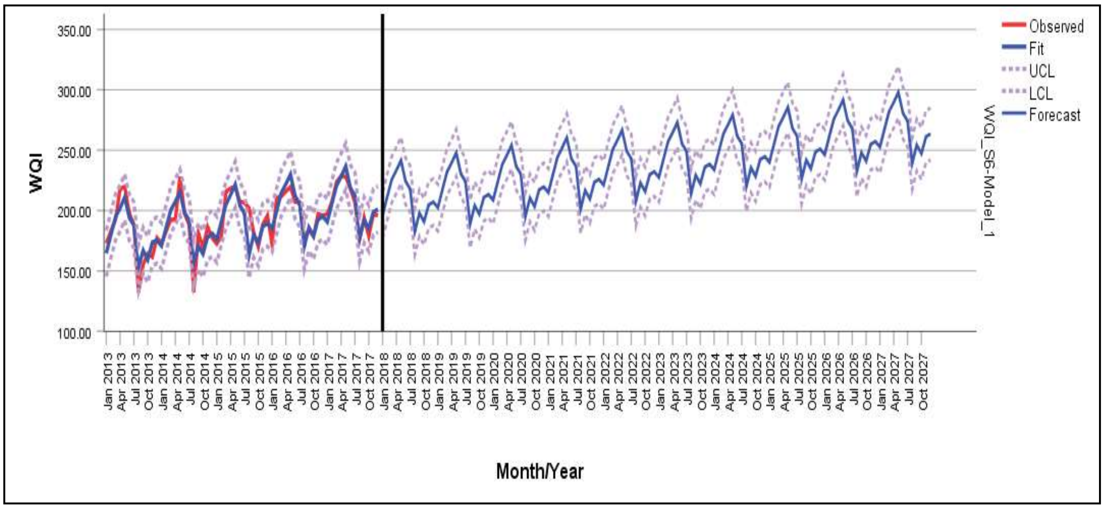
Residual ACF
Residual PACF
Lag
Residual
WQI_S5 - Model_1



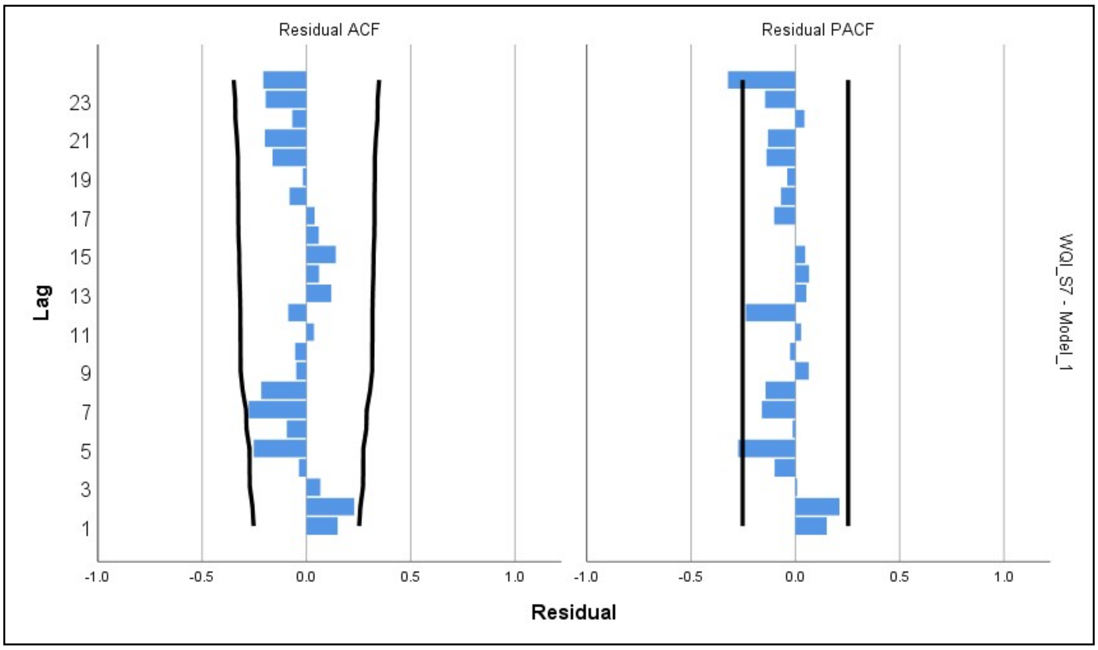
Observed
Fit
UCL
LCL
Forecast
WQI_S5-Model_1
WQI
Month/Year



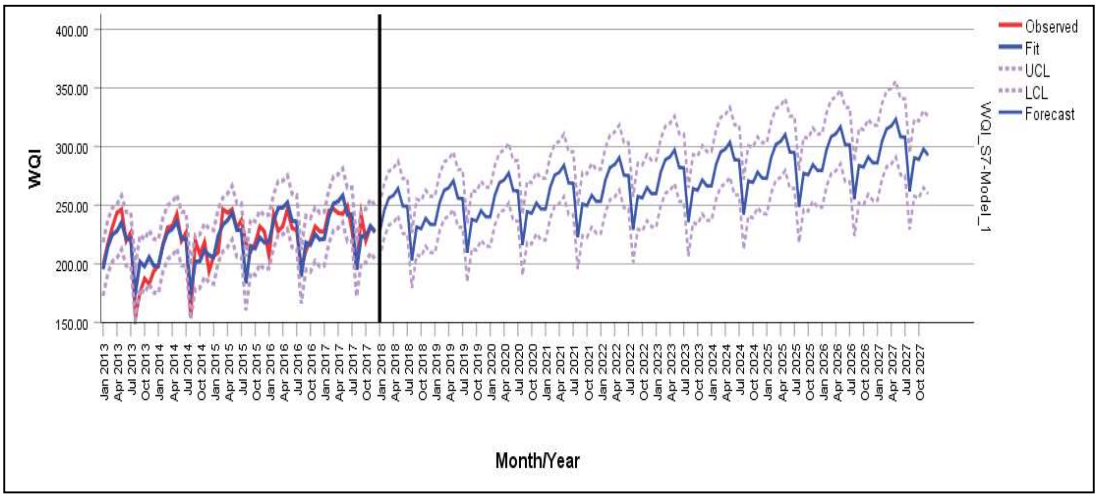
Residual ACF
Residual PACF
Lag
Residual
WQI_S6 - Model_1



Observed
Fit
UCL
LCL
Forecast
WQI_S6-Model_1
WQI
Month/Year



Residual ACF
Residual PACF
Lag
Residual
WQI_S7 - Model_1



WQI
Month/Year
Observed
Fit
UCL
LCL
Forecast
WQI_S7-Model_1

ANNEXURE – III

Predicted value of Arithmetic WQI (2018-2027) by Time-series analysis

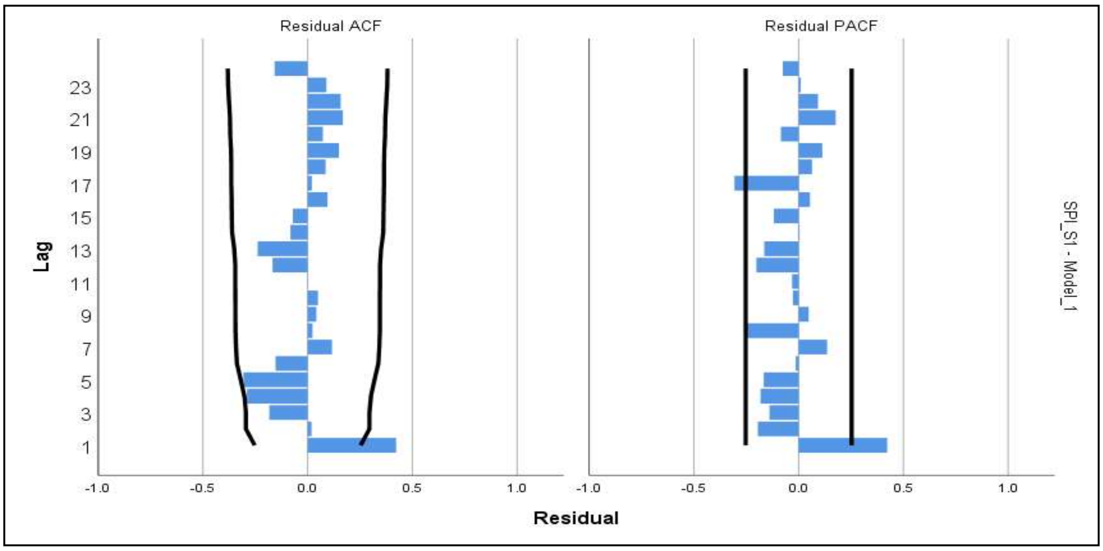
Date	S1	S2	S3	S4	S5	S6	S7
Jan 2018	105.35	112.78	145.00	161.55	179.21	196.15	227.08
Feb 2018	113.63	121.99	160.53	174.89	197.18	211.16	245.52
Mar 2018	119.83	132.58	176.67	189.92	213.13	225.81	256.14
Apr 2018	106.70	137.12	183.53	193.28	223.99	233.35	258.42
May 2018	118.23	145.26	188.00	202.96	227.19	241.54	264.39
Jun 2018	118.70	141.49	177.36	191.88	211.41	224.12	249.38
Jul 2018	108.69	133.61	170.82	185.04	202.65	217.82	249.09
Aug 2018	86.20	107.23	142.24	155.86	172.66	182.47	202.99
Sep 2018	97.80	115.55	156.39	170.95	186.21	197.89	231.34
Oct 2018	99.76	117.31	156.70	166.03	181.54	190.77	230.03
Nov 2018	105.30	119.19	152.81	166.68	190.37	204.76	238.84
Dec 2018	110.04	122.12	158.89	170.85	191.93	207.05	233.66
Jan 2019	106.33	115.58	153.66	169.51	186.40	202.42	233.64
Feb 2019	114.68	124.80	169.18	182.85	204.38	217.43	252.08
Mar 2019	120.94	135.39	185.33	197.88	220.33	232.08	262.70
Apr 2019	107.69	139.93	192.19	201.24	231.19	239.62	264.98
May 2019	119.33	148.07	196.66	210.92	234.38	247.81	270.95
Jun 2019	119.80	144.29	186.02	199.84	218.61	230.39	255.94
Jul 2019	109.70	136.42	179.48	193.00	209.85	224.09	255.65
Aug 2019	87.00	110.04	150.90	163.82	179.85	188.74	209.55
Sep 2019	98.71	118.36	165.05	178.91	193.41	204.16	237.91
Oct 2019	100.68	120.12	165.36	173.99	188.73	197.04	236.59
Nov 2019	106.28	122.00	161.47	174.64	197.56	211.04	245.40
Dec 2019	111.06	124.93	167.55	178.81	199.12	213.32	240.22
Jan 2020	107.32	118.39	162.32	177.47	193.60	208.69	240.20
Feb 2020	115.75	127.61	177.84	190.81	211.57	223.71	258.64
Mar 2020	122.06	138.20	193.99	205.84	227.52	238.35	269.27
Apr 2020	108.69	142.74	200.85	209.20	238.38	245.89	271.54
May 2020	120.44	150.88	205.32	218.88	241.58	254.09	277.51
Jun 2020	120.91	147.10	194.68	207.80	225.80	236.66	262.50
Jul 2020	110.72	139.23	188.14	200.96	217.04	230.36	262.21
Aug 2020	87.80	112.85	159.56	171.78	187.05	195.01	216.11
Sep 2020	99.63	121.17	173.71	186.87	200.60	210.44	244.47
Oct 2020	101.62	122.93	174.01	181.95	195.93	203.31	243.15
Nov 2020	107.27	124.81	170.13	182.60	204.76	217.31	251.96
Dec 2020	112.09	127.74	176.20	186.77	206.32	219.59	246.78
Jan 2021	108.31	121.20	170.98	185.43	200.79	214.96	246.76
Feb 2021	116.82	130.42	186.50	198.77	218.77	229.98	265.20
Mar 2021	123.19	141.01	202.65	213.80	234.72	244.62	275.83

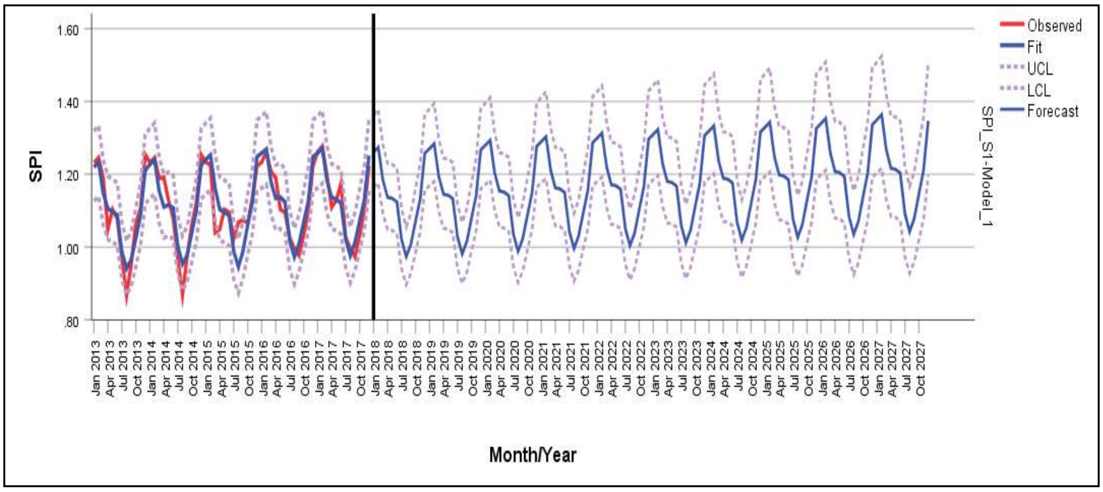
Date	S1	S2	S3	S4	S5	S6	S7
Apr 2021	109.70	145.55	209.50	217.16	245.58	252.16	278.10
May 2021	121.56	153.69	213.98	226.84	248.77	260.36	284.07
Jun 2021	122.04	149.91	203.34	215.76	233.00	242.93	269.06
Jul 2021	111.74	142.04	196.80	208.92	224.24	236.63	268.77
Aug 2021	88.62	115.65	168.22	179.74	194.24	201.29	222.68
Sep 2021	100.55	123.98	182.37	194.83	207.80	216.71	251.03
Oct 2021	102.56	125.74	182.67	189.91	203.12	209.58	249.71
Nov 2021	108.26	127.62	178.78	190.56	211.95	223.58	258.52
Dec 2021	113.13	130.55	184.86	194.73	213.52	225.87	253.34
Jan 2022	109.32	124.01	179.64	193.39	207.99	221.23	253.32
Feb 2022	117.91	133.23	195.16	206.73	225.96	236.25	271.76
Mar 2022	124.34	143.81	211.31	221.76	241.92	250.90	282.39
Apr 2022	110.72	148.36	218.16	225.12	252.77	258.43	284.66
May 2022	122.69	156.49	222.64	234.80	255.97	266.63	290.63
Jun 2022	123.17	152.72	212.00	223.72	240.19	249.21	275.62
Jul 2022	112.78	144.85	205.46	216.88	231.43	242.91	275.33
Aug 2022	89.44	118.46	176.88	187.70	201.44	207.56	229.24
Sep 2022	101.49	126.79	191.03	202.79	215.00	222.98	257.59
Oct 2022	103.51	128.54	191.33	197.87	210.32	215.86	256.27
Nov 2022	109.27	130.43	187.44	198.52	219.15	229.85	265.08
Dec 2022	114.18	133.36	193.52	202.69	220.71	232.14	259.90
Jan 2023	110.34	126.82	188.30	201.35	215.18	227.51	259.88
Feb 2023	119.00	136.03	203.82	214.69	233.16	242.52	278.32
Mar 2023	125.49	146.62	219.97	229.72	249.11	257.17	288.95
Apr 2023	111.75	151.17	226.82	233.08	259.97	264.71	291.22
May 2023	123.83	159.30	231.29	242.76	263.17	272.90	297.19
Jun 2023	124.32	155.53	220.66	231.68	247.39	255.48	282.18
Jul 2023	113.83	147.66	214.12	224.84	238.63	249.18	281.89
Aug 2023	90.28	121.27	185.54	195.66	208.63	213.83	235.80
Sep 2023	102.43	129.59	199.69	210.75	222.19	229.25	264.15
Oct 2023	104.48	131.35	199.99	205.83	217.52	222.13	262.83
Nov 2023	110.29	133.24	196.10	206.48	226.34	236.12	271.64
Dec 2023	115.25	136.16	202.18	210.65	227.91	238.41	266.46
Jan 2024	111.36	129.62	196.96	209.31	222.38	233.78	266.44
Feb 2024	120.11	138.84	212.48	222.65	240.35	248.80	284.88
Mar 2024	126.66	149.43	228.62	237.68	256.31	263.44	295.51
Apr 2024	112.79	153.97	235.48	241.04	267.17	270.98	297.78
May 2024	124.98	162.11	239.95	250.72	270.36	279.17	303.75
Jun 2024	125.47	158.34	229.32	239.64	254.58	261.75	288.74
Jul 2024	114.89	150.46	222.78	232.80	245.82	255.45	288.45
Aug 2024	91.12	124.08	194.20	203.62	215.83	220.10	242.36

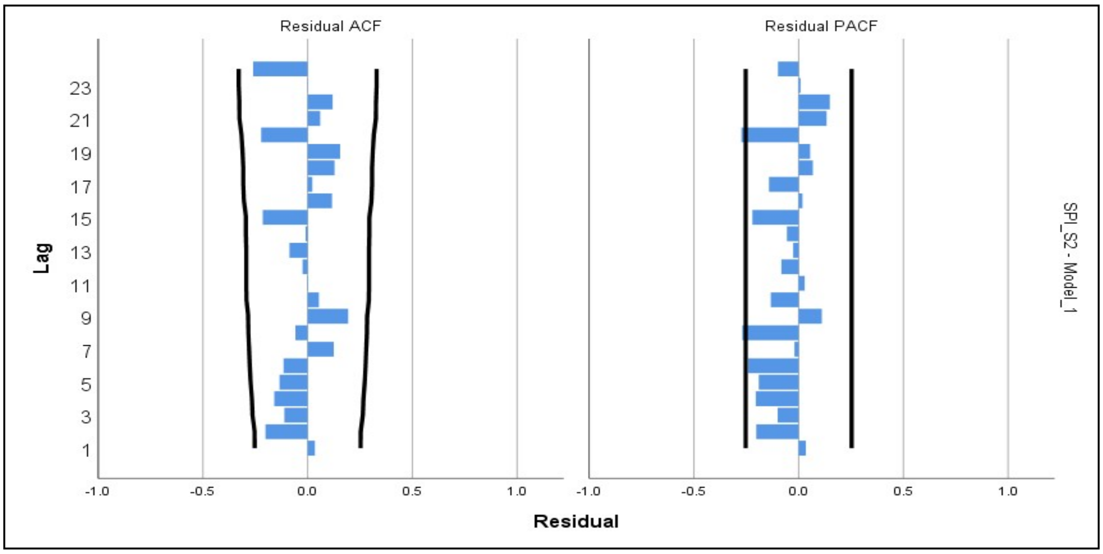
Date	S1	S2	S3	S4	S5	S6	S7
Sep 2024	103.39	132.40	208.34	218.71	229.39	235.53	270.71
Oct 2024	105.45	134.16	208.65	213.79	224.71	228.40	269.39
Nov 2024	111.31	136.04	204.76	214.44	233.54	242.40	278.20
Dec 2024	116.32	138.97	210.84	218.61	235.10	244.68	273.02
Jan 2025	112.40	132.43	205.61	217.27	229.58	240.05	273.00
Feb 2025	121.23	141.65	221.14	230.61	247.55	255.07	291.44
Mar 2025	127.84	152.24	237.28	245.64	263.50	269.71	302.07
Apr 2025	113.84	156.78	244.14	249.00	274.36	277.25	304.34
May 2025	126.14	164.92	248.61	258.68	277.56	285.45	310.31
Jun 2025	126.64	161.14	237.97	247.60	261.78	268.02	295.30
Jul 2025	115.96	153.27	231.44	240.76	253.02	261.72	295.01
Aug 2025	91.97	126.89	202.86	211.58	223.03	226.38	248.92
Sep 2025	104.35	135.21	217.00	226.67	236.58	241.80	277.27
Oct 2025	106.43	136.97	217.31	221.75	231.91	234.67	275.95
Nov 2025	112.35	138.85	213.42	222.40	240.74	248.67	284.76
Dec 2025	117.41	141.78	219.50	226.57	242.30	250.96	279.58
Jan 2026	113.45	135.24	214.27	225.23	236.77	246.32	279.56
Feb 2026	122.36	144.46	229.80	238.57	254.75	261.34	298.00
Mar 2026	129.03	155.05	245.94	253.60	270.70	275.99	308.63
Apr 2026	114.90	159.59	252.80	256.96	281.56	283.52	310.90
May 2026	127.32	167.73	257.27	266.64	284.75	291.72	316.87
Jun 2026	127.82	163.95	246.63	255.56	268.98	274.29	301.86
Jul 2026	117.05	156.08	240.10	248.72	260.21	268.00	301.57
Aug 2026	92.82	129.69	211.52	219.54	230.22	232.65	255.48
Sep 2026	105.32	138.02	225.66	234.63	243.78	248.07	283.83
Oct 2026	107.43	139.78	225.97	229.71	239.10	240.94	282.51
Nov 2026	113.40	141.66	222.08	230.36	247.93	254.94	291.32
Dec 2026	118.50	144.59	228.16	234.53	249.49	257.23	286.14
Jan 2027	114.51	138.05	222.93	233.19	243.97	252.60	286.12
Feb 2027	123.50	147.27	238.46	246.53	261.94	267.61	304.56
Mar 2027	130.24	157.86	254.60	261.56	277.89	282.26	315.19
Apr 2027	115.98	162.40	261.46	264.92	288.75	289.80	317.46
May 2027	128.51	170.54	265.93	274.60	291.95	297.99	323.43
Jun 2027	129.02	166.76	255.29	263.52	276.17	280.57	308.42
Jul 2027	118.14	158.89	248.75	256.68	267.41	274.27	308.13
Aug 2027	93.69	132.50	220.17	227.49	237.42	238.92	262.04
Sep 2027	106.31	140.83	234.32	242.59	250.97	254.34	290.39
Oct 2027	108.43	142.58	234.63	237.67	246.30	247.22	289.07
Nov 2027	114.46	144.47	230.74	238.32	255.13	261.21	297.88
Dec 2027	119.61	147.40	236.82	242.49	256.69	263.50	292.71

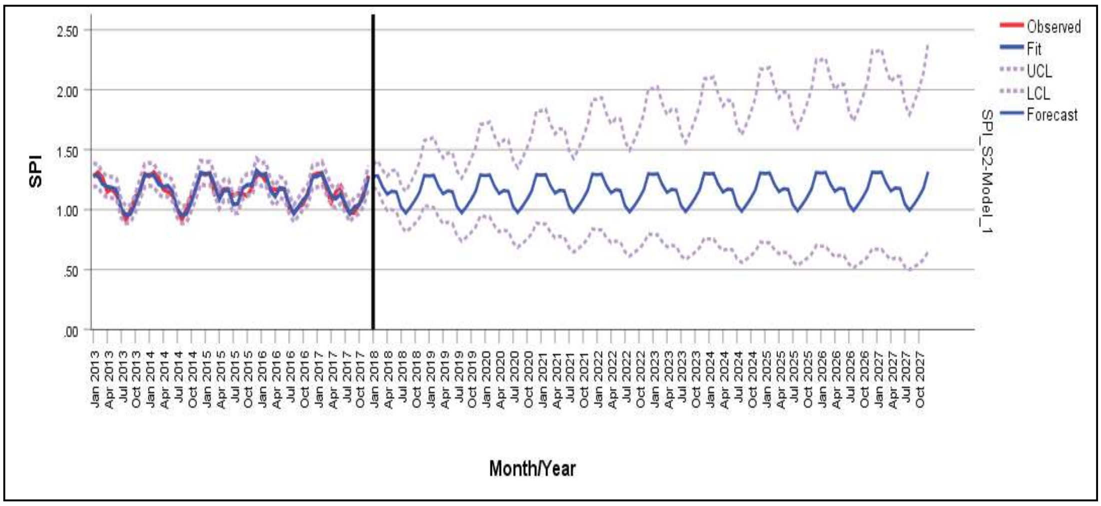
ANNEXURE – IV

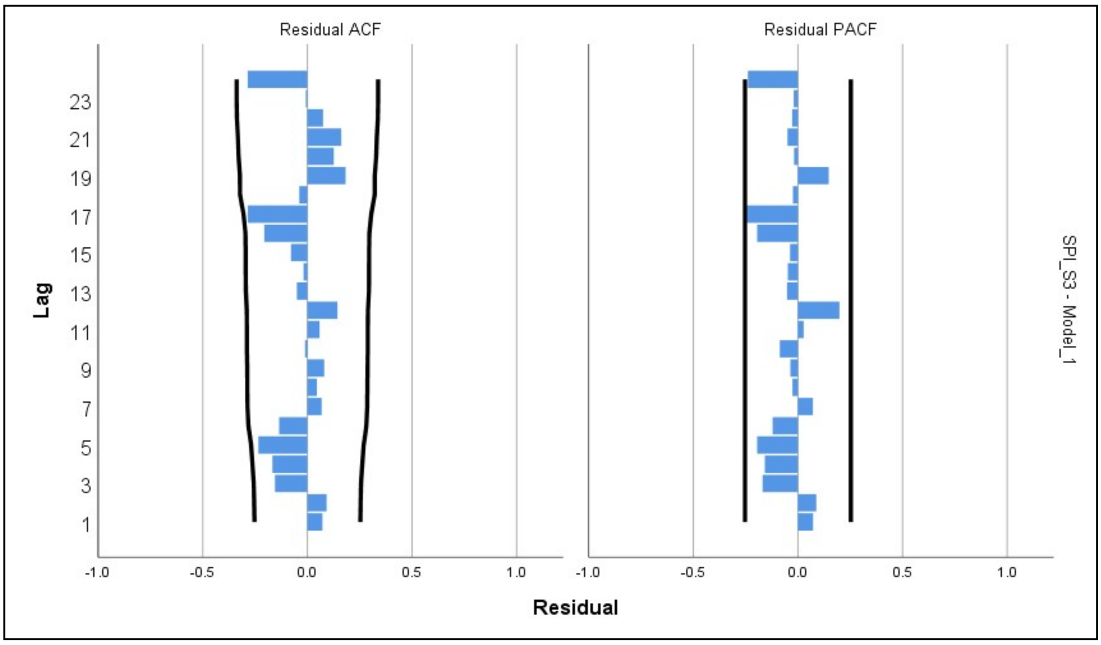
Graphical representation of trend, time series analysis (ACF, PACF, observed, best fit, LCL, UCL) of SPI (S1 – S7)

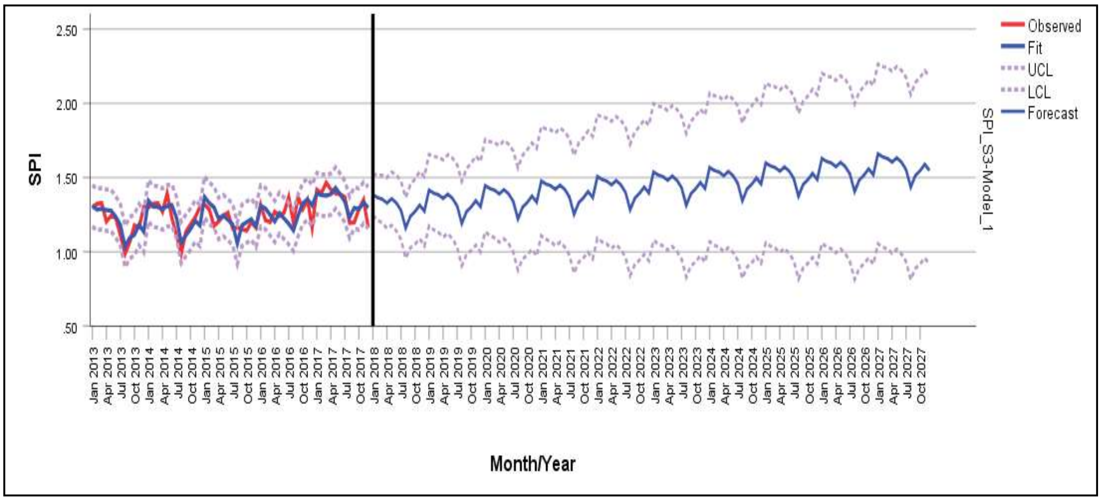


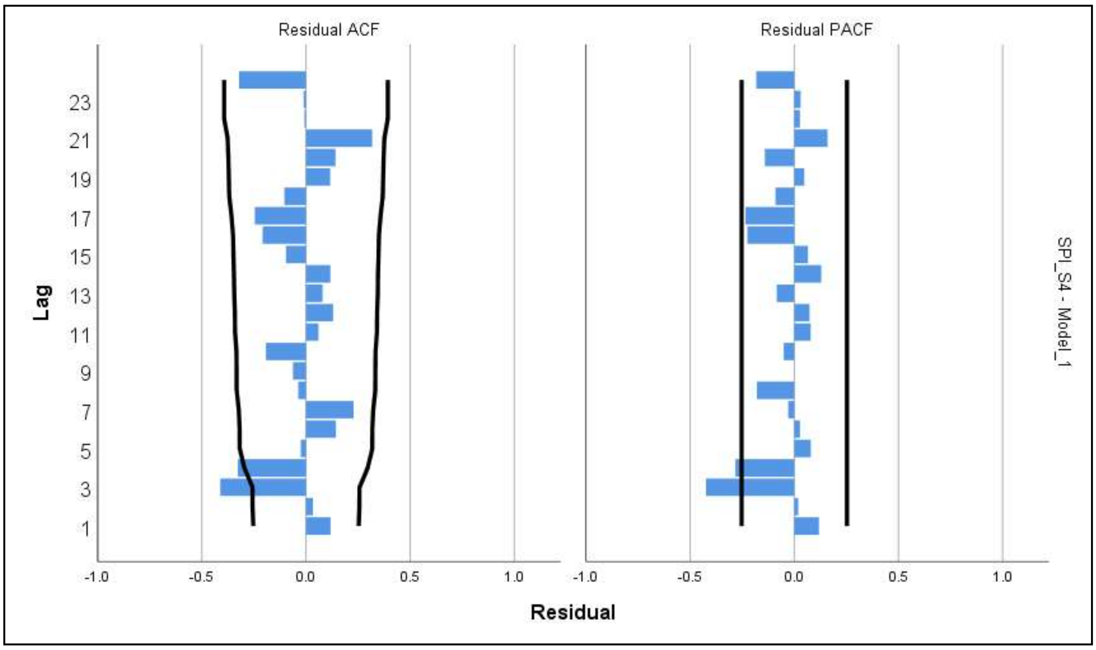




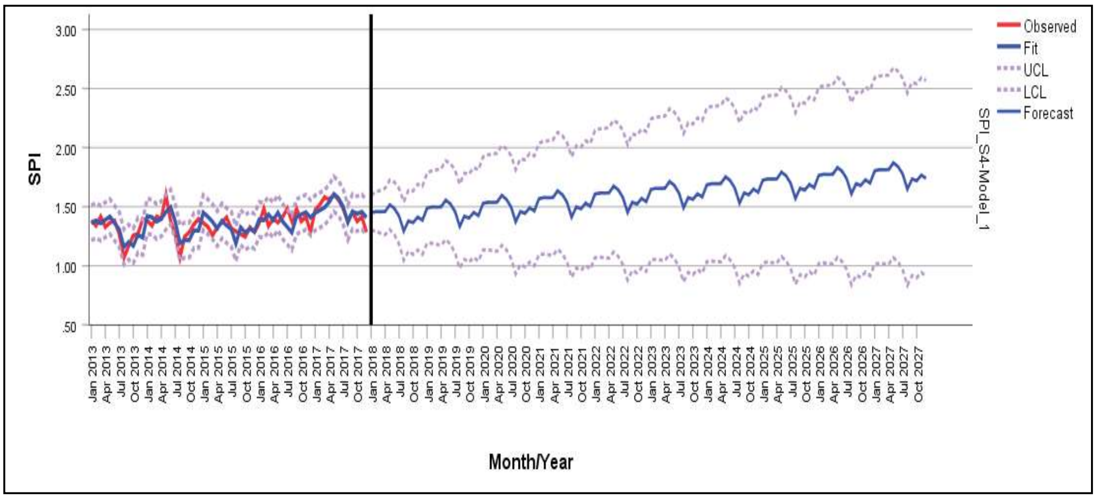

SPI
Month/Year
Observed
Fit
UCL
LCL
Forecast
SPI_S2-Model_1


Residual ACF
Residual PACF
Lag
Residual
SPI_S3 - Model_1

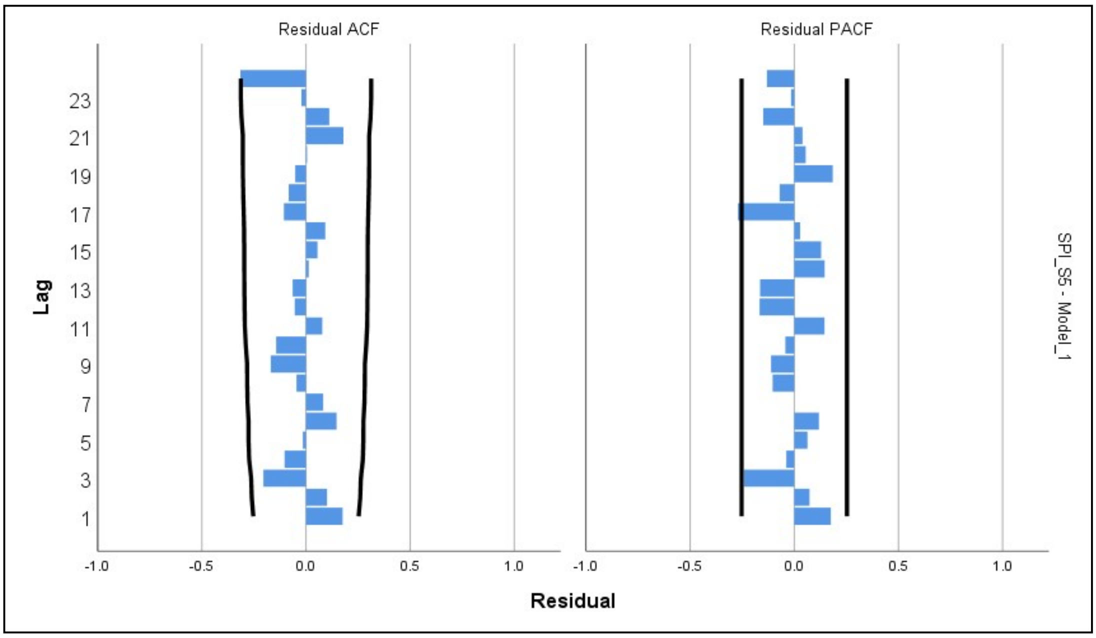

SPI
Month/Year
Observed
Fit
UCL
LCL
Forecast
SPI_S3-Model_1



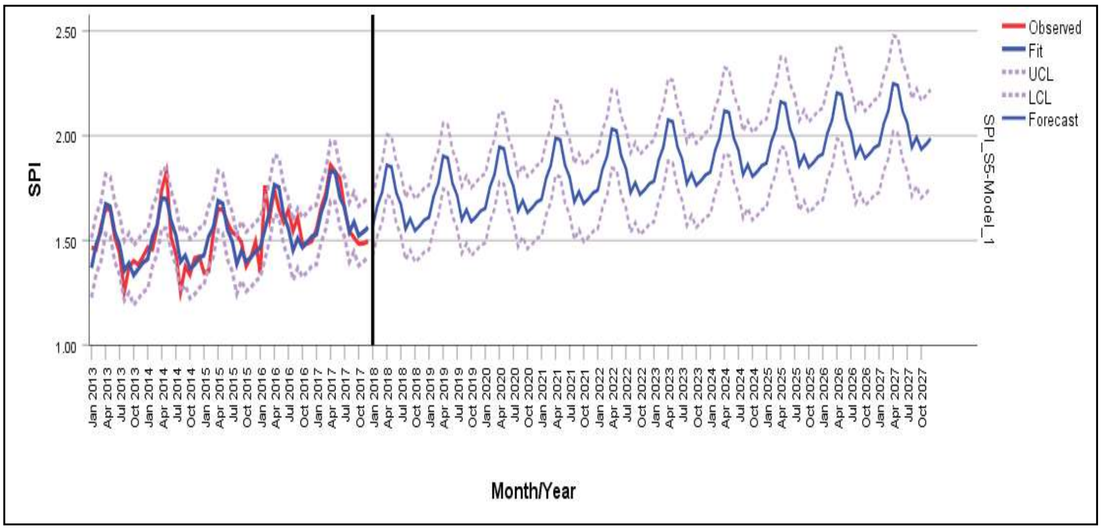
Residual ACF
Residual PACF
Lag
Residual
SPI_S4 - Model_1



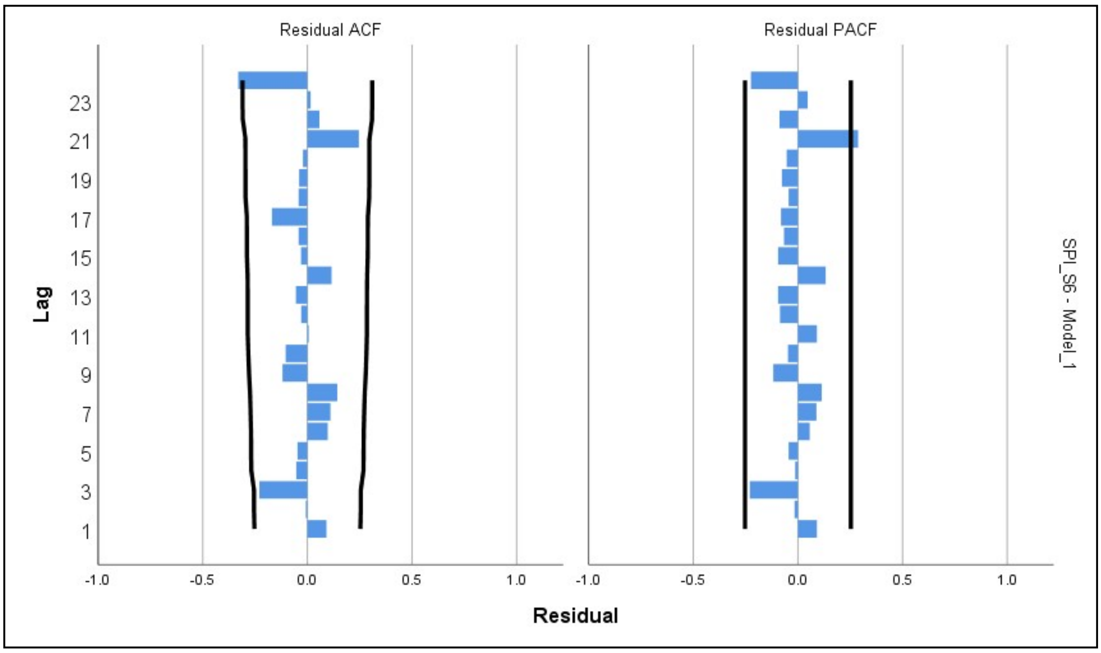
SPI
Month/Year
Observed
Fit
UCL
LCL
Forecast
SPI_S4-Model_1



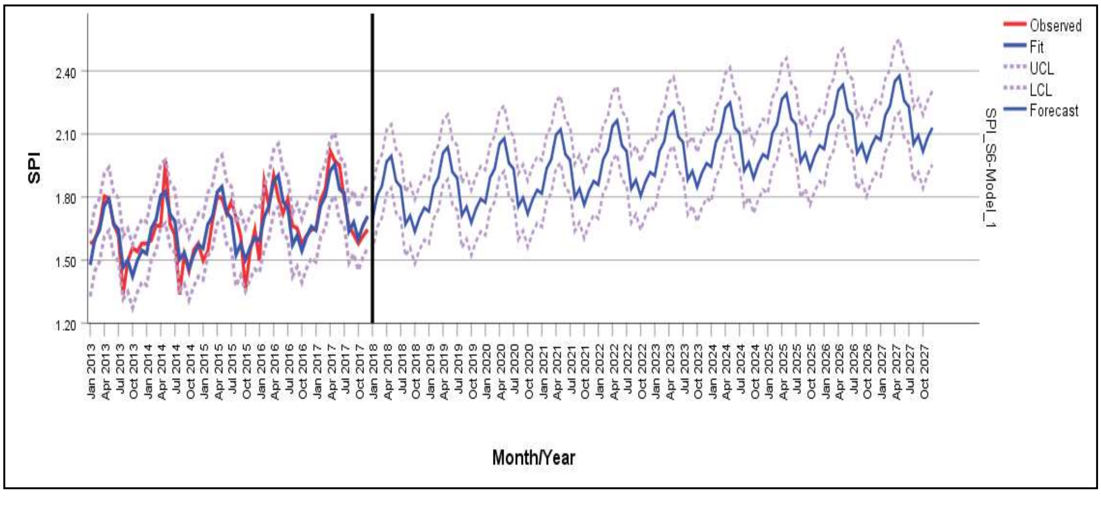
Residual ACF
Residual PACF
Lag
Residual
SPI_S5 - Model_1



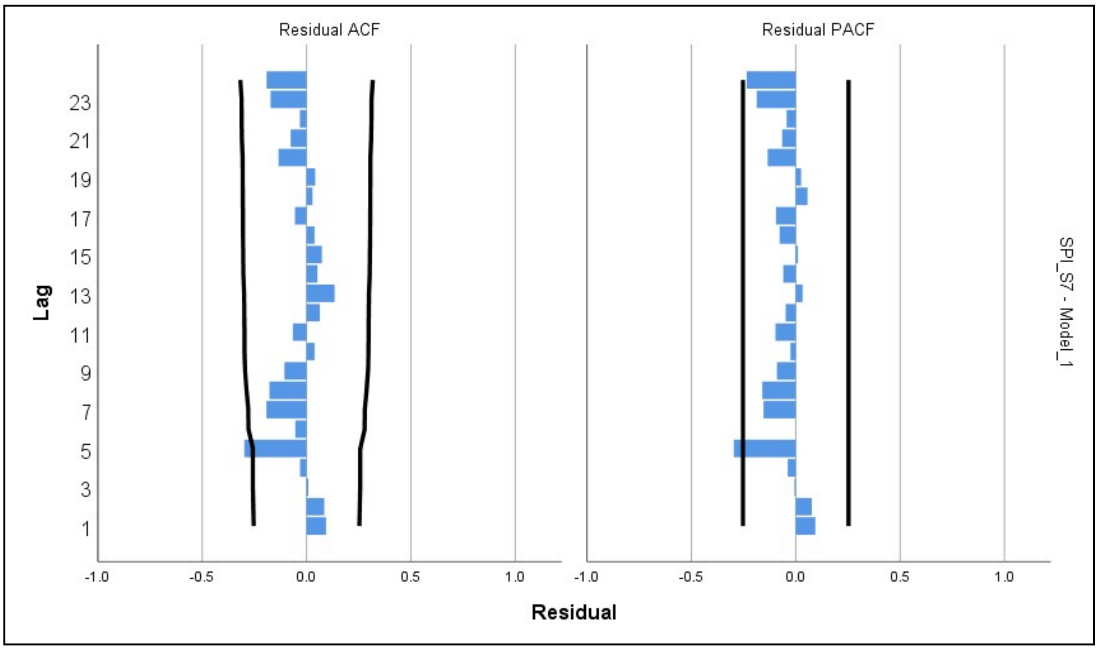
SPI
Month/Year
Observed
Fit
UCL
LCL
Forecast
SPI_S5-Model_1

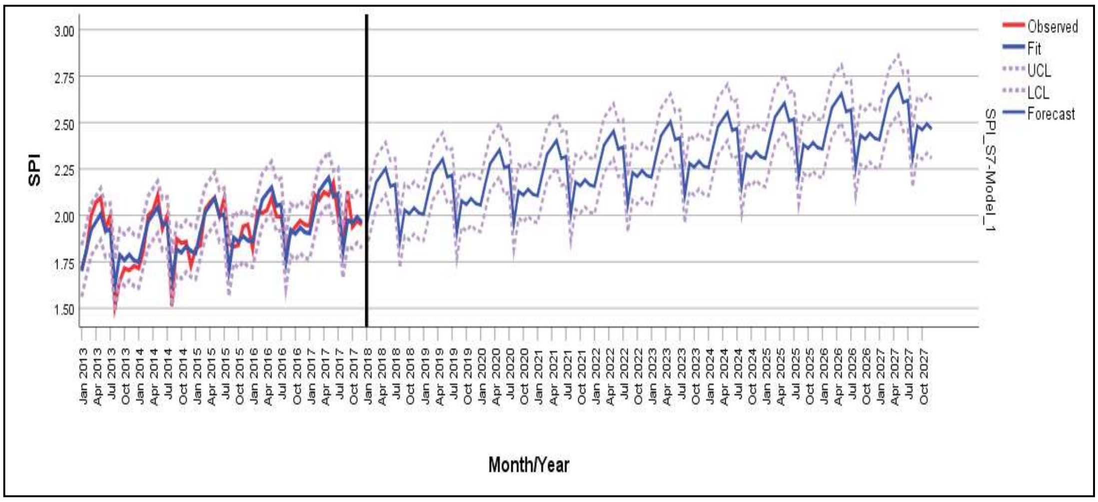


Residual ACF
Residual PACF
Lag
Residual
SPI_S6 - Model_1



SPI
Month/Year
Observed
Fit
UCL
LCL
Forecast
SPI_S6-Model_1


Residual ACF
Residual PACF
Lag
23
21
19
17
15
13
11
9
7
5
3
1
-1.0
-0.5
0.0
0.5
1.0
Residual
SPI_S7 - Model_1


Observed
Fit
UCL
LCL
Forecast
SPI
3.00
2.75
2.50
2.25
2.00
1.75
1.50
SPI_S7-Model_1
Month/Year

ANNEXURE – V

Predicted value of SPI (2018-2027) by Time-series analysis

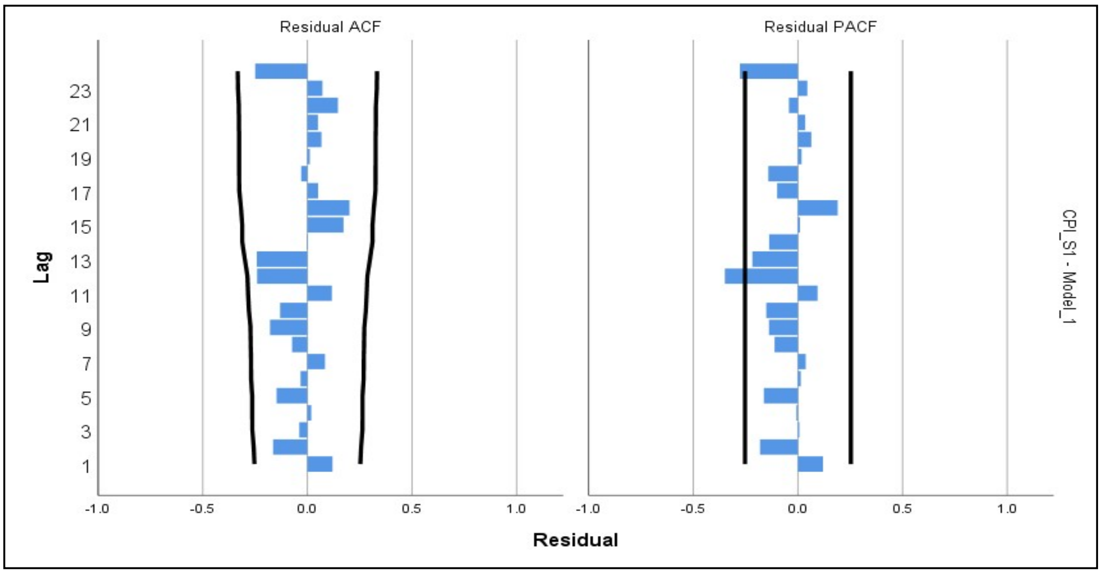
Date	S1	S2	S3	S4	S5	S6	S7
Jan 2018	1.261	1.277	1.385	1.449	1.567	1.690	1.955
Feb 2018	1.274	1.283	1.364	1.459	1.668	1.808	2.070
Mar 2018	1.184	1.191	1.354	1.458	1.731	1.851	2.177
Apr 2018	1.136	1.129	1.329	1.459	1.859	1.968	2.215
May 2018	1.134	1.154	1.358	1.517	1.851	1.994	2.253
Jun 2018	1.124	1.147	1.330	1.485	1.730	1.876	2.156
Jul 2018	1.020	1.021	1.279	1.420	1.672	1.849	2.167
Aug 2018	0.974	0.971	1.161	1.294	1.555	1.670	1.858
Sep 2018	1.007	1.021	1.240	1.380	1.603	1.711	2.029
Oct 2018	1.071	1.080	1.271	1.365	1.547	1.635	2.008
Nov 2018	1.132	1.151	1.314	1.412	1.569	1.702	2.041
Dec 2018	1.258	1.286	1.273	1.386	1.598	1.748	2.013
Jan 2019	1.271	1.281	1.415	1.489	1.610	1.732	2.005
Feb 2019	1.284	1.286	1.395	1.498	1.711	1.850	2.120
Mar 2019	1.193	1.194	1.385	1.497	1.774	1.894	2.228
Apr 2019	1.145	1.132	1.359	1.498	1.903	2.010	2.266
May 2019	1.142	1.157	1.388	1.556	1.894	2.037	2.303
Jun 2019	1.133	1.150	1.360	1.524	1.773	1.918	2.207
Jul 2019	1.028	1.024	1.309	1.459	1.715	1.891	2.217
Aug 2019	0.981	0.973	1.191	1.333	1.599	1.713	1.909
Sep 2019	1.015	1.024	1.270	1.420	1.647	1.754	2.079
Oct 2019	1.079	1.083	1.302	1.404	1.590	1.678	2.059
Nov 2019	1.141	1.154	1.345	1.452	1.612	1.744	2.091
Dec 2019	1.267	1.289	1.304	1.425	1.641	1.791	2.063
Jan 2020	1.280	1.284	1.446	1.528	1.653	1.774	2.056
Feb 2020	1.293	1.289	1.425	1.537	1.754	1.892	2.171
Mar 2020	1.202	1.197	1.415	1.537	1.817	1.936	2.278
Apr 2020	1.154	1.135	1.390	1.538	1.946	2.053	2.316
May 2020	1.151	1.160	1.419	1.596	1.937	2.079	2.353
Jun 2020	1.141	1.153	1.391	1.564	1.817	1.960	2.257
Jul 2020	1.036	1.027	1.340	1.499	1.759	1.934	2.267
Aug 2020	0.989	0.976	1.222	1.373	1.642	1.755	1.959
Sep 2020	1.023	1.027	1.301	1.459	1.690	1.796	2.129
Oct 2020	1.087	1.086	1.332	1.444	1.633	1.720	2.109
Nov 2020	1.149	1.157	1.375	1.491	1.656	1.787	2.141
Dec 2020	1.277	1.293	1.335	1.465	1.684	1.833	2.113
Jan 2021	1.290	1.287	1.476	1.568	1.696	1.817	2.106
Feb 2021	1.303	1.293	1.456	1.577	1.798	1.935	2.221
Mar 2021	1.211	1.201	1.446	1.576	1.860	1.979	2.328

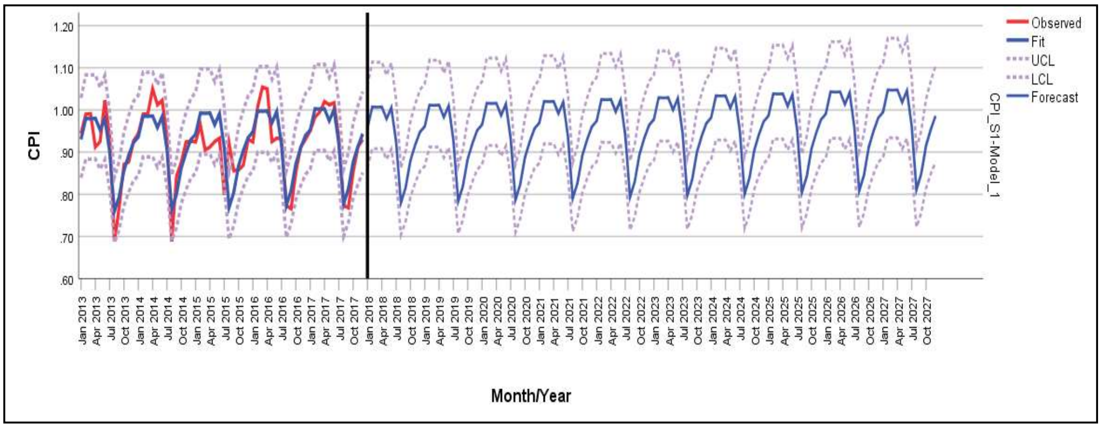
Date	S1	S2	S3	S4	S5	S6	S7
Apr 2021	1.162	1.138	1.420	1.577	1.989	2.095	2.366
May 2021	1.160	1.163	1.449	1.635	1.980	2.121	2.404
Jun 2021	1.150	1.156	1.421	1.603	1.860	2.003	2.307
Jul 2021	1.044	1.030	1.370	1.538	1.802	1.976	2.317
Aug 2021	0.996	0.978	1.252	1.412	1.685	1.798	2.009
Sep 2021	1.030	1.029	1.331	1.499	1.733	1.839	2.179
Oct 2021	1.095	1.089	1.363	1.483	1.677	1.762	2.159
Nov 2021	1.158	1.160	1.406	1.531	1.699	1.829	2.191
Dec 2021	1.287	1.296	1.365	1.504	1.727	1.875	2.164
Jan 2022	1.300	1.291	1.507	1.607	1.740	1.859	2.156
Feb 2022	1.313	1.296	1.486	1.616	1.841	1.977	2.271
Mar 2022	1.220	1.204	1.476	1.616	1.903	2.021	2.378
Apr 2022	1.171	1.141	1.451	1.617	2.032	2.138	2.416
May 2022	1.168	1.166	1.480	1.675	2.024	2.164	2.454
Jun 2022	1.159	1.159	1.452	1.643	1.903	2.045	2.357
Jul 2022	1.051	1.032	1.401	1.578	1.845	2.019	2.368
Aug 2022	1.004	0.981	1.283	1.452	1.728	1.840	2.059
Sep 2022	1.038	1.032	1.362	1.538	1.776	1.881	2.230
Oct 2022	1.104	1.091	1.394	1.522	1.720	1.805	2.209
Nov 2022	1.167	1.163	1.436	1.570	1.742	1.871	2.242
Dec 2022	1.297	1.299	1.396	1.544	1.770	1.918	2.214
Jan 2023	1.309	1.294	1.538	1.647	1.783	1.902	2.206
Feb 2023	1.323	1.299	1.517	1.656	1.884	2.020	2.321
Mar 2023	1.229	1.207	1.507	1.655	1.946	2.063	2.429
Apr 2023	1.180	1.144	1.482	1.656	2.075	2.180	2.467
May 2023	1.177	1.169	1.510	1.714	2.067	2.206	2.504
Jun 2023	1.167	1.162	1.482	1.682	1.946	2.088	2.408
Jul 2023	1.059	1.035	1.432	1.617	1.888	2.061	2.418
Aug 2023	1.011	0.984	1.313	1.491	1.771	1.882	2.110
Sep 2023	1.046	1.035	1.392	1.577	1.819	1.923	2.280
Oct 2023	1.112	1.094	1.424	1.562	1.763	1.847	2.260
Nov 2023	1.176	1.166	1.467	1.610	1.785	1.914	2.292
Dec 2023	1.306	1.303	1.426	1.583	1.814	1.960	2.264
Jan 2024	1.319	1.298	1.568	1.686	1.826	1.944	2.257
Feb 2024	1.333	1.303	1.547	1.695	1.927	2.062	2.372
Mar 2024	1.239	1.210	1.537	1.694	1.990	2.106	2.479
Apr 2024	1.189	1.147	1.512	1.696	2.118	2.222	2.517
May 2024	1.186	1.172	1.541	1.753	2.110	2.249	2.554
Jun 2024	1.176	1.165	1.513	1.721	1.989	2.130	2.458
Jul 2024	1.067	1.038	1.462	1.657	1.931	2.103	2.468
Aug 2024	1.019	0.986	1.344	1.530	1.815	1.925	2.160

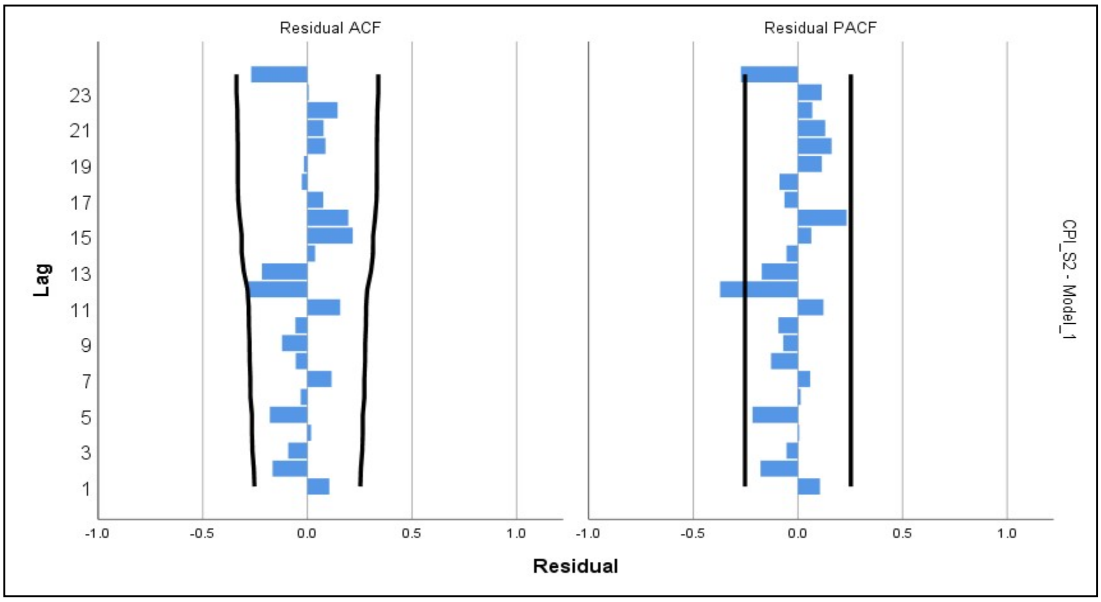
Date	S1	S2	S3	S4	S5	S6	S7
Sep 2024	1.054	1.037	1.423	1.617	1.863	1.966	2.330
Oct 2024	1.120	1.097	1.455	1.601	1.806	1.890	2.310
Nov 2024	1.185	1.169	1.498	1.649	1.828	1.956	2.342
Dec 2024	1.316	1.306	1.457	1.622	1.857	2.002	2.314
Jan 2025	1.329	1.301	1.599	1.725	1.869	1.986	2.307
Feb 2025	1.343	1.306	1.578	1.735	1.970	2.104	2.422
Mar 2025	1.248	1.213	1.568	1.734	2.033	2.148	2.529
Apr 2025	1.198	1.150	1.543	1.735	2.162	2.265	2.567
May 2025	1.195	1.175	1.571	1.793	2.153	2.291	2.605
Jun 2025	1.185	1.169	1.543	1.761	2.032	2.172	2.508
Jul 2025	1.076	1.040	1.493	1.696	1.975	2.146	2.518
Aug 2025	1.027	0.989	1.374	1.570	1.858	1.967	2.210
Sep 2025	1.062	1.040	1.453	1.656	1.906	2.008	2.380
Oct 2025	1.129	1.100	1.485	1.641	1.849	1.932	2.360
Nov 2025	1.194	1.172	1.528	1.689	1.872	1.999	2.392
Dec 2025	1.326	1.310	1.487	1.662	1.900	2.045	2.365
Jan 2026	1.339	1.304	1.629	1.765	1.912	2.029	2.357
Feb 2026	1.353	1.310	1.609	1.774	2.014	2.147	2.472
Mar 2026	1.258	1.216	1.599	1.773	2.076	2.191	2.580
Apr 2026	1.207	1.153	1.573	1.775	2.205	2.307	2.618
May 2026	1.204	1.178	1.602	1.832	2.196	2.333	2.655
Jun 2026	1.194	1.172	1.574	1.800	2.076	2.215	2.558
Jul 2026	1.084	1.043	1.523	1.736	2.018	2.188	2.569
Aug 2026	1.034	0.991	1.405	1.609	1.901	2.010	2.260
Sep 2026	1.070	1.043	1.484	1.696	1.949	2.051	2.431
Oct 2026	1.137	1.103	1.516	1.680	1.893	1.974	2.410
Nov 2026	1.203	1.175	1.559	1.728	1.915	2.041	2.443
Dec 2026	1.336	1.313	1.518	1.701	1.943	2.087	2.415
Jan 2027	1.350	1.308	1.660	1.804	1.956	2.071	2.407
Feb 2027	1.364	1.313	1.639	1.814	2.057	2.189	2.522
Mar 2027	1.267	1.220	1.629	1.813	2.119	2.233	2.630
Apr 2027	1.216	1.156	1.604	1.814	2.248	2.350	2.668
May 2027	1.213	1.181	1.633	1.872	2.239	2.376	2.705
Jun 2027	1.203	1.175	1.605	1.840	2.119	2.257	2.609
Jul 2027	1.092	1.046	1.554	1.775	2.061	2.231	2.619
Aug 2027	1.042	0.994	1.436	1.649	1.944	2.052	2.311
Sep 2027	1.078	1.045	1.515	1.735	1.992	2.093	2.481
Oct 2027	1.146	1.106	1.546	1.720	1.936	2.017	2.461
Nov 2027	1.212	1.178	1.589	1.767	1.958	2.083	2.493
Dec 2027	1.346	1.316	1.548	1.741	1.986	2.130	2.465

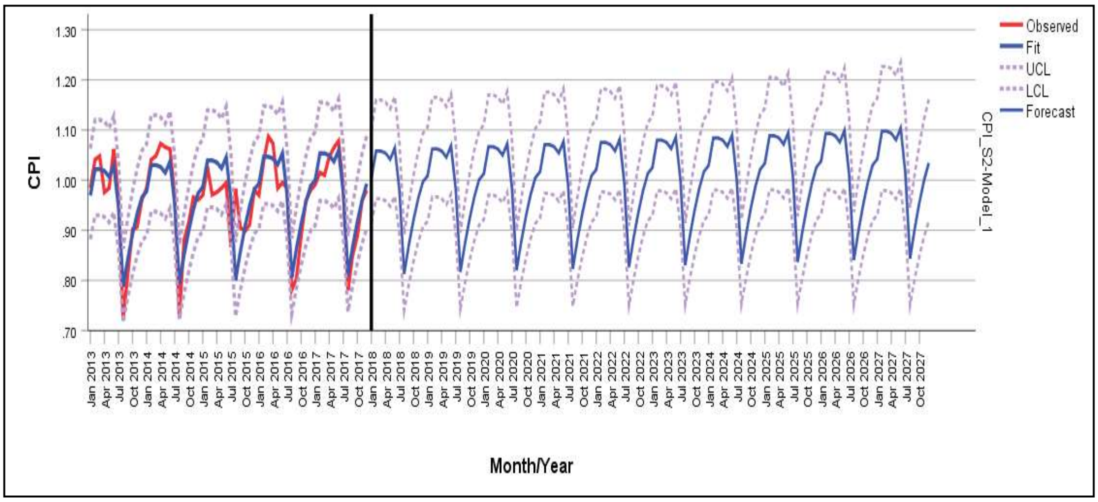
ANNEXURE – VI

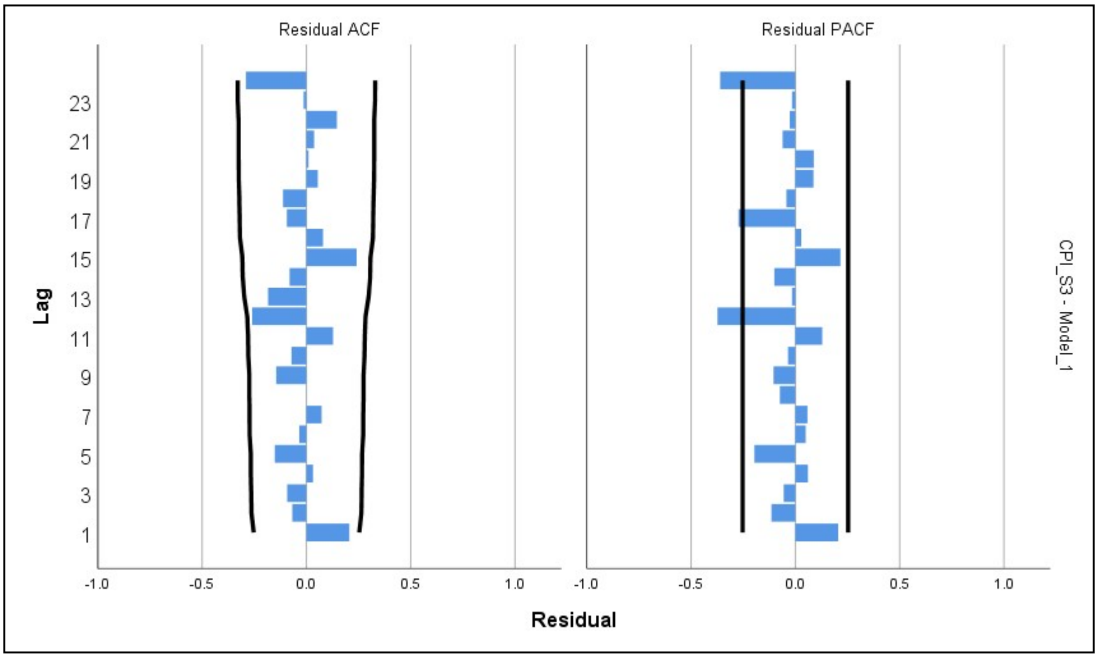
Graphical representation of trend, time series analysis (ACF, PACF, observed, best fit, LCL, UCL) of CPI (S1 – S7)

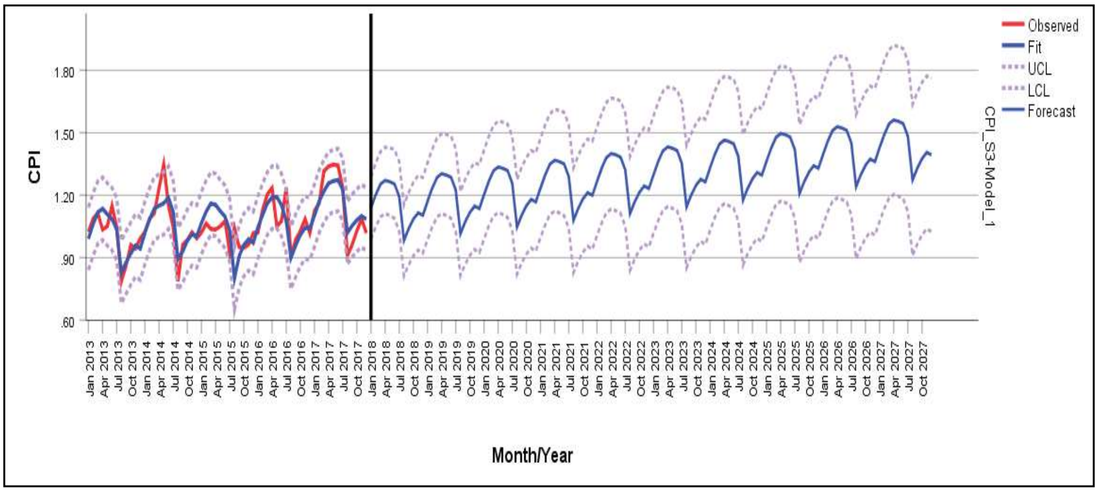


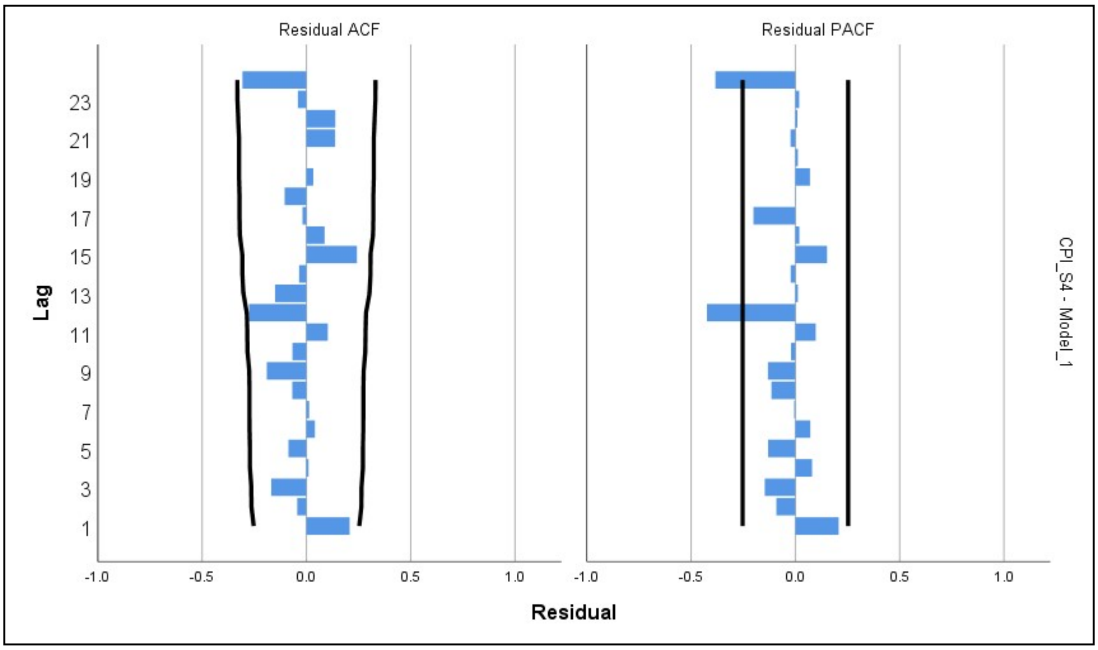


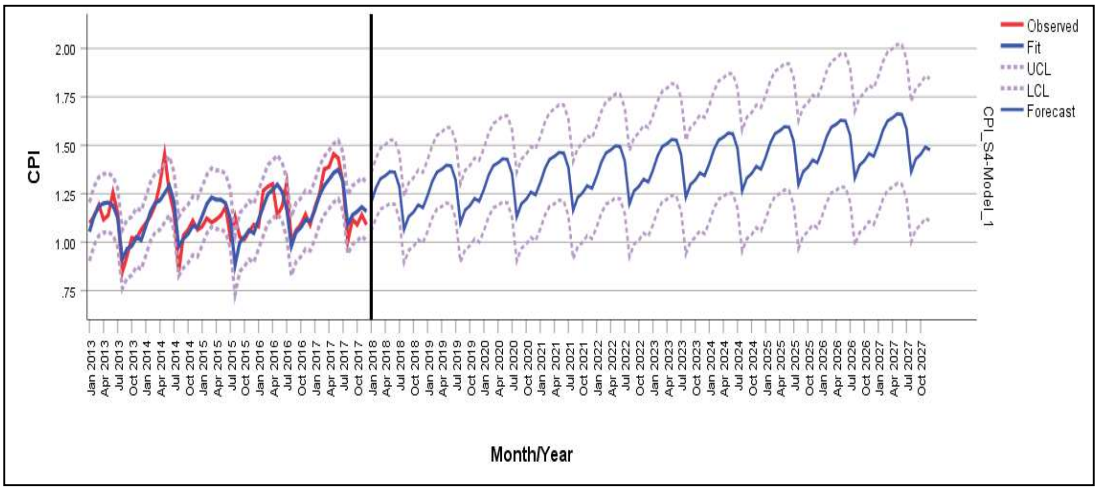


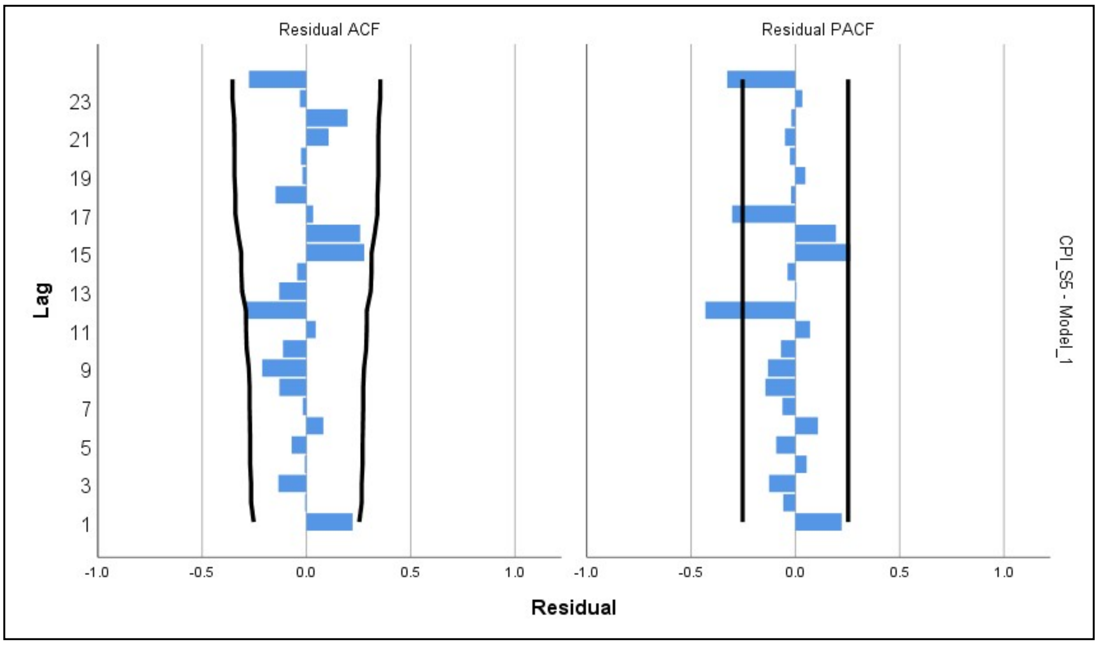

Observed
Fit
UCL
LCL
Forecast
CPI
CPI_S2-Model_1
Month/Year

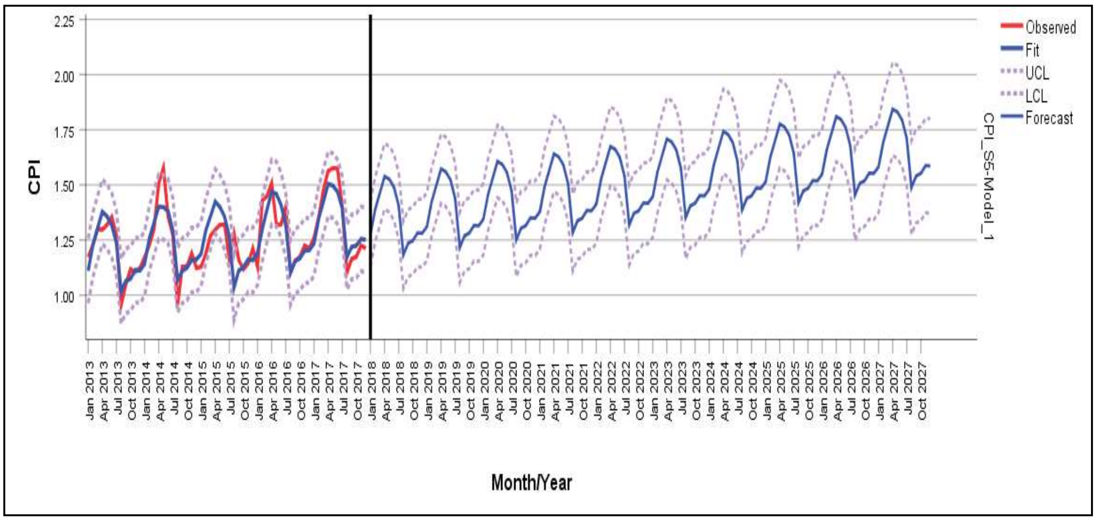

Residual ACF
Residual PACF
Lag
Residual
CPI_S3 - Model_1


Observed
Fit
UCL
LCL
Forecast
CPI
CPI_S3-Model_1
Month/Year

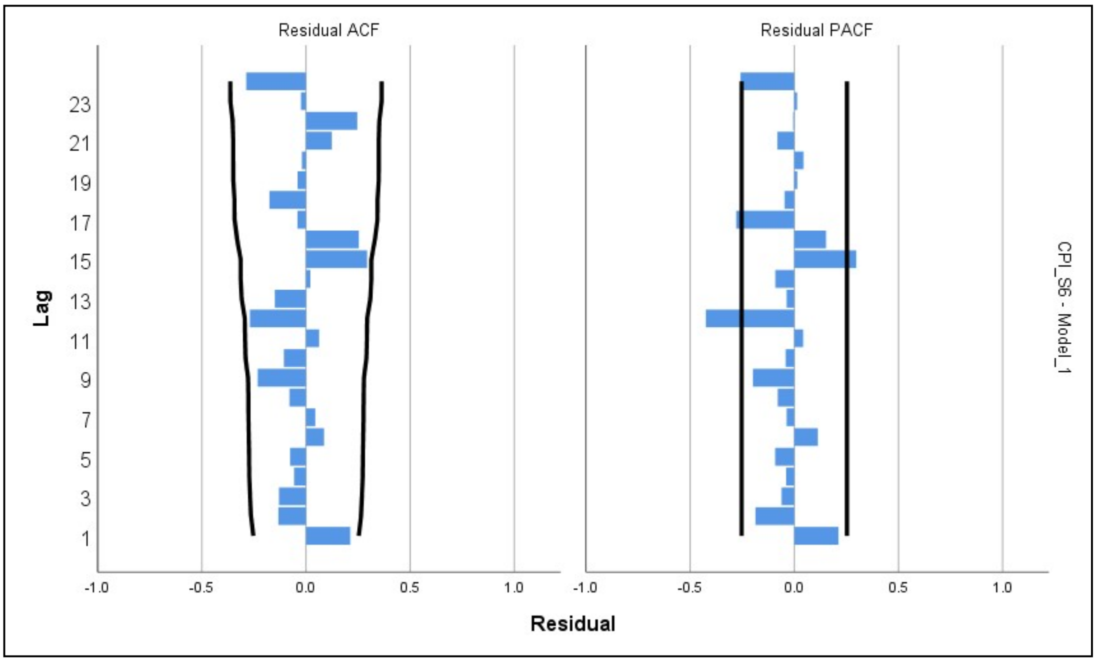

Residual ACF
Residual PACF
Lag
23
21
19
17
15
13
11
9
7
5
3
1
-1.0
-0.5
0.0
0.5
1.0
Residual
CPI_S4 - Model_1


Observed
Fit
UCL
LCL
Forecast
CPI
2.00
1.75
1.50
1.25
1.00
.75
CPI_S4-Model_1
Month/Year

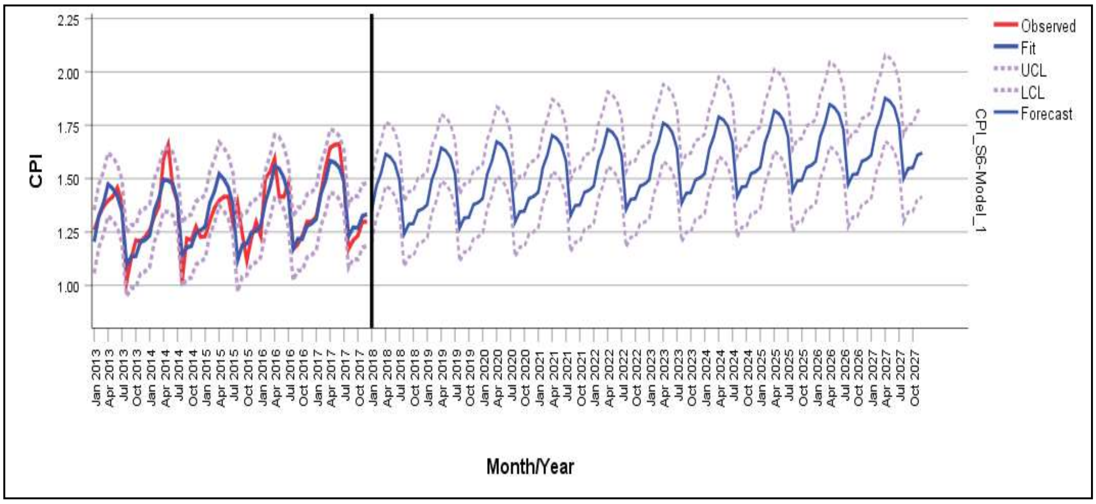

Residual ACF
Residual PACF
Lag
23
21
19
17
15
13
11
9
7
5
3
1
-1.0
-0.5
0.0
0.5
1.0
Residual
CPI_S5 - Model_1



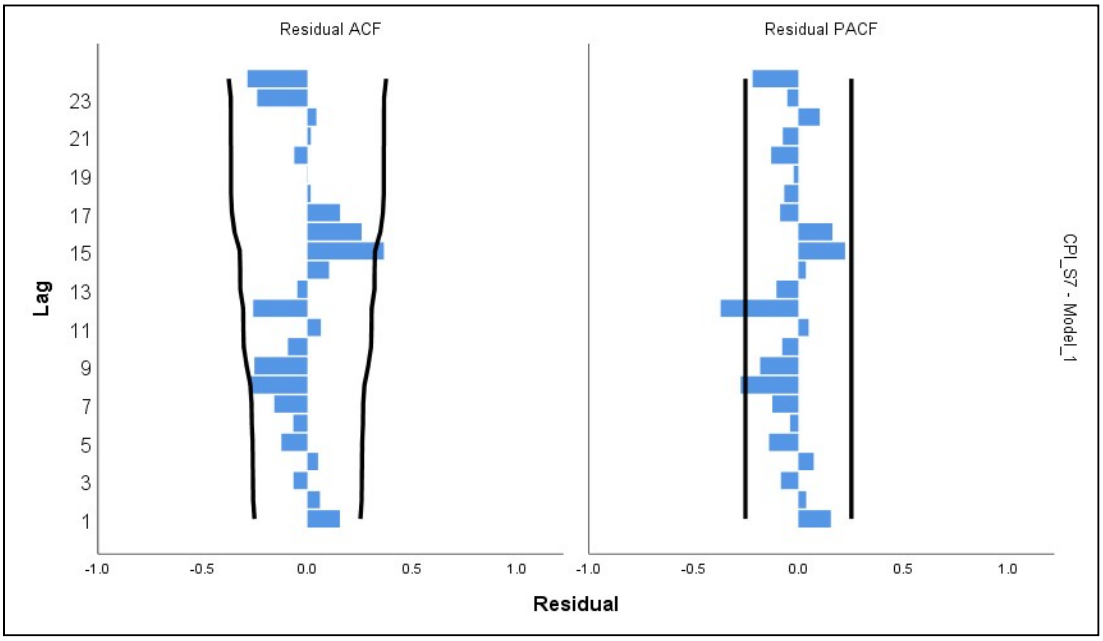
Observed
Fit
UCL
LCL
Forecast
CPI_S5-Model_1
CPI
Month/Year



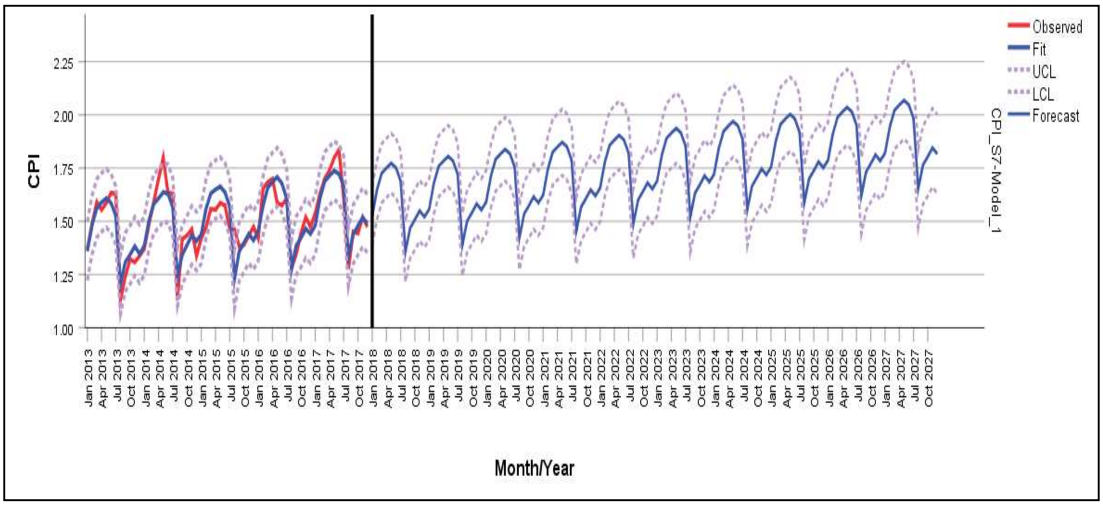
Residual ACF
Residual PACF
Lag
Residual
CPI_S6 - Model_1



Observed
Fit
UCL
LCL
Forecast
CPI_S6-Model_1
CPI
Month/Year



Residual ACF
Residual PACF
Lag
Residual
CPI_S7 - Model_1



Observed
Fit
UCL
LCL
Forecast
CPI
Month/Year
CPI_S7-Model_1

ANNEXURE – VII

Predicted value of CPI (2018-2027) by Time-series analysis

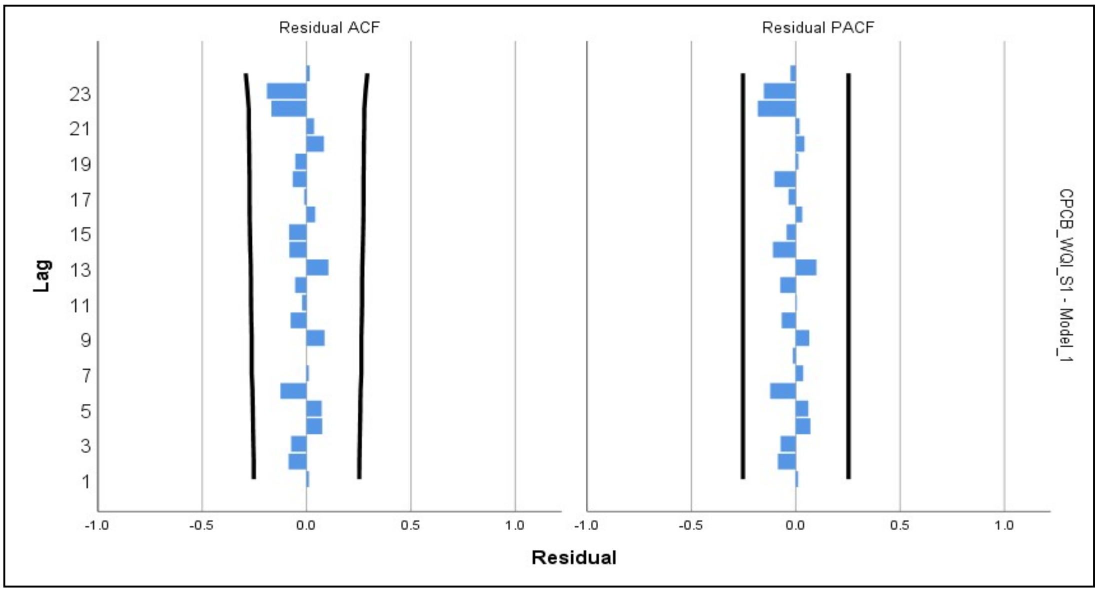
Date	S1	S2	S3	S4	S5	S6	S7
Jan 2018	0.957	1.005	1.138	1.206	1.277	1.349	1.525
Feb 2018	1.007	1.058	1.202	1.280	1.389	1.465	1.647
Mar 2018	1.007	1.058	1.253	1.329	1.464	1.525	1.726
Apr 2018	1.007	1.054	1.271	1.343	1.539	1.615	1.751
May 2018	0.979	1.042	1.265	1.364	1.526	1.601	1.773
Jun 2018	1.005	1.064	1.254	1.361	1.489	1.570	1.752
Jul 2018	0.925	0.978	1.192	1.286	1.405	1.495	1.689
Aug 2018	0.780	0.814	0.983	1.066	1.183	1.240	1.358
Sep 2018	0.816	0.871	1.040	1.133	1.236	1.287	1.469
Oct 2018	0.880	0.921	1.085	1.155	1.247	1.289	1.508
Nov 2018	0.917	0.964	1.116	1.192	1.282	1.349	1.550
Dec 2018	0.948	0.997	1.103	1.178	1.281	1.358	1.521
Jan 2019	0.961	1.009	1.170	1.239	1.311	1.378	1.557
Feb 2019	1.012	1.062	1.234	1.313	1.423	1.494	1.680
Mar 2019	1.011	1.062	1.285	1.362	1.498	1.554	1.759
Apr 2019	1.012	1.058	1.303	1.376	1.573	1.644	1.783
May 2019	0.983	1.046	1.297	1.397	1.560	1.631	1.806
Jun 2019	1.010	1.068	1.286	1.394	1.523	1.600	1.785
Jul 2019	0.929	0.982	1.225	1.319	1.439	1.524	1.722
Aug 2019	0.784	0.817	1.015	1.099	1.217	1.269	1.390
Sep 2019	0.820	0.875	1.072	1.166	1.270	1.316	1.502
Oct 2019	0.884	0.925	1.118	1.188	1.281	1.318	1.541
Nov 2019	0.921	0.968	1.148	1.226	1.316	1.378	1.583
Dec 2019	0.952	1.001	1.136	1.211	1.315	1.388	1.554
Jan 2020	0.965	1.013	1.203	1.273	1.345	1.407	1.590
Feb 2020	1.016	1.067	1.266	1.346	1.457	1.523	1.713
Mar 2020	1.015	1.067	1.317	1.395	1.532	1.583	1.792
Apr 2020	1.016	1.063	1.336	1.409	1.606	1.673	1.816
May 2020	0.987	1.050	1.329	1.430	1.594	1.660	1.839
Jun 2020	1.014	1.073	1.318	1.428	1.557	1.629	1.818
Jul 2020	0.933	0.986	1.257	1.352	1.472	1.553	1.755
Aug 2020	0.787	0.820	1.048	1.132	1.251	1.298	1.423
Sep 2020	0.823	0.878	1.105	1.199	1.304	1.345	1.535
Oct 2020	0.888	0.929	1.150	1.221	1.315	1.347	1.574
Nov 2020	0.925	0.972	1.180	1.259	1.350	1.407	1.616
Dec 2020	0.956	1.005	1.168	1.245	1.349	1.417	1.587
Jan 2021	0.969	1.017	1.235	1.306	1.379	1.436	1.623
Feb 2021	1.020	1.071	1.299	1.380	1.491	1.552	1.746
Mar 2021	1.020	1.071	1.349	1.428	1.566	1.612	1.825

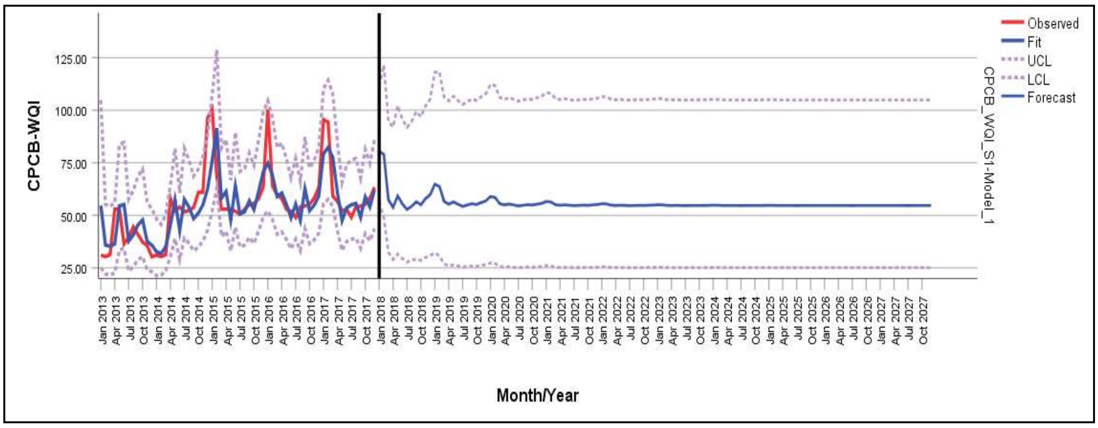
Date	S1	S2	S3	S4	S5	S6	S7
Apr 2021	1.020	1.067	1.368	1.442	1.640	1.702	1.849
May 2021	0.992	1.054	1.362	1.463	1.628	1.689	1.871
Jun 2021	1.019	1.077	1.351	1.461	1.591	1.658	1.851
Jul 2021	0.937	0.990	1.289	1.386	1.506	1.582	1.788
Aug 2021	0.790	0.824	1.080	1.165	1.285	1.327	1.456
Sep 2021	0.827	0.882	1.137	1.232	1.338	1.374	1.567
Oct 2021	0.892	0.932	1.182	1.254	1.349	1.376	1.607
Nov 2021	0.929	0.976	1.212	1.292	1.384	1.436	1.648
Dec 2021	0.960	1.009	1.200	1.278	1.383	1.446	1.619
Jan 2022	0.973	1.021	1.267	1.339	1.412	1.465	1.656
Feb 2022	1.025	1.075	1.331	1.413	1.525	1.581	1.779
Mar 2022	1.024	1.075	1.382	1.461	1.599	1.641	1.857
Apr 2022	1.025	1.071	1.400	1.475	1.674	1.731	1.882
May 2022	0.996	1.058	1.394	1.496	1.662	1.718	1.904
Jun 2022	1.023	1.081	1.383	1.494	1.625	1.687	1.883
Jul 2022	0.941	0.994	1.321	1.419	1.540	1.611	1.820
Aug 2022	0.794	0.827	1.112	1.198	1.318	1.356	1.489
Sep 2022	0.831	0.885	1.169	1.266	1.372	1.403	1.600
Oct 2022	0.896	0.936	1.214	1.287	1.383	1.406	1.639
Nov 2022	0.933	0.980	1.245	1.325	1.418	1.465	1.681
Dec 2022	0.964	1.013	1.232	1.311	1.417	1.475	1.652
Jan 2023	0.978	1.025	1.299	1.372	1.446	1.494	1.689
Feb 2023	1.029	1.080	1.363	1.446	1.559	1.610	1.812
Mar 2023	1.029	1.080	1.414	1.494	1.633	1.670	1.890
Apr 2023	1.029	1.076	1.432	1.509	1.708	1.760	1.915
May 2023	1.000	1.063	1.426	1.530	1.696	1.747	1.937
Jun 2023	1.027	1.086	1.415	1.527	1.659	1.716	1.916
Jul 2023	0.945	0.998	1.354	1.452	1.574	1.640	1.853
Aug 2023	0.797	0.831	1.144	1.231	1.352	1.385	1.522
Sep 2023	0.834	0.889	1.201	1.299	1.406	1.432	1.633
Oct 2023	0.899	0.940	1.247	1.320	1.417	1.435	1.672
Nov 2023	0.937	0.984	1.277	1.358	1.452	1.494	1.714
Dec 2023	0.969	1.017	1.265	1.344	1.451	1.504	1.685
Jan 2024	0.982	1.029	1.332	1.405	1.480	1.523	1.722
Feb 2024	1.034	1.084	1.395	1.479	1.592	1.639	1.844
Mar 2024	1.033	1.084	1.446	1.528	1.667	1.699	1.923
Apr 2024	1.034	1.080	1.464	1.542	1.742	1.789	1.948
May 2024	1.005	1.067	1.458	1.563	1.729	1.776	1.970
Jun 2024	1.032	1.090	1.447	1.560	1.693	1.745	1.949
Jul 2024	0.949	1.002	1.386	1.485	1.608	1.669	1.886
Aug 2024	0.801	0.834	1.177	1.265	1.386	1.414	1.555

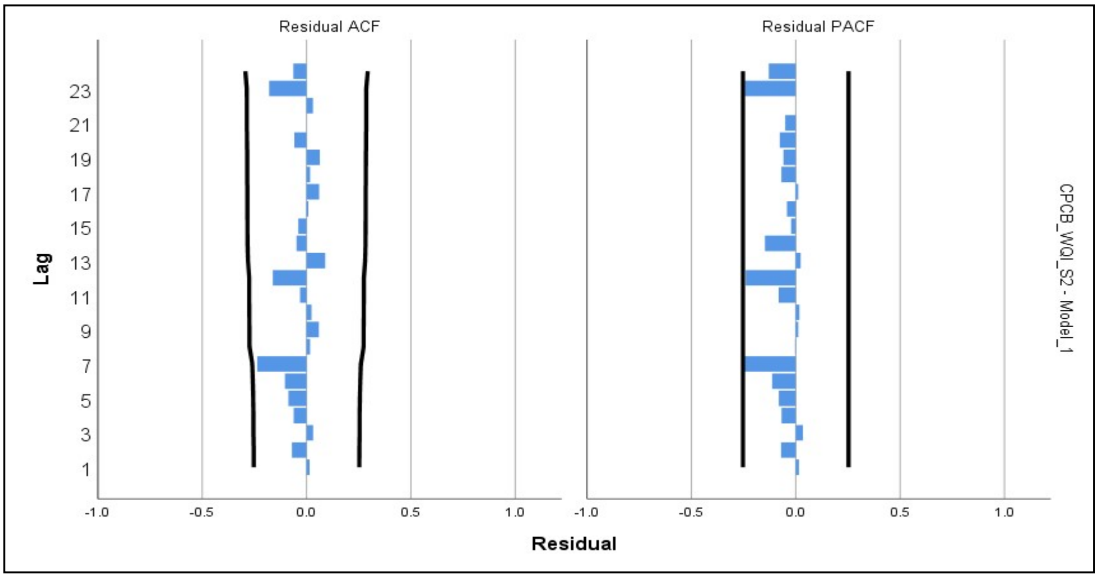
Date	S1	S2	S3	S4	S5	S6	S7
Sep 2024	0.838	0.892	1.233	1.332	1.439	1.461	1.666
Oct 2024	0.903	0.944	1.279	1.354	1.450	1.464	1.705
Nov 2024	0.942	0.988	1.309	1.391	1.486	1.523	1.747
Dec 2024	0.973	1.022	1.297	1.377	1.485	1.533	1.718
Jan 2025	0.986	1.033	1.364	1.438	1.514	1.552	1.755
Feb 2025	1.038	1.089	1.428	1.512	1.626	1.668	1.877
Mar 2025	1.038	1.089	1.478	1.561	1.701	1.729	1.956
Apr 2025	1.038	1.084	1.497	1.575	1.776	1.818	1.981
May 2025	1.009	1.072	1.490	1.596	1.763	1.805	2.003
Jun 2025	1.036	1.095	1.479	1.593	1.727	1.774	1.982
Jul 2025	0.953	1.006	1.418	1.518	1.642	1.698	1.919
Aug 2025	0.804	0.837	1.209	1.298	1.420	1.443	1.588
Sep 2025	0.842	0.896	1.266	1.365	1.473	1.490	1.699
Oct 2025	0.907	0.948	1.311	1.387	1.484	1.493	1.738
Nov 2025	0.946	0.992	1.341	1.424	1.520	1.553	1.780
Dec 2025	0.977	1.026	1.329	1.410	1.518	1.562	1.751
Jan 2026	0.991	1.038	1.396	1.471	1.548	1.581	1.788
Feb 2026	1.043	1.093	1.460	1.545	1.660	1.697	1.910
Mar 2026	1.042	1.093	1.511	1.594	1.735	1.758	1.989
Apr 2026	1.043	1.089	1.529	1.608	1.810	1.847	2.014
May 2026	1.014	1.076	1.523	1.629	1.797	1.834	2.036
Jun 2026	1.041	1.099	1.512	1.626	1.761	1.803	2.015
Jul 2026	0.957	1.010	1.450	1.551	1.676	1.727	1.952
Aug 2026	0.808	0.841	1.241	1.331	1.454	1.472	1.621
Sep 2026	0.845	0.900	1.298	1.398	1.507	1.519	1.732
Oct 2026	0.911	0.952	1.343	1.420	1.518	1.522	1.771
Nov 2026	0.950	0.996	1.374	1.458	1.553	1.582	1.813
Dec 2026	0.981	1.030	1.361	1.443	1.552	1.591	1.784
Jan 2027	0.995	1.042	1.428	1.505	1.582	1.611	1.820
Feb 2027	1.048	1.098	1.492	1.578	1.694	1.727	1.943
Mar 2027	1.047	1.098	1.543	1.627	1.769	1.787	2.022
Apr 2027	1.048	1.093	1.561	1.641	1.844	1.876	2.046
May 2027	1.018	1.080	1.555	1.662	1.831	1.863	2.069
Jun 2027	1.046	1.104	1.544	1.660	1.795	1.832	2.048
Jul 2027	0.962	1.015	1.483	1.584	1.710	1.756	1.985
Aug 2027	0.811	0.844	1.273	1.364	1.488	1.501	1.653
Sep 2027	0.849	0.904	1.330	1.431	1.541	1.548	1.765
Oct 2027	0.915	0.956	1.376	1.453	1.552	1.551	1.804
Nov 2027	0.954	1.000	1.406	1.491	1.587	1.611	1.846
Dec 2027	0.986	1.034	1.393	1.476	1.586	1.620	1.817

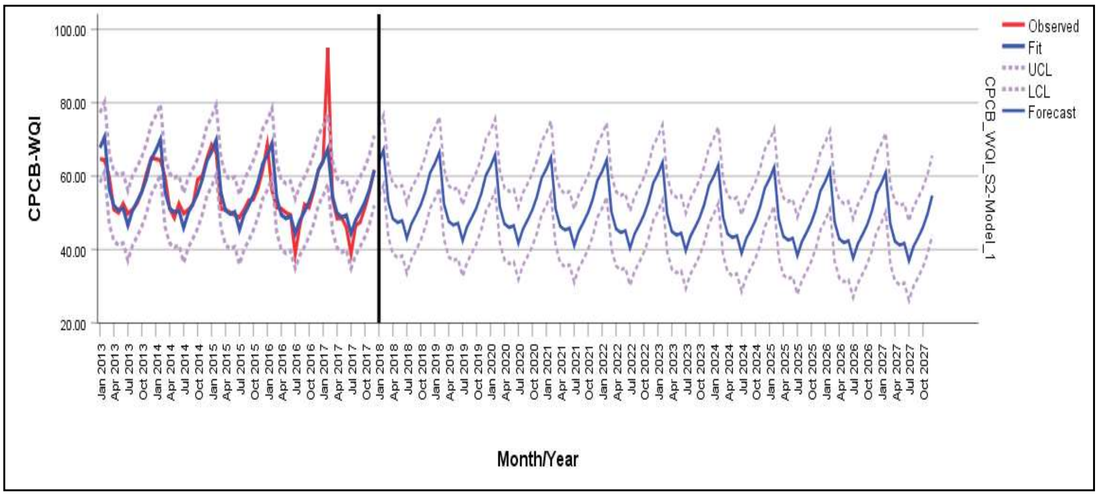
ANNEXURE – VIII

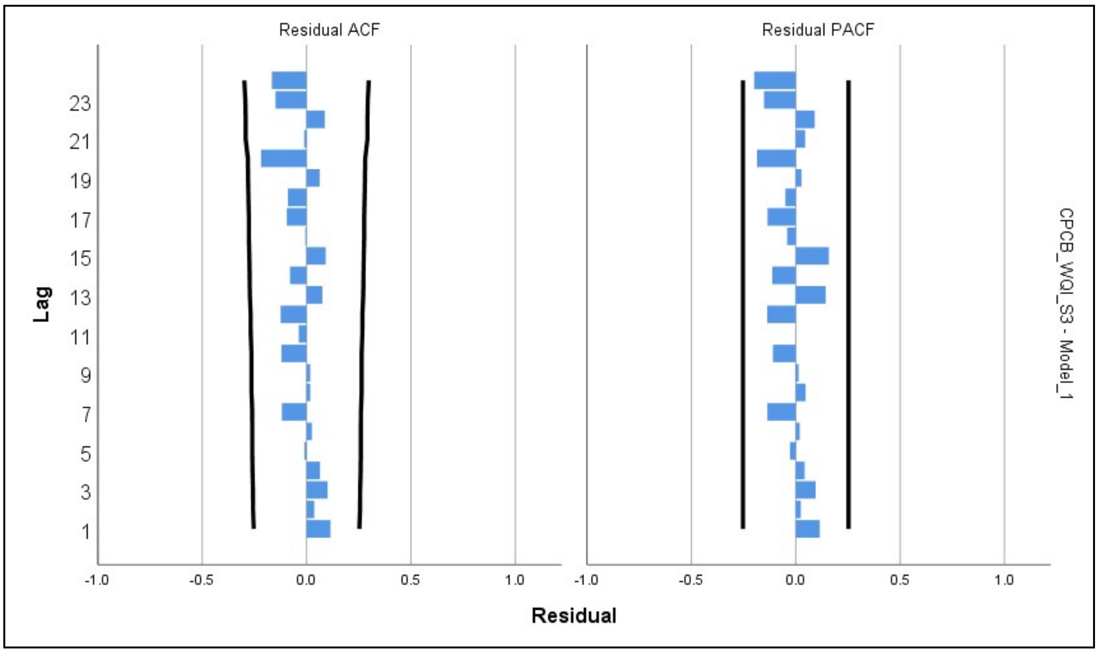
Graphical representation of trend, time series analysis (ACF, PACF, observed, best fit, LCL, UCL) of CPCB-WQI (S1 – S7)

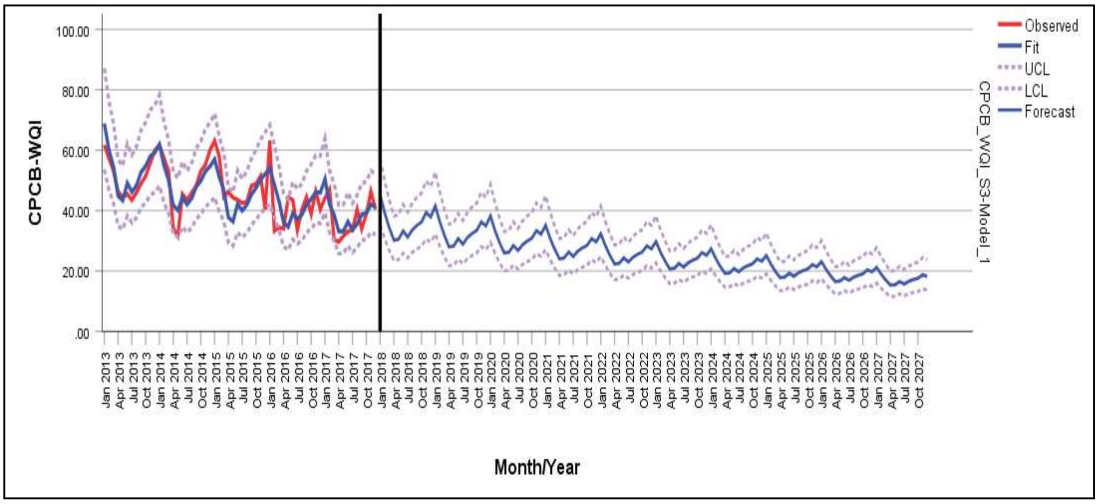


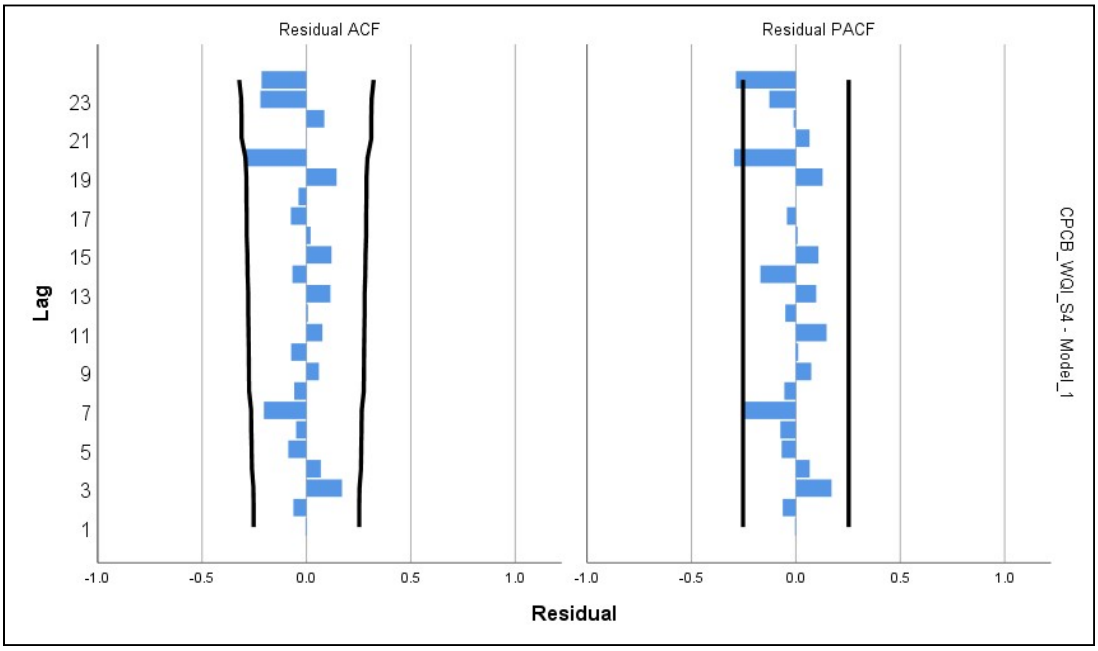


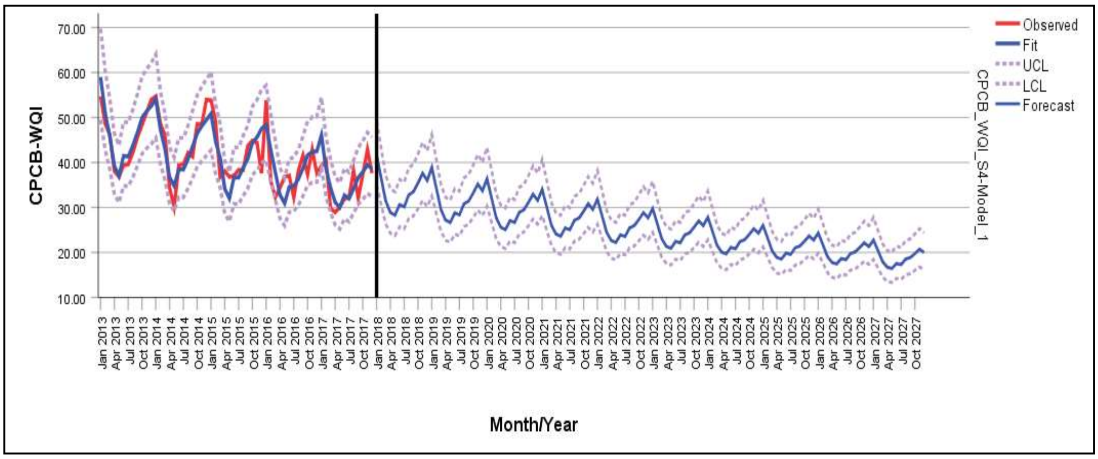


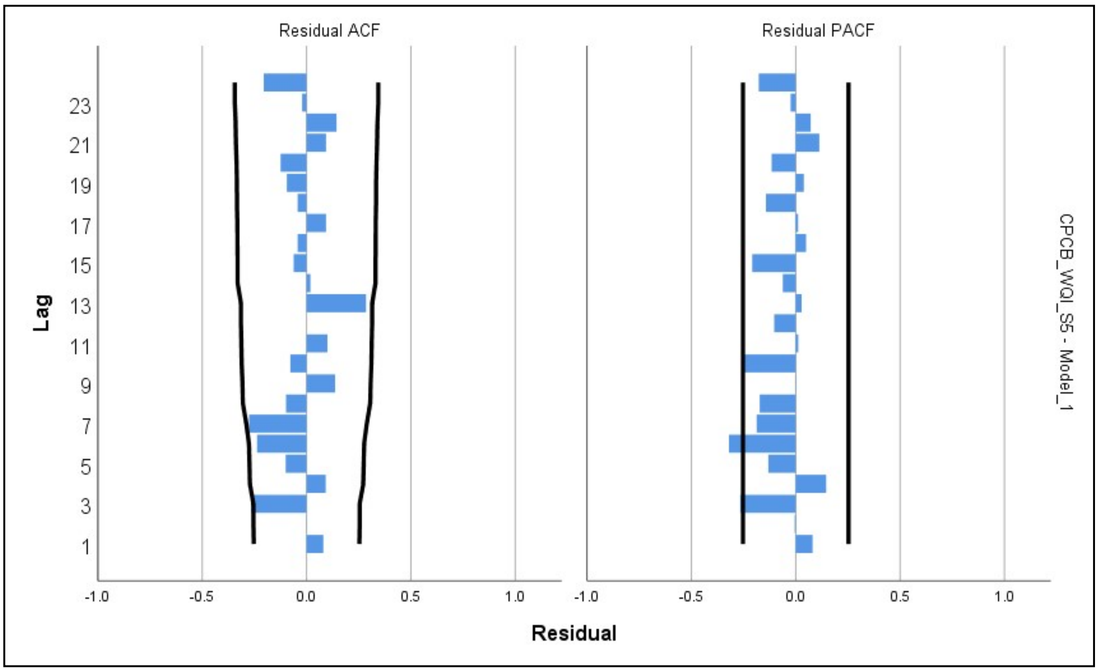

Observed
Fit
UCL
LCL
Forecast
CPCB-WQI
CPCB_WQI_S2-Model_1
Month/Year

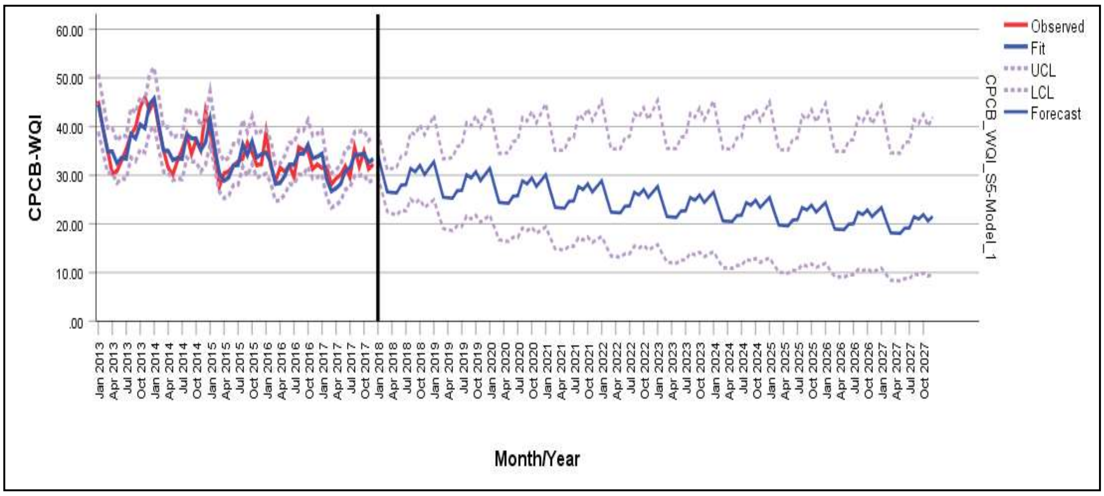

Residual ACF
Residual PACF
Lag
Residual
CPCB_WQI_S3 - Model_1

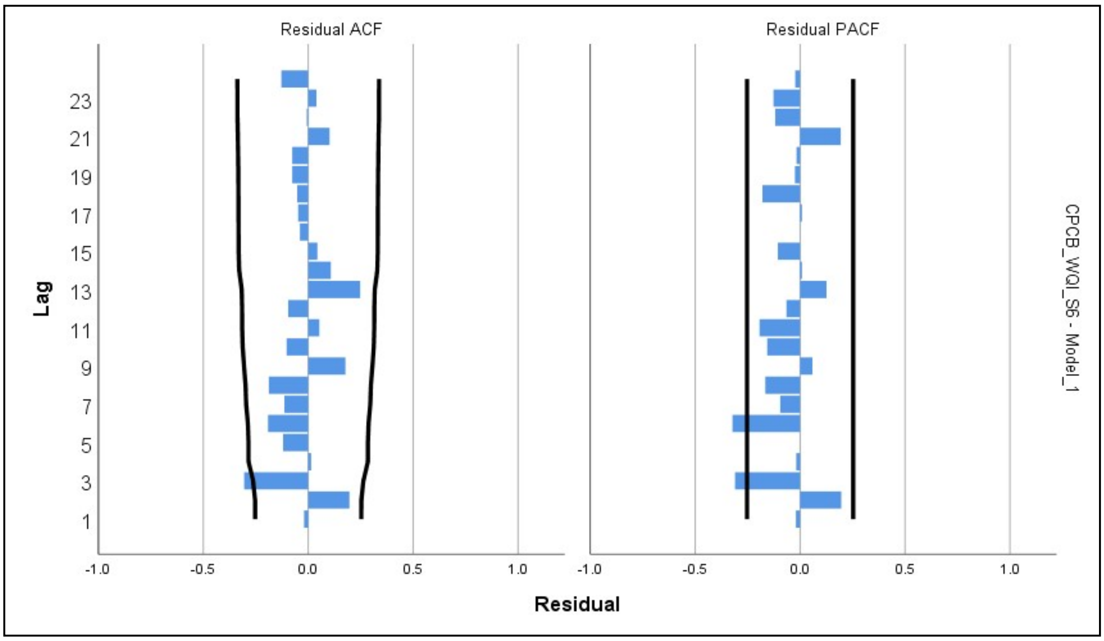

Observed
Fit
UCL
LCL
Forecast
CPCB-WQI
CPCB_WQI_S3-Model_1
Month/Year

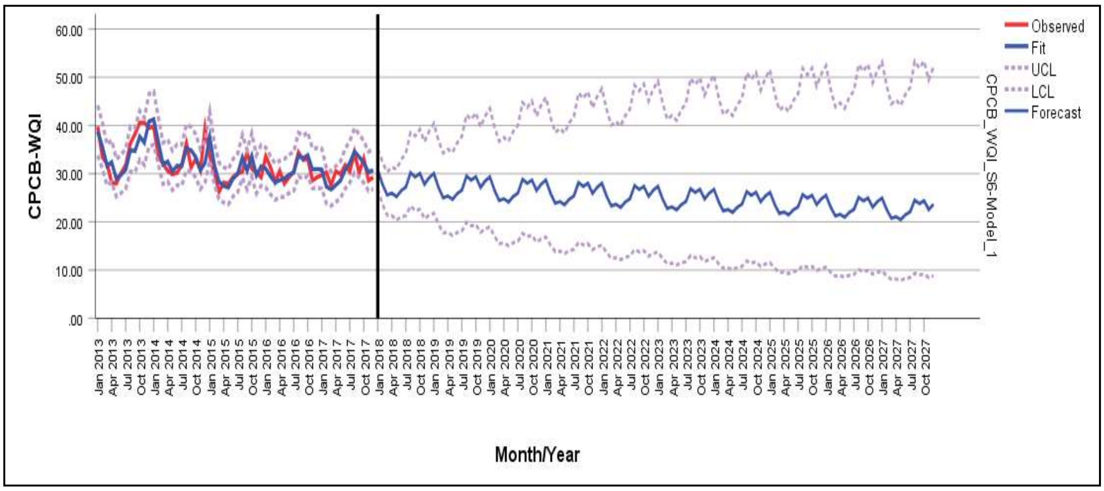

Residual ACF
Residual PACF
Lag
Residual
CPCB_WQI_S4 - Model_1

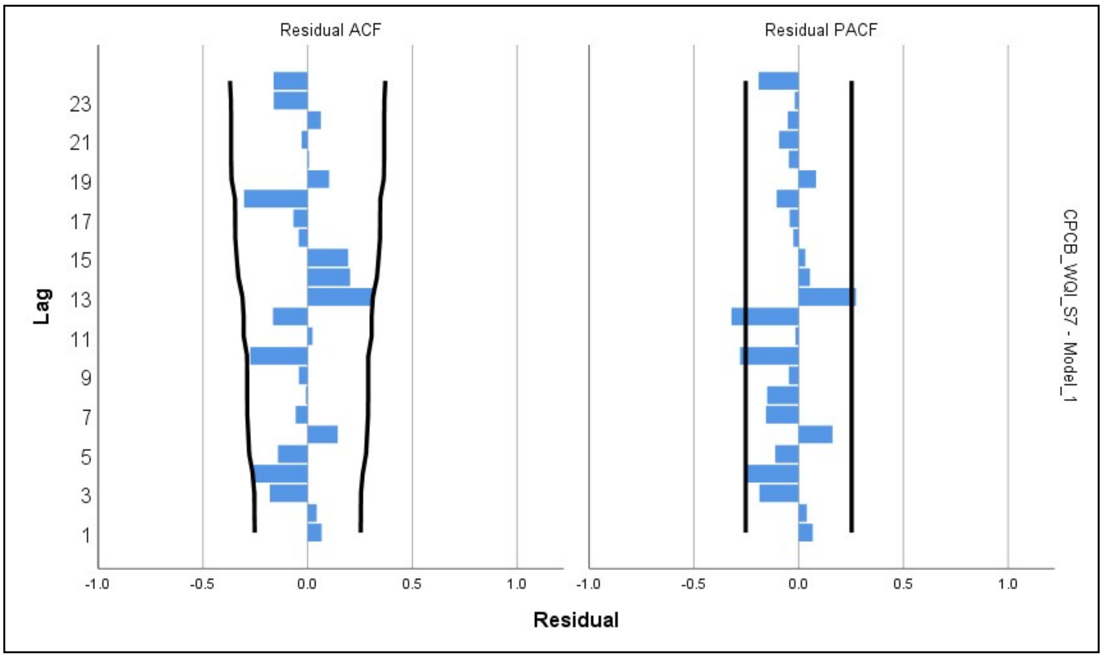

CPCB-WQI
Month/Year
Observed
Fit
UCL
LCL
Forecast
CPCB_WQI_S4-Model_1

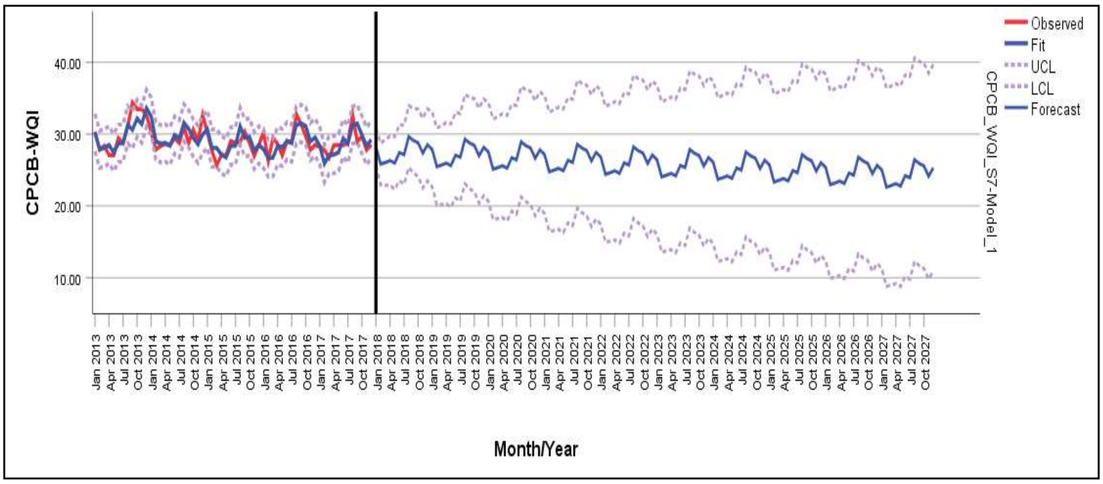

Residual ACF
Residual PACF
Lag
Residual
CPCB_WQI_S5 - Model_1


CPCB-WQI
Month/Year
Observed
Fit
UCL
LCL
Forecast
CPCB_WQI_S5-Model_1


Residual ACF
Residual PACF
Lag
Residual
CPCB_WQI_S6 - Model_1


CPCB-WQI
Month/Year
Observed
Fit
UCL
LCL
Forecast
CPCB_WQI_S6-Model_1


Residual ACF
Residual PACF
Lag
Residual
CPCB_WQI_S7 - Model_1


Observed
Fit
UCL
LCL
Forecast
CPCB-WQI
CPCB_WQI_S7-Model_1
Month/Year

ANNEXURE – IX

Predicted value of CPCB-WQI (2018-2027) by Time-series analysis

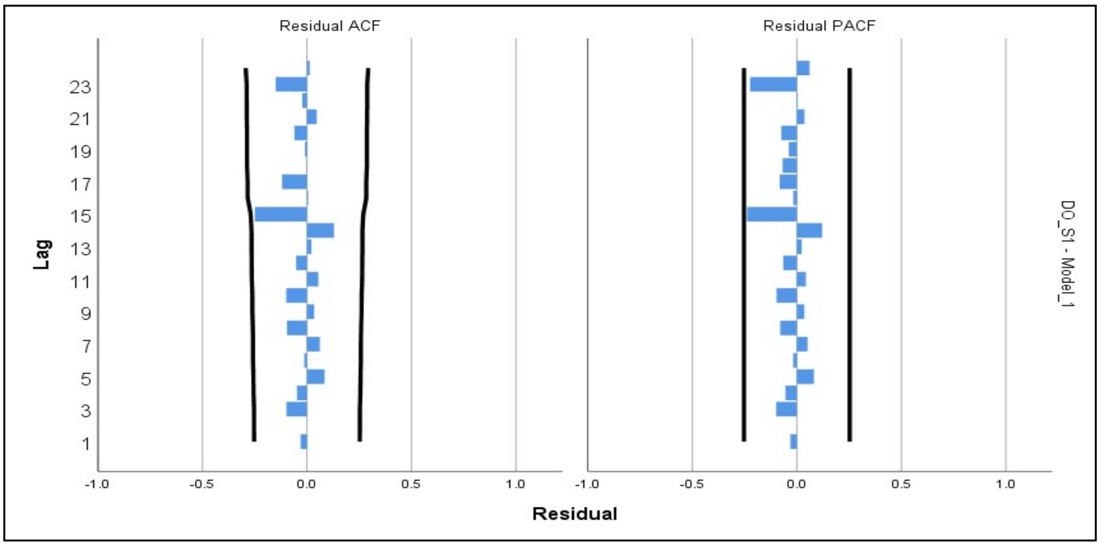
Date	S1	S2	S3	S4	S5	S6	S7
Jan 2018	80.49	64.01	45.22	41.59	34.19	30.75	28.23
Feb 2018	79.04	67.14	39.25	36.47	30.28	27.79	25.82
Mar 2018	57.29	53.08	34.31	31.35	26.56	25.58	26.05
Apr 2018	53.80	48.38	30.19	28.87	26.45	25.96	26.31
May 2018	59.24	47.36	30.50	28.30	26.37	25.24	25.97
Jun 2018	55.40	47.89	33.24	30.64	27.98	26.48	27.42
Jul 2018	52.79	43.10	31.21	30.14	28.04	27.19	27.13
Aug 2018	54.32	47.05	33.61	32.84	31.39	30.21	29.65
Sep 2018	56.46	49.48	35.11	33.48	30.71	29.32	29.11
Oct 2018	55.03	52.18	36.23	35.45	32.05	30.05	28.79
Nov 2018	57.98	55.82	39.36	37.60	30.14	27.78	27.35
Dec 2018	59.81	60.88	37.90	35.99	31.47	29.16	28.51
Jan 2019	64.84	63.32	41.58	38.90	32.77	30.04	27.87
Feb 2019	63.73	66.46	36.20	34.18	29.03	27.15	25.47
Mar 2019	56.61	52.40	31.73	29.47	25.46	24.99	25.69
Apr 2019	55.29	47.69	28.00	27.17	25.36	25.37	25.96
May 2019	56.39	46.68	28.28	26.64	25.28	24.66	25.61
Jun 2019	55.27	47.20	30.76	28.80	26.82	25.87	27.06
Jul 2019	54.25	42.42	28.91	28.33	26.88	26.57	26.77
Aug 2019	54.94	46.37	31.08	30.82	30.09	29.51	29.29
Sep 2019	55.51	48.80	32.43	31.41	29.44	28.65	28.75
Oct 2019	55.15	51.50	33.43	33.22	30.73	29.36	28.43
Nov 2019	56.11	55.13	36.25	35.19	28.89	27.14	26.99
Dec 2019	56.87	60.19	34.93	33.71	30.16	28.49	28.15
Jan 2020	58.96	62.64	38.24	36.38	31.41	29.35	27.51
Feb 2020	58.51	65.77	33.39	32.04	27.83	26.53	25.11
Mar 2020	55.49	51.71	29.35	27.69	24.41	24.42	25.34
Apr 2020	54.91	47.01	25.97	25.57	24.31	24.78	25.60
May 2020	55.42	45.99	26.22	25.08	24.23	24.09	25.26
Jun 2020	54.93	46.52	28.45	27.07	25.71	25.28	26.71
Jul 2020	54.48	41.73	26.78	26.64	25.77	25.96	26.42
Aug 2020	54.80	45.68	28.74	28.93	28.84	28.83	28.93
Sep 2020	55.05	48.11	29.95	29.47	28.22	27.99	28.39
Oct 2020	54.90	50.81	30.85	31.13	29.45	28.69	28.08
Nov 2020	55.33	54.45	33.38	32.94	27.69	26.51	26.63
Dec 2020	55.66	59.51	32.19	31.57	28.91	27.84	27.80
Jan 2021	56.56	61.95	35.16	34.02	30.11	28.67	27.16
Feb 2021	56.36	65.09	30.79	30.03	26.68	25.92	24.75
Mar 2021	55.03	51.03	27.15	26.03	23.40	23.86	24.98

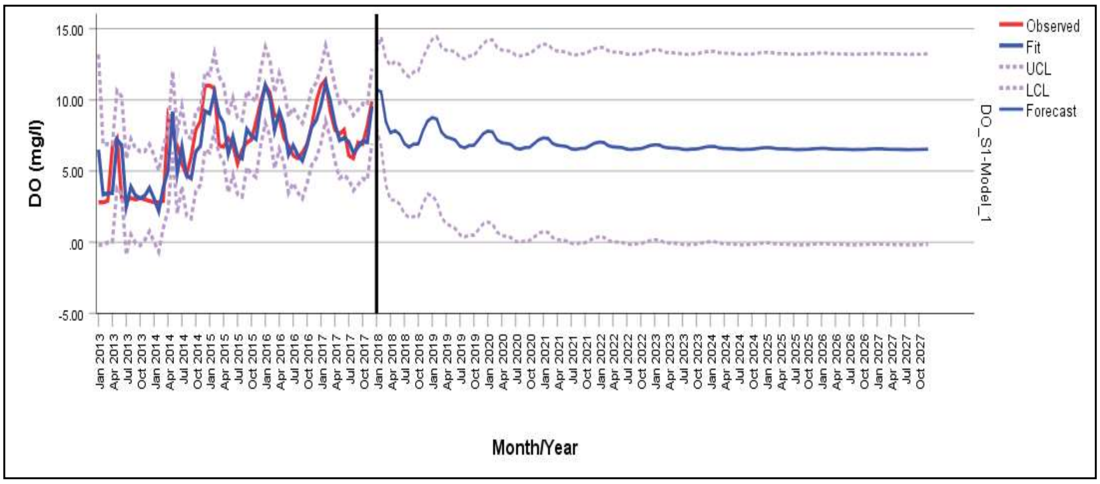
Date	S1	S2	S3	S4	S5	S6	S7
Apr 2021	54.77	46.32	24.08	24.07	23.30	24.21	25.24
May 2021	55.00	45.31	24.31	23.61	23.23	23.54	24.90
Jun 2021	54.78	45.83	26.33	25.44	24.65	24.70	26.35
Jul 2021	54.58	41.05	24.81	25.04	24.70	25.36	26.06
Aug 2021	54.72	45.00	26.58	27.15	27.65	28.17	28.58
Sep 2021	54.83	47.43	27.67	27.65	27.05	27.35	28.04
Oct 2021	54.76	50.13	28.47	29.17	28.23	28.03	27.72
Nov 2021	54.95	53.76	30.75	30.83	26.55	25.90	26.28
Dec 2021	55.10	58.82	29.67	29.57	27.72	27.20	27.44
Jan 2022	55.50	61.27	32.33	31.81	28.87	28.02	26.80
Feb 2022	55.41	64.40	28.40	28.15	25.57	25.32	24.40
Mar 2022	54.82	50.34	25.11	24.46	22.43	23.31	24.62
Apr 2022	54.70	45.64	22.34	22.65	22.34	23.66	24.89
May 2022	54.80	44.62	22.53	22.22	22.27	22.99	24.54
Jun 2022	54.71	45.15	24.36	23.91	23.63	24.13	25.99
Jul 2022	54.61	40.36	22.98	23.54	23.68	24.78	25.70
Aug 2022	54.68	44.31	24.57	25.48	26.51	27.52	28.22
Sep 2022	54.73	46.74	25.56	25.94	25.93	26.72	27.68
Oct 2022	54.70	49.44	26.28	27.33	27.07	27.38	27.36
Nov 2022	54.78	53.08	28.32	28.86	25.45	25.31	25.92
Dec 2022	54.85	58.14	27.34	27.70	26.57	26.57	27.08
Jan 2023	55.03	60.58	29.73	29.75	27.67	27.37	26.44
Feb 2023	54.99	63.72	26.20	26.39	24.52	24.74	24.04
Mar 2023	54.72	49.66	23.23	22.99	21.50	22.77	24.27
Apr 2023	54.67	44.95	20.71	21.32	21.41	23.11	24.53
May 2023	54.71	43.94	20.89	20.92	21.34	22.47	24.19
Jun 2023	54.67	44.46	22.53	22.48	22.65	23.57	25.64
Jul 2023	54.63	39.68	21.29	22.13	22.70	24.21	25.35
Aug 2023	54.66	43.63	22.72	23.92	25.41	26.89	27.86
Sep 2023	54.68	46.06	23.60	24.33	24.86	26.10	27.32
Oct 2023	54.67	48.76	24.25	25.61	25.95	26.75	27.01
Nov 2023	54.71	52.39	26.08	27.01	24.40	24.73	25.56
Dec 2023	54.74	57.45	25.20	25.94	25.47	25.96	26.73
Jan 2024	54.82	59.90	27.34	27.82	26.53	26.74	26.09
Feb 2024	54.80	63.04	24.16	24.73	23.50	24.17	23.68
Mar 2024	54.68	48.97	21.48	21.60	20.61	22.25	23.91
Apr 2024	54.65	44.27	19.21	20.06	20.53	22.58	24.17
May 2024	54.68	43.25	19.37	19.69	20.46	21.95	23.83
Jun 2024	54.66	43.78	20.85	21.13	21.71	23.03	25.28
Jul 2024	54.64	38.99	19.72	20.81	21.76	23.65	24.99
Aug 2024	54.65	42.94	21.01	22.45	24.36	26.27	27.51

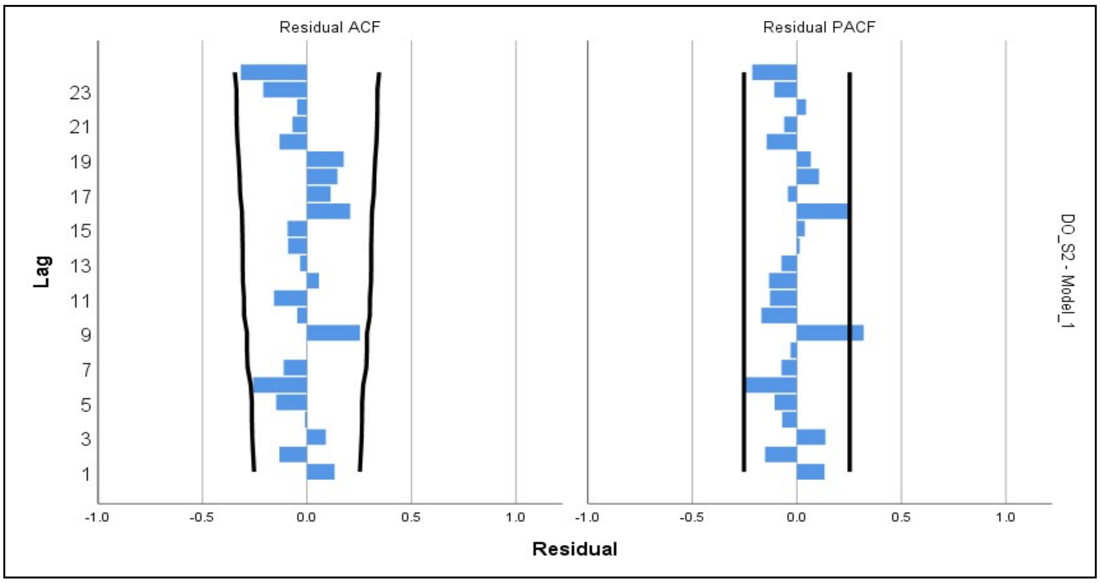
Date	S1	S2	S3	S4	S5	S6	S7
Sep 2024	54.66	45.37	21.80	22.83	23.83	25.50	26.97
Oct 2024	54.65	48.07	22.38	24.00	24.87	26.14	26.65
Nov 2024	54.67	51.71	24.02	25.28	23.39	24.16	25.21
Dec 2024	54.68	56.77	23.23	24.30	24.42	25.37	26.37
Jan 2025	54.72	59.22	25.14	26.02	25.43	26.13	25.73
Feb 2025	54.71	62.35	22.28	23.18	22.53	23.62	23.33
Mar 2025	54.66	48.29	19.87	20.30	19.76	21.74	23.55
Apr 2025	54.65	43.58	17.82	18.88	19.68	22.06	23.82
May 2025	54.66	42.57	17.96	18.54	19.62	21.45	23.47
Jun 2025	54.65	43.09	19.29	19.86	20.81	22.50	24.92
Jul 2025	54.64	38.31	18.27	19.56	20.86	23.11	24.63
Aug 2025	54.65	42.26	19.43	21.07	23.35	25.67	27.15
Sep 2025	54.65	44.69	20.14	21.41	22.84	24.92	26.61
Oct 2025	54.65	47.39	20.65	22.49	23.84	25.54	26.29
Nov 2025	54.66	51.03	22.12	23.66	22.42	23.60	24.85
Dec 2025	54.66	56.08	21.41	22.76	23.41	24.78	26.01
Jan 2026	54.68	58.53	23.12	24.34	24.38	25.53	25.37
Feb 2026	54.67	61.67	20.55	21.73	21.60	23.07	22.97
Mar 2026	54.65	47.60	18.38	19.08	18.94	21.24	23.20
Apr 2026	54.65	42.90	16.52	17.77	18.87	21.56	23.46
May 2026	54.65	41.89	16.65	17.45	18.80	20.95	23.12
Jun 2026	54.65	42.41	17.85	18.67	19.95	21.99	24.57
Jul 2026	54.64	37.62	16.93	18.39	20.00	22.58	24.28
Aug 2026	54.64	41.57	17.97	19.78	22.38	25.08	26.79
Sep 2026	54.65	44.00	18.60	20.09	21.90	24.34	26.25
Oct 2026	54.65	46.70	19.06	21.07	22.86	24.95	25.94
Nov 2026	54.65	50.34	20.38	22.14	21.49	23.06	24.49
Dec 2026	54.65	55.40	19.73	21.31	22.44	24.21	25.65
Jan 2027	54.66	57.85	21.26	22.76	23.37	24.94	25.02
Feb 2027	54.66	60.98	18.96	20.37	20.70	22.54	22.61
Mar 2027	54.65	46.92	17.00	17.93	18.16	20.75	22.84
Apr 2027	54.64	42.22	15.33	16.72	18.09	21.06	23.10
May 2027	54.65	41.20	15.43	16.43	18.03	20.47	22.76
Jun 2027	54.64	41.73	16.51	17.54	19.13	21.48	24.21
Jul 2027	54.64	36.94	15.68	17.29	19.17	22.06	23.92
Aug 2027	54.64	40.89	16.61	18.56	21.46	24.50	26.43
Sep 2027	54.64	43.32	17.18	18.85	20.99	23.79	25.90
Oct 2027	54.64	46.02	17.59	19.75	21.91	24.38	25.58
Nov 2027	54.65	49.66	18.77	20.73	20.60	22.53	24.14
Dec 2027	54.65	54.72	18.18	19.96	21.51	23.66	25.30

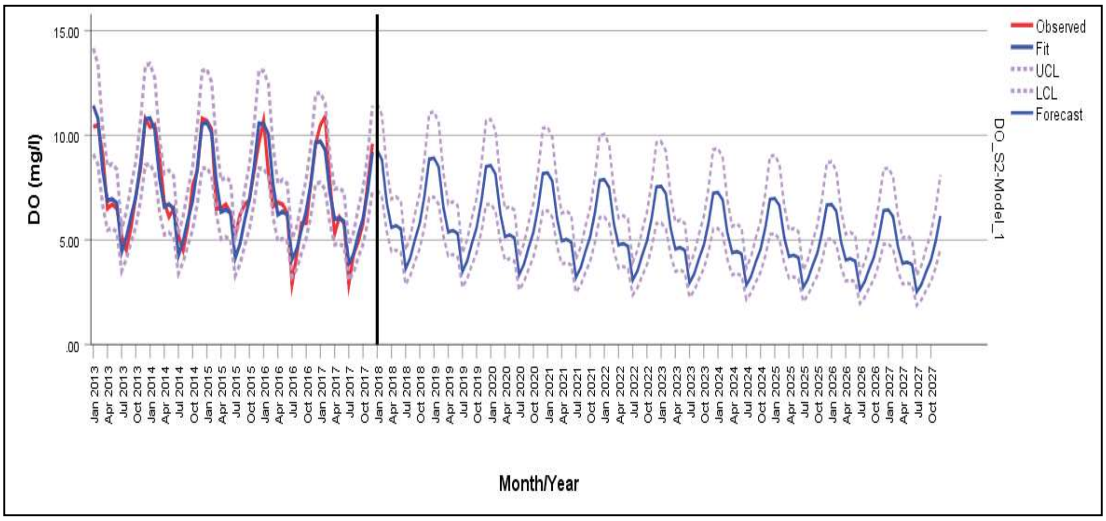
ANNEXURE – X

Graphical representation of trend, time series analysis (ACF, PACF, observed, best fit, LCL, UCL) of DO (S1 – S7)

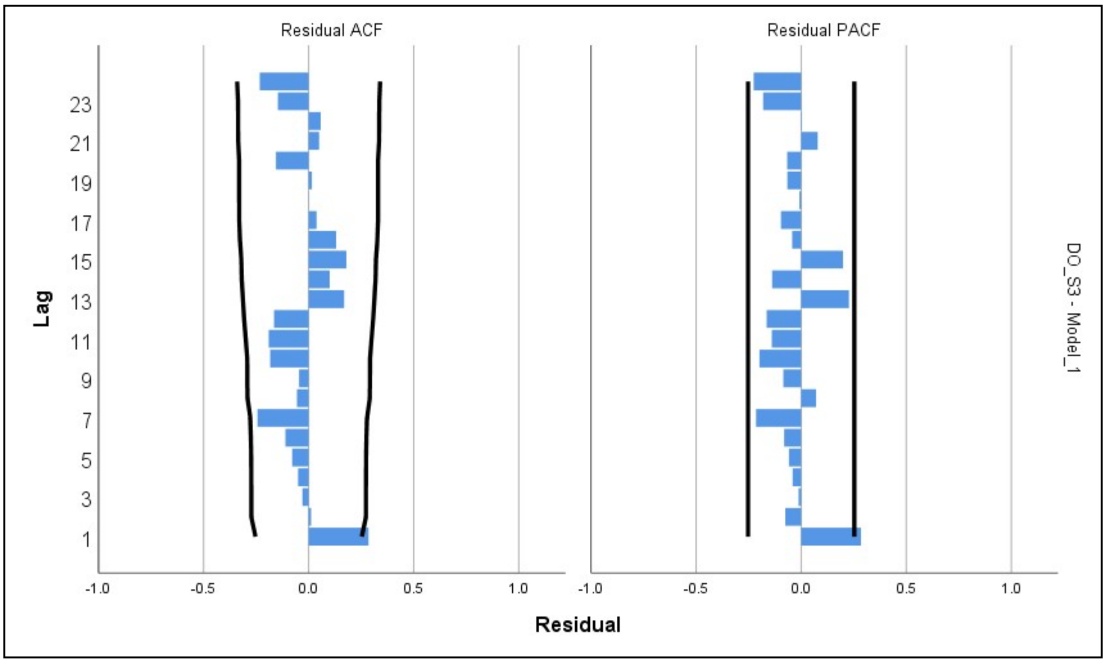




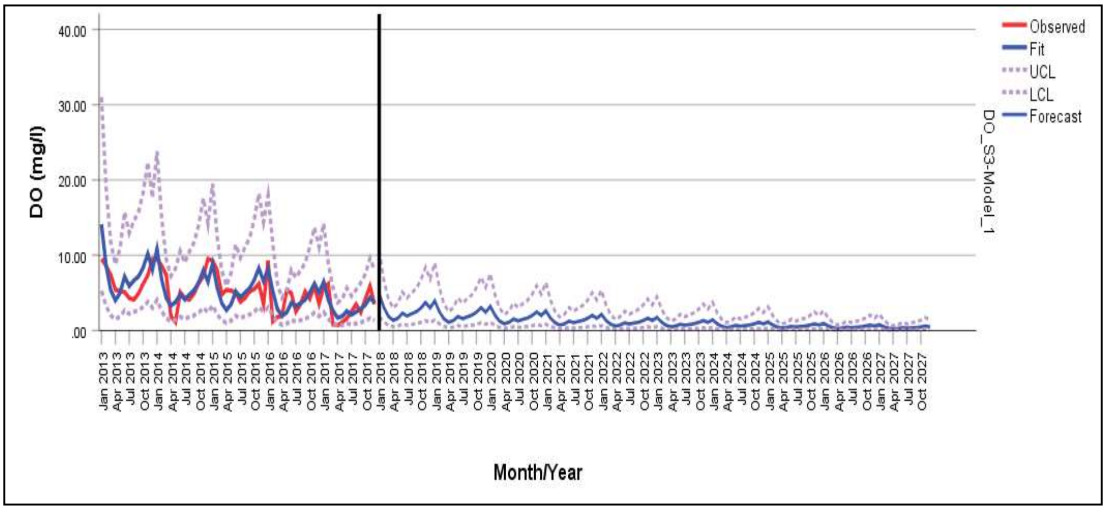




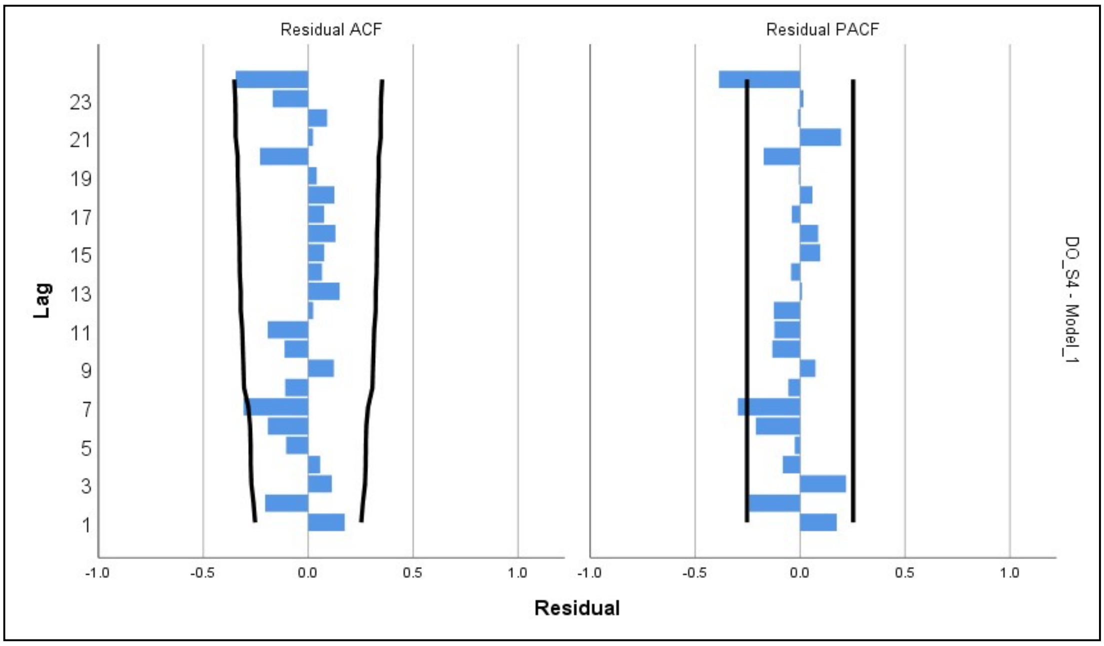
DO (mg/l)
Month/Year
Observed
Fit
UCL
LCL
Forecast
DO_S2-Model_1



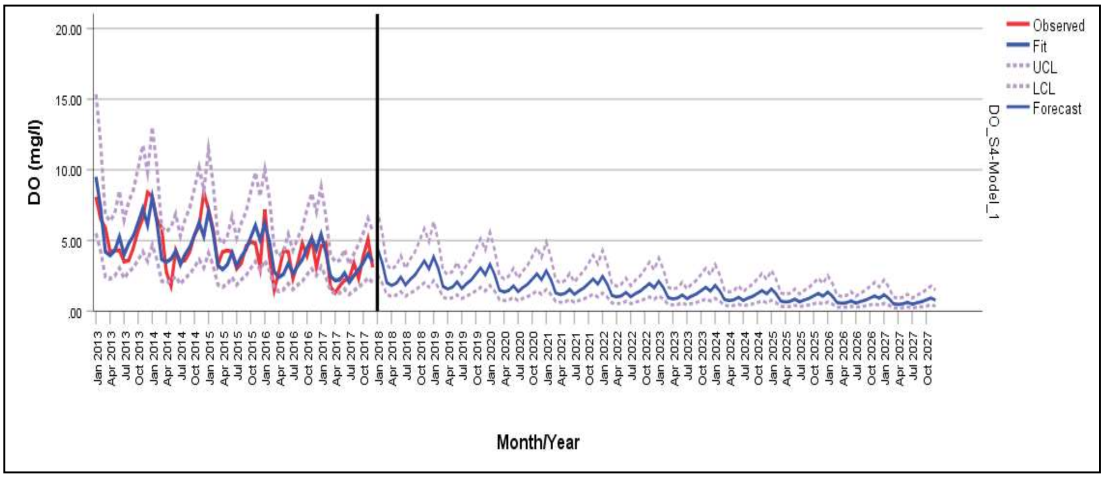
Residual ACF
Residual PACF
Lag
Residual
DO_S3 - Model_1



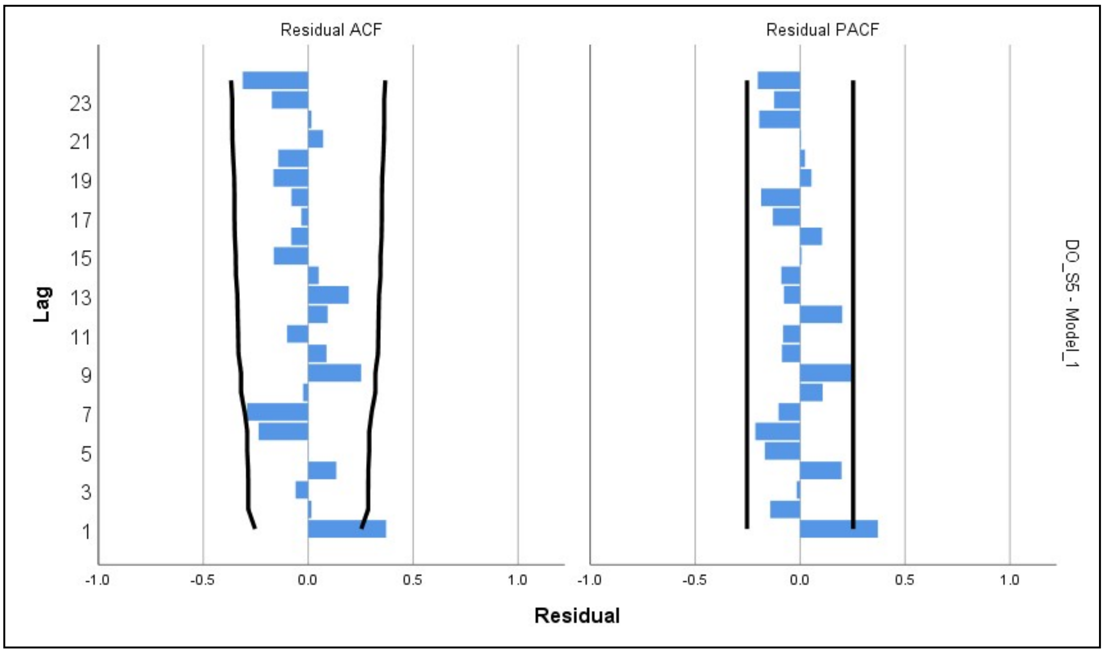
DO (mg/l)
Month/Year
Observed
Fit
UCL
LCL
Forecast
DO_S3-Model_1



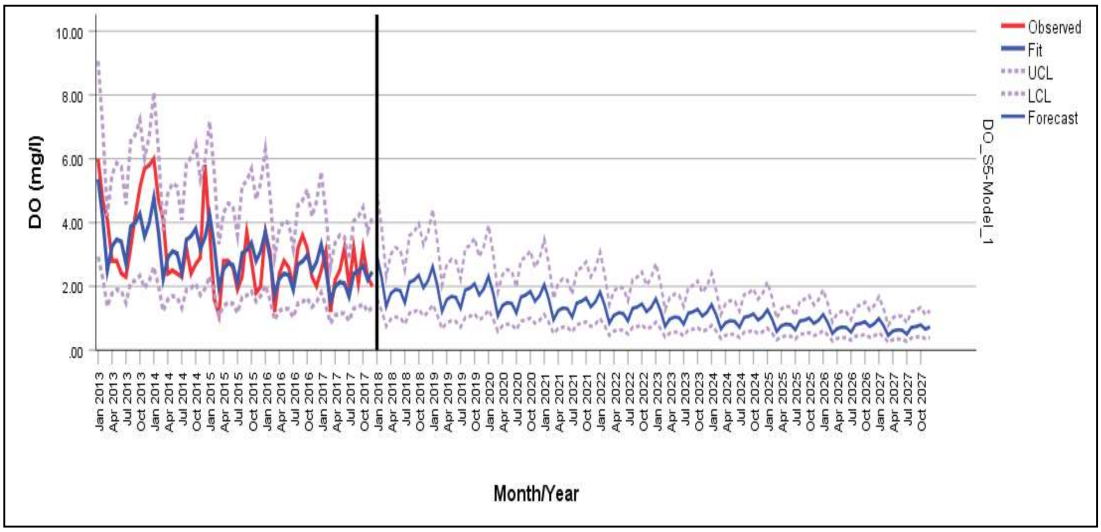
Residual ACF
Residual PACF
Lag
23
21
19
17
15
13
11
9
7
5
3
1
-1.0
-0.5
0.0
0.5
1.0
Residual
DO_S4 - Model_1

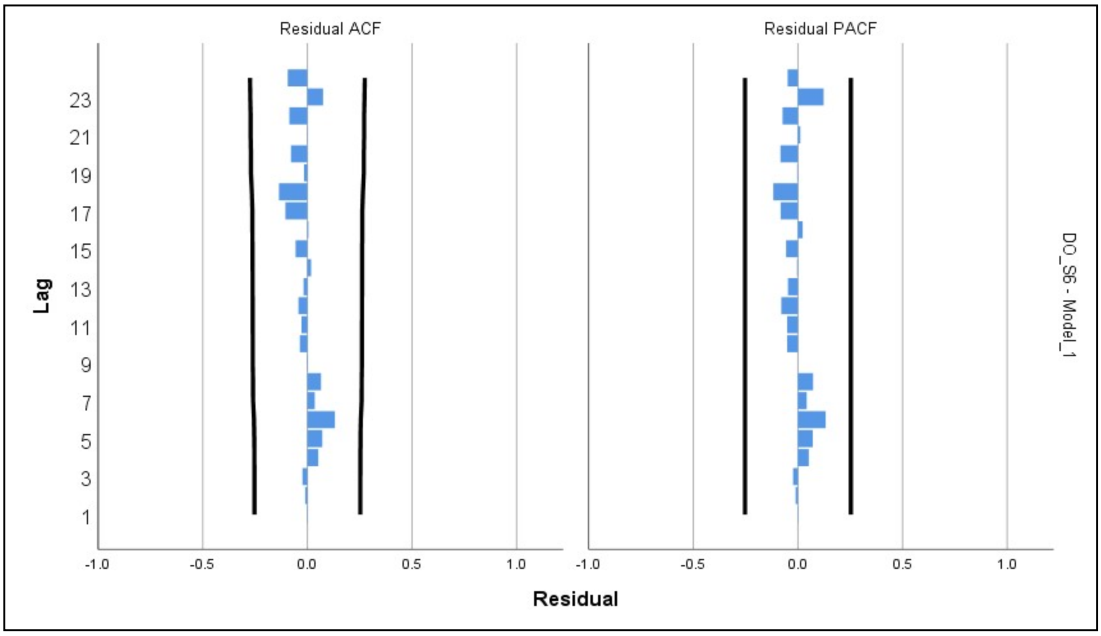


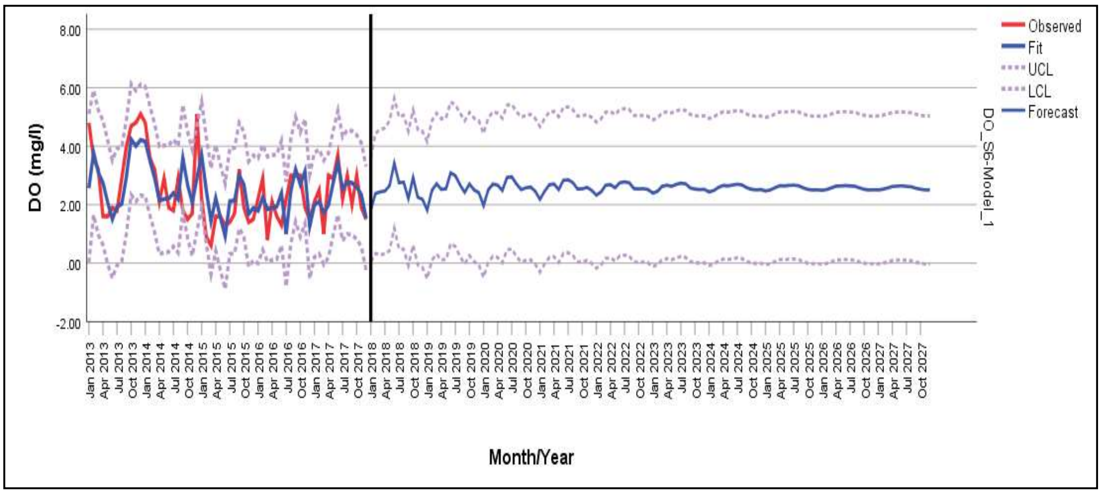
DO (mg/l)
20.00
15.00
10.00
5.00
.00
Observed
Fit
UCL
LCL
Forecast
DO_S4-Model_1
Month/Year

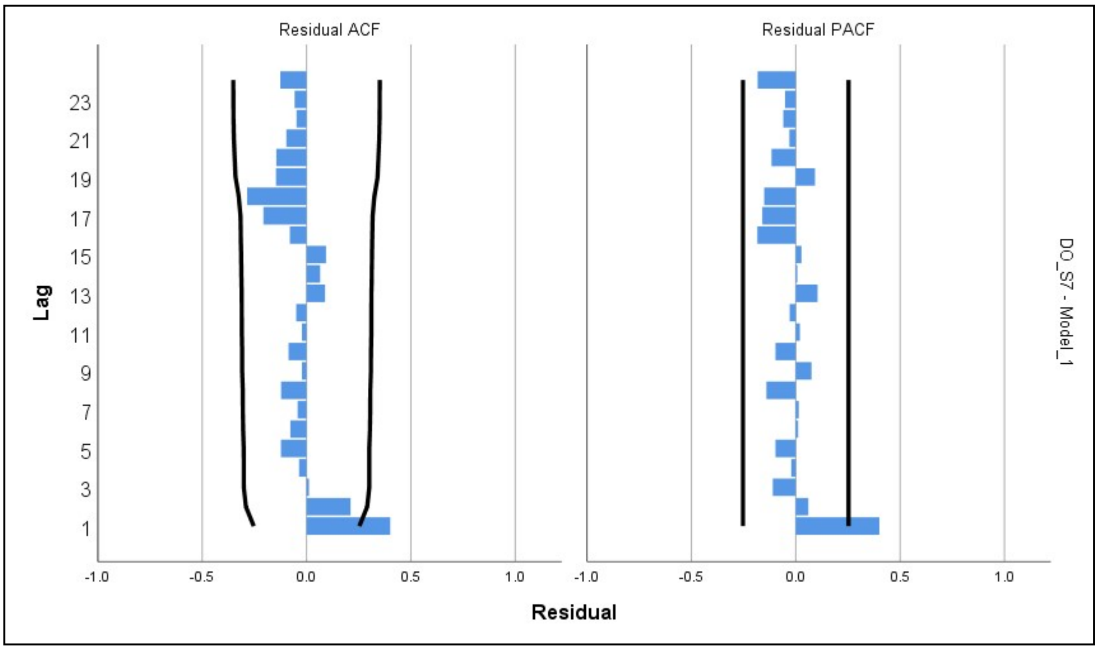


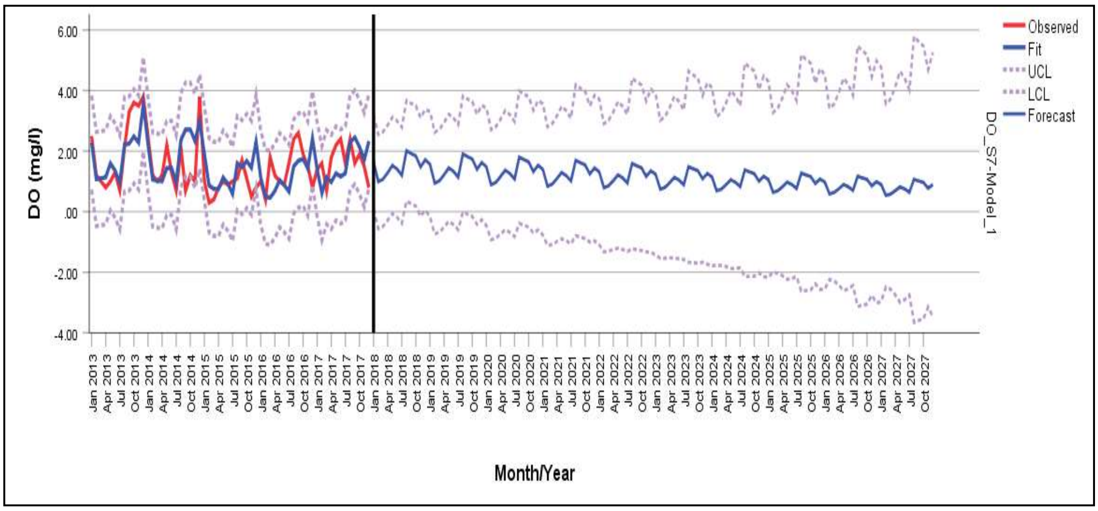
Residual ACF
Residual PACF
Lag
23
21
19
17
15
13
11
9
7
5
3
1
-1.0
-0.5
0.0
0.5
1.0
Residual
DO_S5 - Model_1


Observed
Fit
UCL
LCL
Forecast
DO_S5-Model_1
DO (mg/l)
Month/Year


Residual ACF
Residual PACF
Lag
Residual
DO_S6 - Model_1


Observed
Fit
UCL
LCL
Forecast
DO_S6-Model_1
DO (mg/l)
Month/Year


Residual ACF
Residual PACF
Lag
23
21
19
17
15
13
11
9
7
5
3
1
-1.0
-0.5
0.0
0.5
1.0
Residual
DO_S7 - Model_1


Observed
Fit
UCL
LCL
Forecast
DO (mg/l)
6.00
4.00
2.00
.00
-2.00
-4.00
DO_S7-Model_1
Month/Year

ANNEXURE – XI

Predicted value of DO (2018-2027) by Time-series analysis

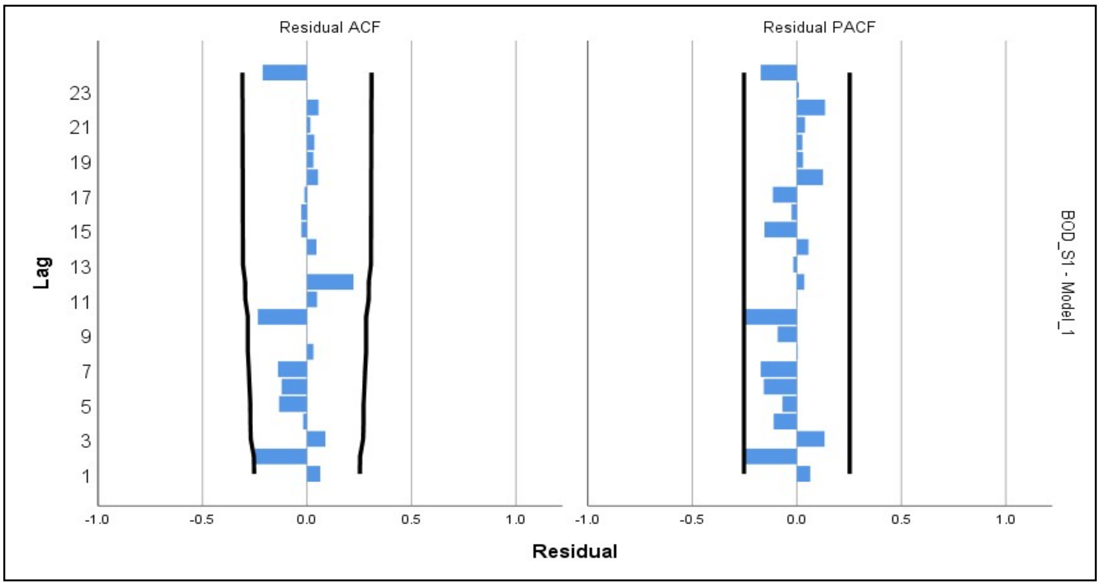
Date	S1	S2	S3	S4	S5	S6	S7
Jan 2018	10.71	9.28	4.84	4.46	2.95	1.83	1.65
Feb 2018	10.57	8.83	3.05	3.47	2.28	2.39	0.99
Mar 2018	8.47	6.81	1.87	2.01	1.37	2.43	1.07
Apr 2018	7.68	5.60	1.35	1.83	1.78	2.47	1.29
May 2018	7.84	5.68	1.61	1.96	1.90	2.65	1.53
Jun 2018	7.58	5.53	2.29	2.41	1.86	3.42	1.41
Jul 2018	6.93	3.63	1.93	1.86	1.49	2.75	1.20
Aug 2018	6.68	4.15	2.22	2.25	2.13	2.77	2.01
Sep 2018	6.89	5.03	2.49	2.56	2.20	2.21	1.92
Oct 2018	6.91	5.82	2.98	3.04	2.35	2.93	1.84
Nov 2018	7.82	7.11	3.71	3.55	1.95	2.25	1.48
Dec 2018	8.51	8.87	3.00	2.99	2.18	2.18	1.72
Jan 2019	8.76	8.91	3.94	3.84	2.61	1.81	1.57
Feb 2019	8.65	8.48	2.48	2.99	2.02	2.49	0.94
Mar 2019	7.73	6.54	1.52	1.74	1.21	2.72	1.02
Apr 2019	7.40	5.37	1.10	1.57	1.58	2.52	1.22
May 2019	7.30	5.46	1.31	1.69	1.68	2.54	1.45
Jun 2019	7.17	5.31	1.87	2.08	1.65	3.09	1.33
Jul 2019	6.74	3.48	1.57	1.60	1.32	2.99	1.14
Aug 2019	6.63	3.99	1.81	1.94	1.89	2.67	1.91
Sep 2019	6.79	4.83	2.03	2.20	1.95	2.42	1.82
Oct 2019	6.80	5.58	2.43	2.62	2.08	2.71	1.74
Nov 2019	7.20	6.83	3.03	3.06	1.73	2.50	1.40
Dec 2019	7.62	8.51	2.44	2.58	1.93	2.41	1.62
Jan 2020	7.81	8.56	3.21	3.31	2.32	1.97	1.48
Feb 2020	7.76	8.14	2.02	2.58	1.79	2.51	0.89
Mar 2020	7.19	6.28	1.24	1.50	1.08	2.71	0.96
Apr 2020	6.99	5.16	0.90	1.36	1.40	2.67	1.15
May 2020	6.93	5.24	1.07	1.46	1.49	2.48	1.37
Jun 2020	6.87	5.10	1.52	1.79	1.46	2.93	1.26
Jul 2020	6.60	3.34	1.28	1.38	1.17	2.96	1.08
Aug 2020	6.54	3.83	1.48	1.67	1.67	2.71	1.80
Sep 2020	6.65	4.64	1.66	1.90	1.72	2.52	1.72
Oct 2020	6.66	5.36	1.98	2.26	1.84	2.57	1.64
Nov 2020	6.93	6.56	2.47	2.64	1.53	2.61	1.32
Dec 2020	7.20	8.17	1.99	2.22	1.71	2.46	1.53
Jan 2021	7.32	8.22	2.62	2.85	2.05	2.18	1.40
Feb 2021	7.30	7.82	1.65	2.22	1.59	2.46	0.84
Mar 2021	6.93	6.03	1.01	1.29	0.95	2.69	0.91

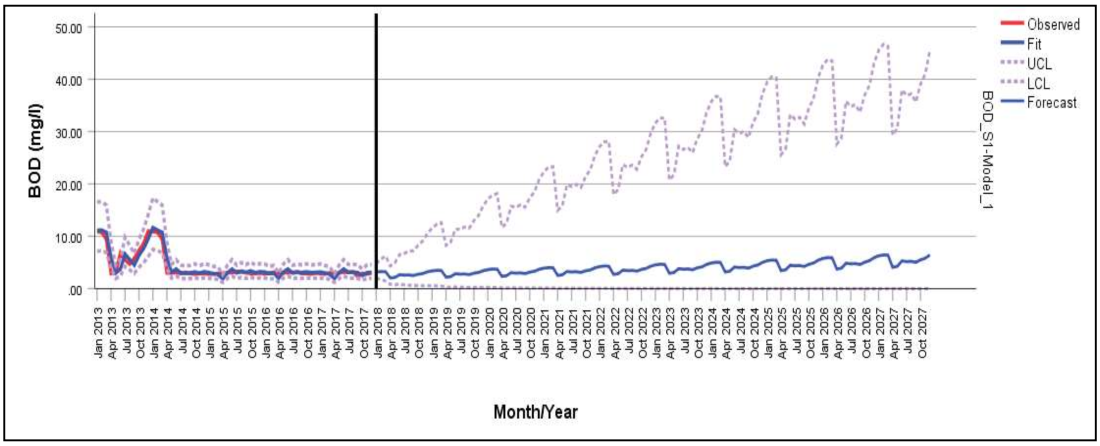
Date	S1	S2	S3	S4	S5	S6	S7
Apr 2021	6.80	4.95	0.73	1.17	1.24	2.71	1.09
May 2021	6.77	5.03	0.87	1.26	1.32	2.51	1.29
Jun 2021	6.73	4.89	1.24	1.54	1.30	2.83	1.19
Jul 2021	6.56	3.21	1.05	1.19	1.03	2.85	1.01
Aug 2021	6.52	3.67	1.20	1.44	1.48	2.75	1.70
Sep 2021	6.59	4.45	1.35	1.64	1.53	2.53	1.62
Oct 2021	6.60	5.15	1.61	1.95	1.63	2.54	1.55
Nov 2021	6.77	6.30	2.01	2.27	1.36	2.59	1.24
Dec 2021	6.95	7.85	1.62	1.92	1.51	2.49	1.44
Jan 2022	7.03	7.89	2.13	2.46	1.82	2.32	1.32
Feb 2022	7.02	7.51	1.35	1.91	1.41	2.44	0.79
Mar 2022	6.78	5.79	0.82	1.11	0.84	2.67	0.85
Apr 2022	6.70	4.76	0.59	1.01	1.10	2.69	1.02
May 2022	6.68	4.83	0.71	1.08	1.17	2.58	1.21
Jun 2022	6.65	4.70	1.01	1.33	1.15	2.75	1.12
Jul 2022	6.54	3.08	0.85	1.02	0.92	2.78	0.95
Aug 2022	6.51	3.53	0.98	1.24	1.31	2.75	1.59
Sep 2022	6.56	4.28	1.10	1.41	1.35	2.55	1.52
Oct 2022	6.57	4.94	1.31	1.68	1.45	2.54	1.45
Nov 2022	6.68	6.05	1.64	1.96	1.20	2.54	1.16
Dec 2022	6.79	7.54	1.32	1.65	1.34	2.52	1.35
Jan 2023	6.84	7.57	1.74	2.12	1.61	2.39	1.23
Feb 2023	6.83	7.21	1.10	1.65	1.25	2.45	0.74
Mar 2023	6.68	5.56	0.67	0.96	0.75	2.63	0.80
Apr 2023	6.63	4.57	0.48	0.87	0.97	2.67	0.96
May 2023	6.61	4.64	0.58	0.93	1.04	2.63	1.13
Jun 2023	6.60	4.51	0.82	1.15	1.02	2.69	1.04
Jul 2023	6.53	2.96	0.69	0.88	0.81	2.74	0.89
Aug 2023	6.51	3.39	0.80	1.07	1.16	2.71	1.49
Sep 2023	6.54	4.11	0.90	1.22	1.20	2.57	1.42
Oct 2023	6.54	4.75	1.07	1.45	1.28	2.53	1.35
Nov 2023	6.62	5.80	1.34	1.69	1.07	2.52	1.09
Dec 2023	6.69	7.24	1.08	1.42	1.19	2.52	1.26
Jan 2024	6.72	7.27	1.42	1.83	1.43	2.43	1.15
Feb 2024	6.72	6.92	0.89	1.42	1.10	2.48	0.69
Mar 2024	6.62	5.34	0.55	0.82	0.66	2.59	0.75
Apr 2024	6.58	4.38	0.40	0.75	0.86	2.66	0.89
May 2024	6.58	4.45	0.47	0.80	0.92	2.64	1.06
Jun 2024	6.56	4.33	0.67	0.99	0.90	2.67	0.97
Jul 2024	6.52	2.84	0.57	0.76	0.72	2.70	0.83
Aug 2024	6.51	3.25	0.65	0.92	1.03	2.68	1.38

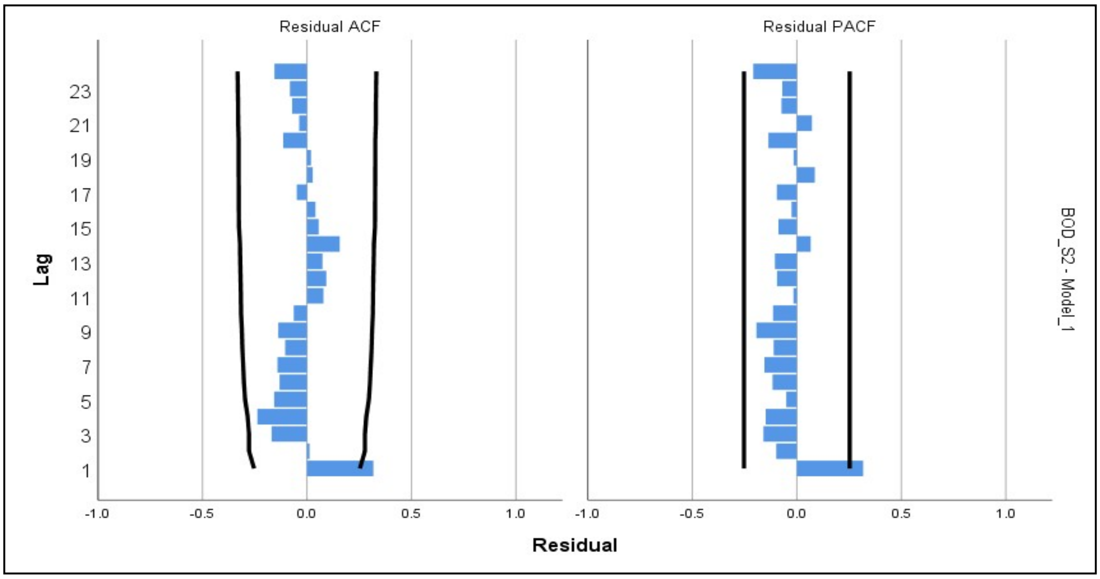
Date	S1	S2	S3	S4	S5	S6	S7
Sep 2024	6.53	3.94	0.73	1.05	1.06	2.58	1.31
Oct 2024	6.53	4.56	0.87	1.25	1.14	2.52	1.26
Nov 2024	6.58	5.57	1.09	1.45	0.95	2.51	1.01
Dec 2024	6.63	6.95	0.88	1.23	1.05	2.52	1.17
Jan 2025	6.65	6.98	1.16	1.57	1.26	2.47	1.07
Feb 2025	6.64	6.65	0.73	1.23	0.98	2.50	0.64
Mar 2025	6.58	5.13	0.45	0.71	0.59	2.58	0.69
Apr 2025	6.56	4.21	0.32	0.64	0.76	2.65	0.82
May 2025	6.55	4.28	0.39	0.69	0.82	2.64	0.98
Jun 2025	6.54	4.16	0.55	0.85	0.80	2.66	0.90
Jul 2025	6.51	2.73	0.46	0.66	0.64	2.67	0.76
Aug 2025	6.51	3.12	0.53	0.79	0.91	2.65	1.28
Sep 2025	6.52	3.79	0.60	0.90	0.94	2.58	1.21
Oct 2025	6.52	4.37	0.71	1.07	1.01	2.52	1.16
Nov 2025	6.55	5.35	0.89	1.25	0.84	2.50	0.93
Dec 2025	6.58	6.67	0.72	1.06	0.93	2.51	1.08
Jan 2026	6.60	6.70	0.94	1.36	1.12	2.49	0.98
Feb 2026	6.59	6.38	0.59	1.06	0.87	2.52	0.59
Mar 2026	6.55	4.92	0.36	0.61	0.52	2.57	0.64
Apr 2026	6.54	4.04	0.26	0.56	0.68	2.63	0.76
May 2026	6.53	4.11	0.31	0.60	0.72	2.64	0.90
Jun 2026	6.53	3.99	0.45	0.73	0.71	2.65	0.82
Jul 2026	6.51	2.62	0.38	0.56	0.57	2.64	0.70
Aug 2026	6.51	3.00	0.43	0.68	0.81	2.63	1.17
Sep 2026	6.51	3.63	0.49	0.78	0.83	2.57	1.11
Oct 2026	6.51	4.20	0.58	0.93	0.89	2.53	1.06
Nov 2026	6.53	5.14	0.72	1.08	0.74	2.50	0.85
Dec 2026	6.55	6.40	0.58	0.91	0.83	2.51	0.99
Jan 2027	6.56	6.44	0.77	1.17	0.99	2.50	0.90
Feb 2027	6.56	6.13	0.48	0.91	0.77	2.53	0.54
Mar 2027	6.54	4.73	0.30	0.53	0.46	2.57	0.58
Apr 2027	6.53	3.88	0.21	0.48	0.60	2.62	0.69
May 2027	6.52	3.94	0.26	0.51	0.64	2.63	0.82
Jun 2027	6.52	3.83	0.36	0.63	0.63	2.64	0.75
Jul 2027	6.51	2.52	0.31	0.49	0.50	2.63	0.64
Aug 2027	6.51	2.88	0.35	0.59	0.72	2.61	1.07
Sep 2027	6.51	3.49	0.40	0.67	0.74	2.56	1.01
Oct 2027	6.51	4.03	0.47	0.80	0.79	2.53	0.97
Nov 2027	6.52	4.93	0.59	0.93	0.66	2.50	0.77
Dec 2027	6.54	6.15	0.48	0.78	0.73	2.51	0.90

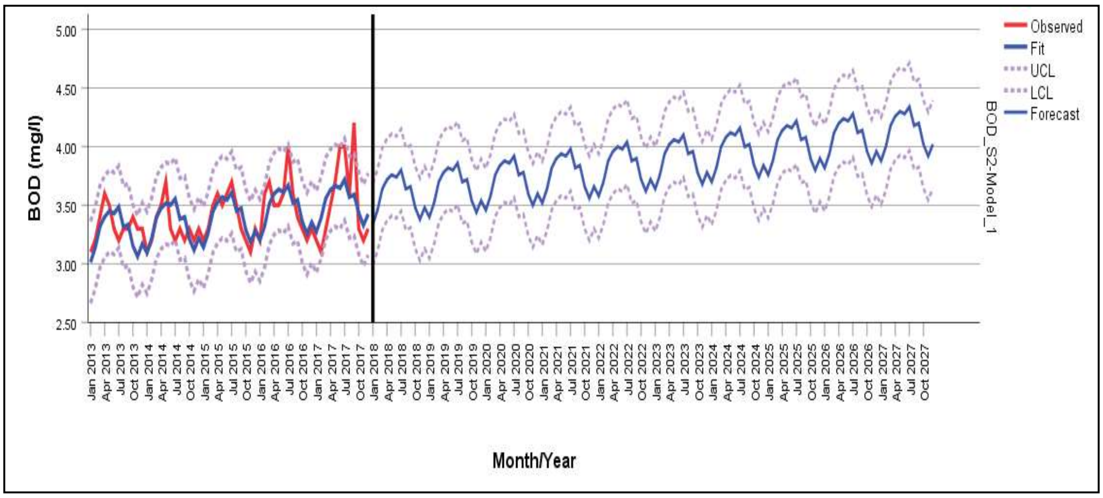
ANNEXURE – XII

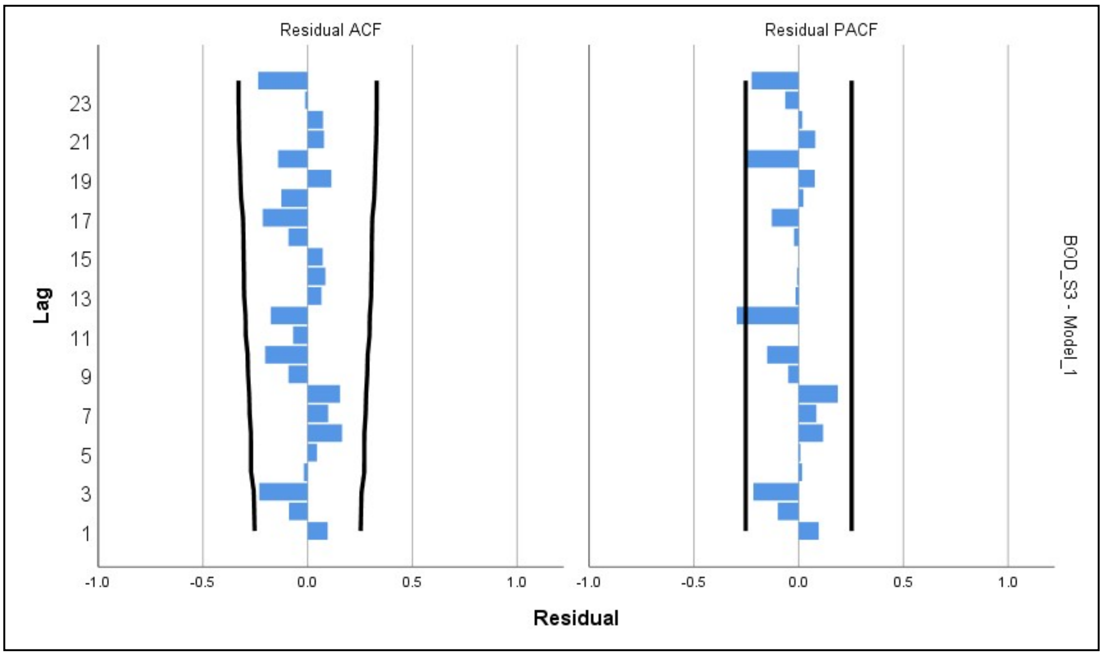
Graphical representation of trend, time series analysis (ACF, PACF, observed, best fit, LCL, UCL) of BOD (S1 – S7)

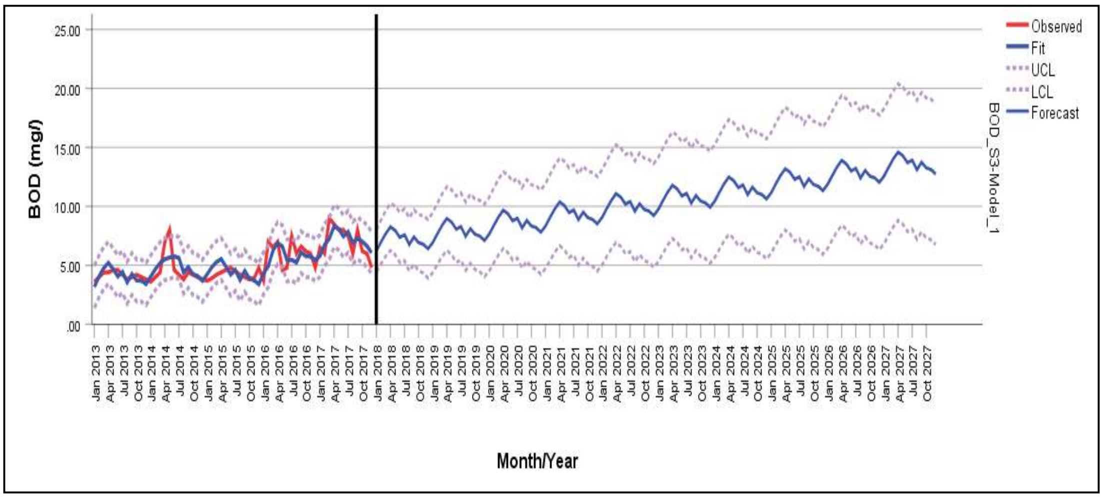


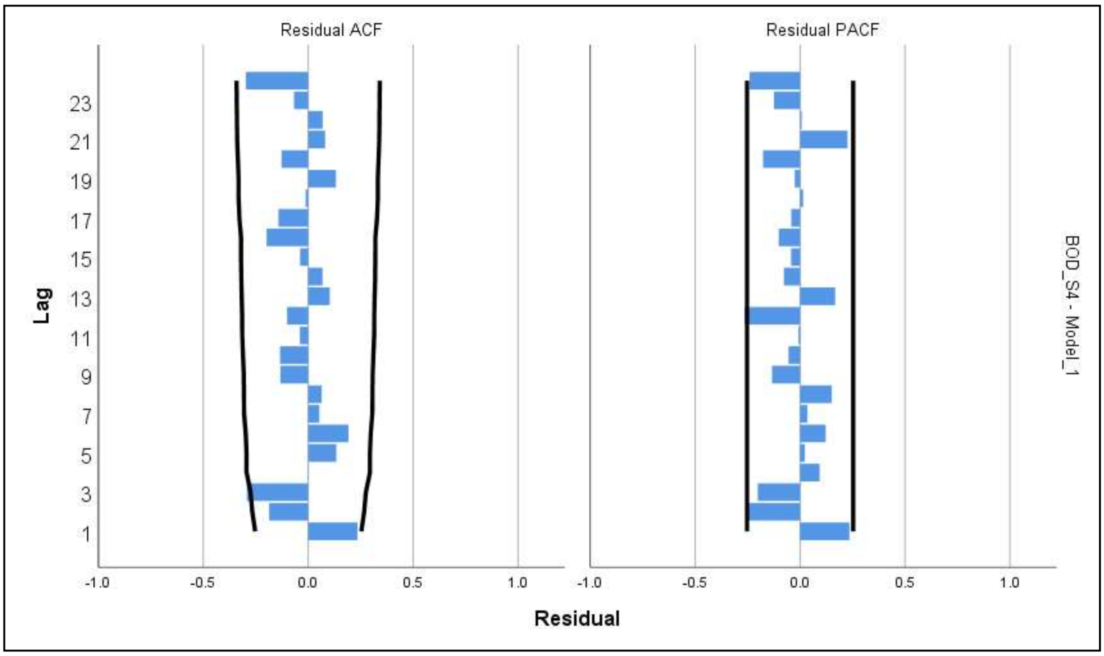


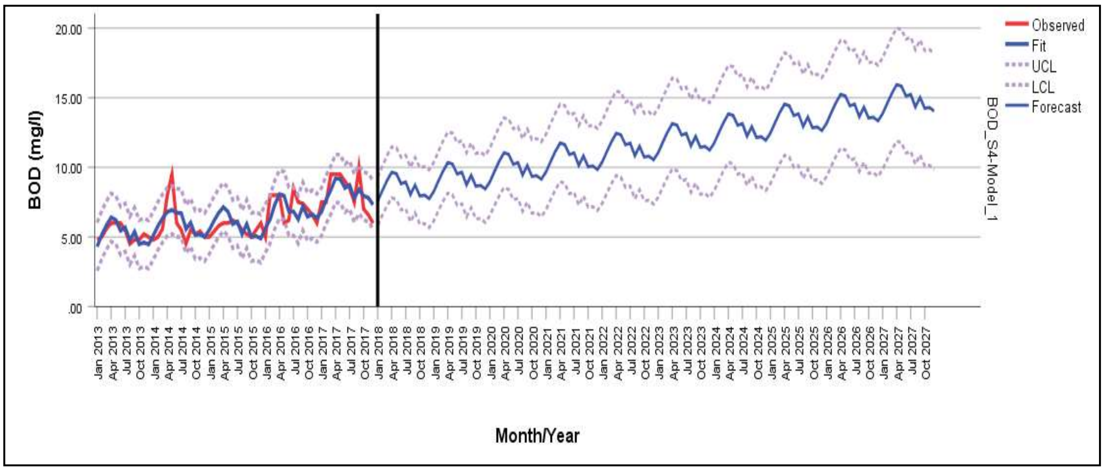


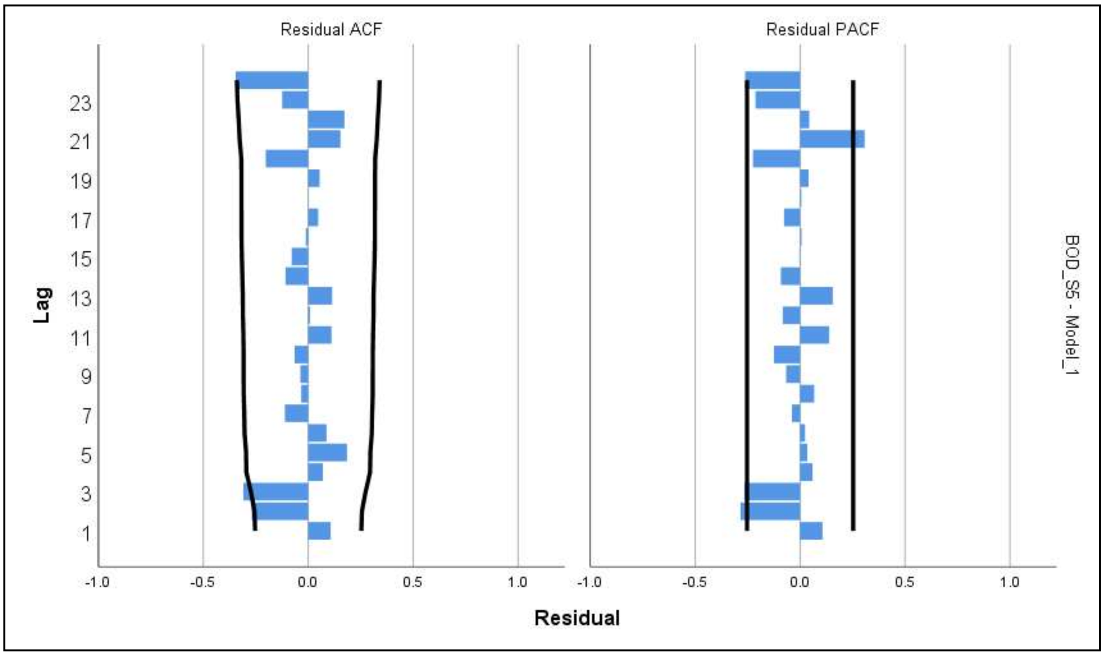

BOD (mg/l)
Month/Year
Observed
Fit
UCL
LCL
Forecast
BOD_S2-Model_1

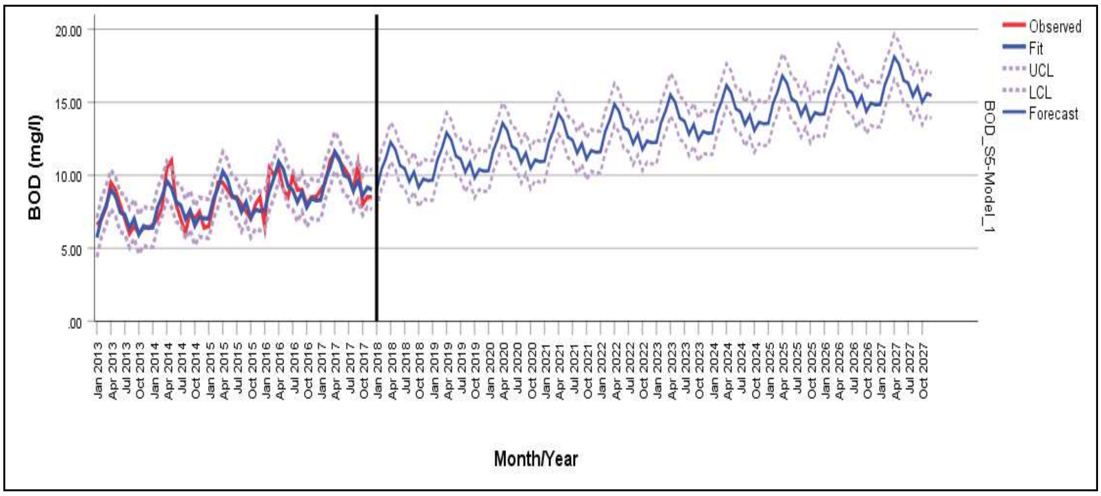

Residual ACF
Residual PACF
Lag
Residual
BOD_S3 - Model_1

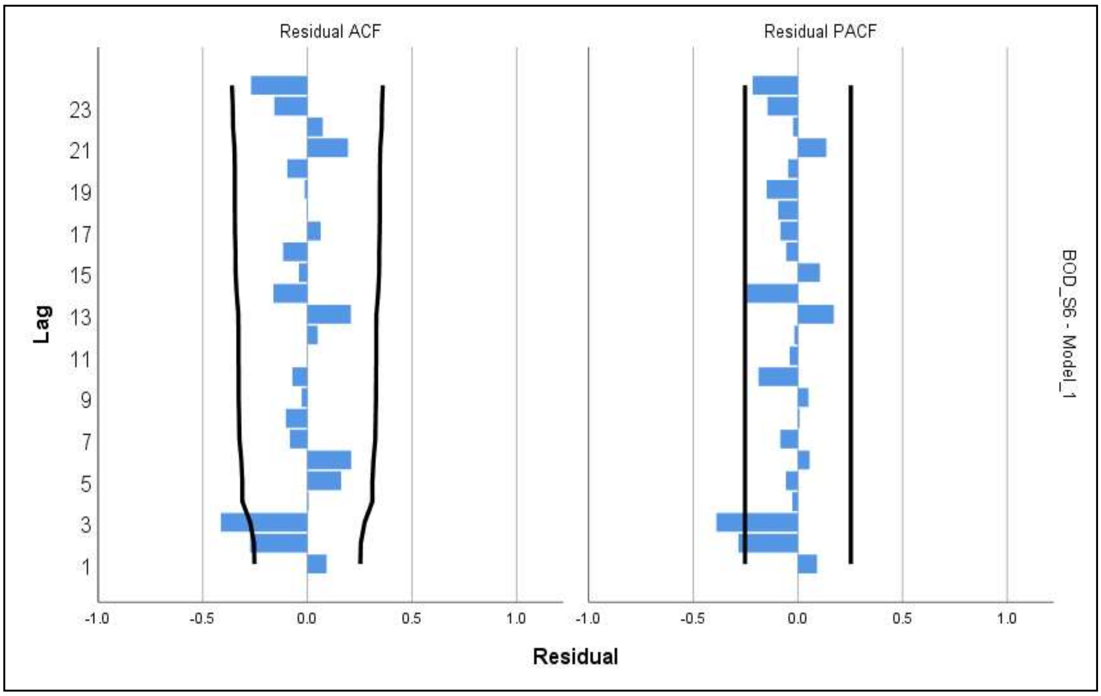

BOD (mg/l)
Month/Year
Observed
Fit
UCL
LCL
Forecast
BOD_S3-Model_1

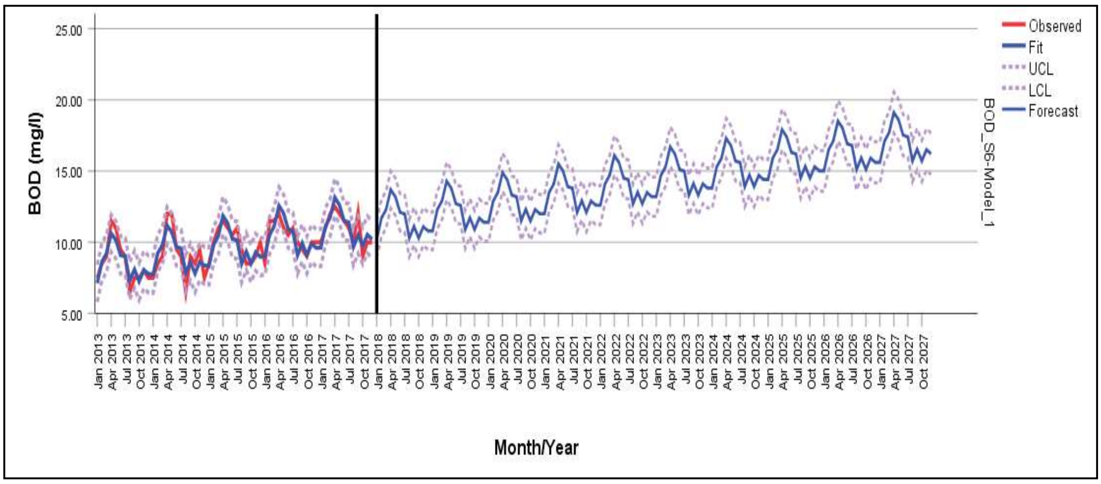

Residual ACF
Residual PACF
Lag
Residual
BOD_S4 - Model_1

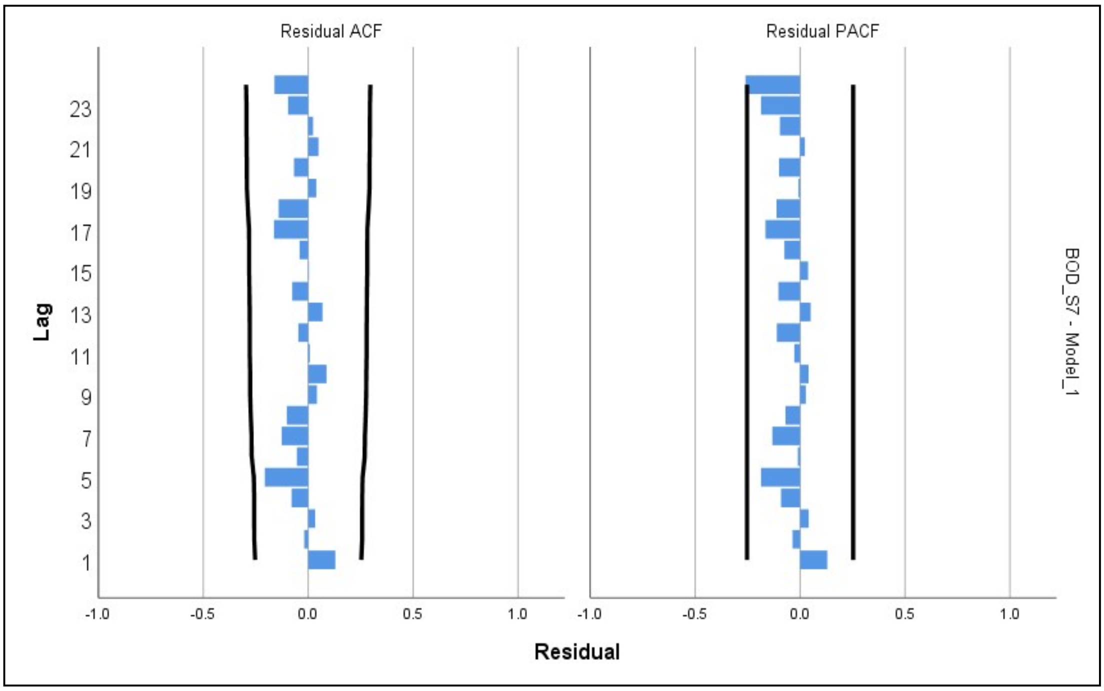

BOD (mg/l)
Month/Year
Observed
Fit
UCL
LCL
Forecast
BOD_S4-Model_1

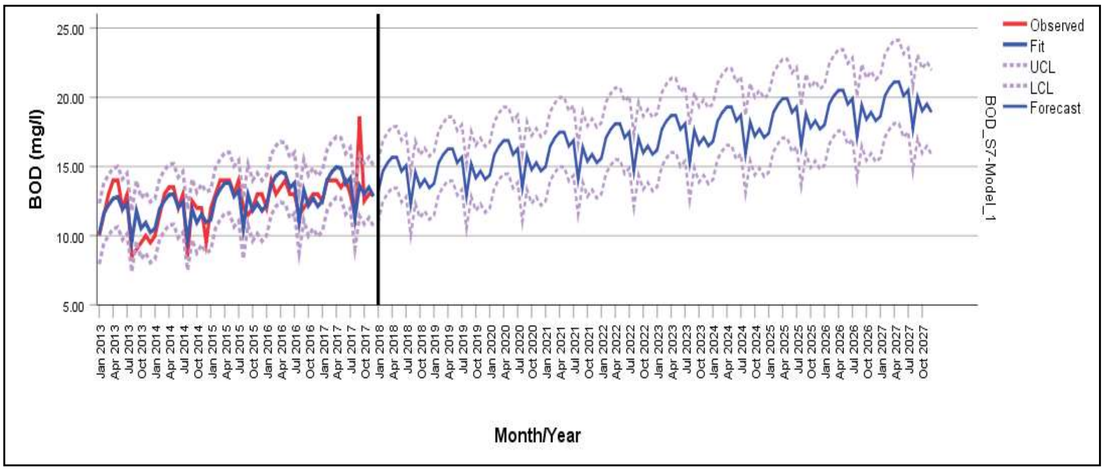

Residual ACF
Residual PACF
Lag
Residual
BOD_S5 - Model_1


BOD (mg/l)
Month/Year
Observed
Fit
UCL
LCL
Forecast
BOD_S5-Model_1


Residual ACF
Residual PACF
Lag
Residual
BOD_S6 - Model_1


BOD (mg/l)
Month/Year
Observed
Fit
UCL
LCL
Forecast
BOD_S6-Model_1


Residual ACF
Residual PACF
Lag
Residual
BOD_S7 - Model_1


Observed
Fit
UCL
LCL
Forecast
BOD (mg/l)
Month/Year
BOD_S7-Model_1

ANNEXURE – XIII

Predicted value of BOD (2018-2027) by Time-series analysis

Date	S1	S2	S3	S4	S5	S6	S7
Jan 2018	3.18	3.34	6.22	7.57	9.01	10.19	13.16
Feb 2018	3.25	3.46	6.98	8.33	10.37	11.69	14.66
Mar 2018	3.23	3.64	7.70	9.05	11.19	12.29	15.26
Apr 2018	2.05	3.72	8.26	9.65	12.27	13.69	15.66
May 2018	2.14	3.76	7.96	9.55	11.77	13.19	15.66
Jun 2018	2.66	3.74	7.36	8.83	10.67	12.09	14.66
Jul 2018	2.59	3.80	7.58	8.95	10.47	11.99	15.06
Aug 2018	2.61	3.64	6.76	8.05	9.57	10.29	12.26
Sep 2018	2.51	3.66	7.40	8.73	10.23	11.11	14.58
Oct 2018	2.75	3.48	6.92	7.95	9.17	10.29	13.56
Nov 2018	2.89	3.38	6.78	8.01	9.75	11.09	14.06
Dec 2018	3.21	3.48	6.40	7.75	9.63	10.79	13.46
Jan 2019	3.40	3.40	6.92	8.27	9.66	10.79	13.77
Feb 2019	3.48	3.52	7.68	9.03	11.02	12.29	15.27
Mar 2019	3.46	3.70	8.40	9.75	11.84	12.89	15.87
Apr 2019	2.19	3.78	8.96	10.35	12.92	14.29	16.27
May 2019	2.29	3.82	8.66	10.25	12.42	13.80	16.27
Jun 2019	2.85	3.80	8.06	9.53	11.32	12.70	15.27
Jul 2019	2.77	3.86	8.28	9.65	11.12	12.60	15.67
Aug 2019	2.80	3.70	7.46	8.75	10.22	10.90	12.87
Sep 2019	2.68	3.72	8.10	9.43	10.88	11.72	15.19
Oct 2019	2.95	3.54	7.62	8.65	9.82	10.90	14.17
Nov 2019	3.09	3.44	7.48	8.71	10.40	11.70	14.67
Dec 2019	3.44	3.54	7.10	8.45	10.28	11.40	14.07
Jan 2020	3.64	3.46	7.63	8.97	10.30	11.40	14.37
Feb 2020	3.73	3.58	8.39	9.73	11.66	12.90	15.87
Mar 2020	3.71	3.76	9.11	10.45	12.49	13.50	16.47
Apr 2020	2.35	3.84	9.67	11.05	13.57	14.90	16.87
May 2020	2.46	3.88	9.37	10.95	13.07	14.40	16.87
Jun 2020	3.05	3.86	8.77	10.23	11.97	13.30	15.87
Jul 2020	2.97	3.92	8.99	10.35	11.77	13.20	16.27
Aug 2020	3.00	3.76	8.17	9.45	10.87	11.50	13.47
Sep 2020	2.88	3.78	8.81	10.13	11.53	12.32	15.79
Oct 2020	3.17	3.60	8.33	9.35	10.47	11.50	14.77
Nov 2020	3.32	3.50	8.19	9.41	11.05	12.30	15.27
Dec 2020	3.69	3.60	7.81	9.15	10.93	12.00	14.67
Jan 2021	3.91	3.52	8.33	9.66	10.95	12.00	14.98
Feb 2021	4.01	3.64	9.09	10.42	12.31	13.50	16.48
Mar 2021	3.98	3.82	9.81	11.14	13.13	14.10	17.08

Date	S1	S2	S3	S4	S5	S6	S7
Apr 2021	2.53	3.90	10.37	11.74	14.21	15.50	17.48
May 2021	2.64	3.94	10.07	11.64	13.71	15.00	17.48
Jun 2021	3.28	3.92	9.47	10.92	12.61	13.90	16.48
Jul 2021	3.19	3.98	9.69	11.04	12.41	13.80	16.88
Aug 2021	3.23	3.82	8.87	10.14	11.51	12.10	14.08
Sep 2021	3.10	3.84	9.51	10.82	12.17	12.92	16.40
Oct 2021	3.41	3.66	9.03	10.05	11.11	12.10	15.38
Nov 2021	3.57	3.56	8.89	10.11	11.69	12.90	15.88
Dec 2021	3.97	3.66	8.51	9.85	11.58	12.60	15.28
Jan 2022	4.21	3.58	9.04	10.36	11.60	12.60	15.59
Feb 2022	4.32	3.70	9.80	11.12	12.96	14.10	17.09
Mar 2022	4.29	3.88	10.52	11.84	13.78	14.70	17.69
Apr 2022	2.72	3.96	11.08	12.44	14.86	16.10	18.09
May 2022	2.84	4.00	10.78	12.34	14.36	15.60	18.09
Jun 2022	3.54	3.98	10.18	11.62	13.26	14.50	17.09
Jul 2022	3.44	4.04	10.40	11.74	13.06	14.40	17.49
Aug 2022	3.48	3.88	9.58	10.84	12.16	12.70	14.69
Sep 2022	3.34	3.90	10.22	11.52	12.82	13.52	17.01
Oct 2022	3.67	3.72	9.74	10.74	11.76	12.70	15.99
Nov 2022	3.85	3.62	9.60	10.80	12.34	13.50	16.49
Dec 2022	4.28	3.72	9.22	10.54	12.22	13.20	15.89
Jan 2023	4.54	3.64	9.74	11.06	12.25	13.20	16.19
Feb 2023	4.66	3.76	10.50	11.82	13.61	14.70	17.69
Mar 2023	4.63	3.94	11.22	12.54	14.43	15.30	18.29
Apr 2023	2.94	4.02	11.78	13.14	15.51	16.70	18.69
May 2023	3.07	4.06	11.48	13.04	15.01	16.20	18.69
Jun 2023	3.82	4.04	10.88	12.32	13.91	15.10	17.69
Jul 2023	3.72	4.10	11.10	12.44	13.71	15.00	18.09
Aug 2023	3.76	3.94	10.28	11.54	12.81	13.30	15.29
Sep 2023	3.61	3.96	10.92	12.22	13.47	14.12	17.61
Oct 2023	3.97	3.78	10.44	11.44	12.41	13.30	16.59
Nov 2023	4.16	3.68	10.30	11.50	12.99	14.10	17.09
Dec 2023	4.63	3.78	9.92	11.24	12.87	13.80	16.49
Jan 2024	4.91	3.70	10.44	11.76	12.90	13.80	16.80
Feb 2024	5.03	3.82	11.20	12.52	14.26	15.30	18.30
Mar 2024	5.01	4.00	11.92	13.24	15.08	15.90	18.90
Apr 2024	3.18	4.08	12.48	13.84	16.16	17.30	19.30
May 2024	3.32	4.12	12.18	13.74	15.66	16.80	19.30
Jun 2024	4.13	4.10	11.58	13.02	14.56	15.70	18.30
Jul 2024	4.02	4.16	11.80	13.14	14.36	15.60	18.70
Aug 2024	4.07	4.00	10.98	12.24	13.46	13.90	15.90

Date	S1	S2	S3	S4	S5	S6	S7
Sep 2024	3.91	4.02	11.62	12.92	14.12	14.72	18.22
Oct 2024	4.29	3.84	11.14	12.14	13.06	13.90	17.20
Nov 2024	4.51	3.74	11.01	12.20	13.64	14.70	17.70
Dec 2024	5.01	3.84	10.63	11.94	13.52	14.40	17.10
Jan 2025	5.31	3.76	11.15	12.46	13.55	14.40	17.40
Feb 2025	5.45	3.88	11.91	13.22	14.91	15.90	18.90
Mar 2025	5.43	4.06	12.63	13.94	15.73	16.50	19.50
Apr 2025	3.45	4.14	13.19	14.54	16.81	17.90	19.90
May 2025	3.60	4.18	12.89	14.44	16.31	17.40	19.90
Jun 2025	4.48	4.16	12.29	13.72	15.21	16.30	18.90
Jul 2025	4.36	4.22	12.51	13.84	15.01	16.20	19.30
Aug 2025	4.41	4.06	11.69	12.94	14.11	14.51	16.50
Sep 2025	4.24	4.08	12.33	13.62	14.77	15.33	18.82
Oct 2025	4.66	3.90	11.85	12.84	13.71	14.51	17.80
Nov 2025	4.89	3.80	11.71	12.90	14.29	15.31	18.30
Dec 2025	5.44	3.90	11.33	12.64	14.17	15.01	17.70
Jan 2026	5.77	3.82	11.85	13.16	14.20	15.01	18.01
Feb 2026	5.92	3.94	12.61	13.92	15.56	16.51	19.51
Mar 2026	5.89	4.12	13.33	14.64	16.38	17.11	20.11
Apr 2026	3.74	4.20	13.89	15.24	17.46	18.51	20.51
May 2026	3.91	4.24	13.59	15.14	16.96	18.01	20.51
Jun 2026	4.87	4.22	12.99	14.42	15.86	16.91	19.51
Jul 2026	4.74	4.28	13.21	14.54	15.66	16.81	19.91
Aug 2026	4.80	4.12	12.39	13.64	14.76	15.11	17.11
Sep 2026	4.61	4.14	13.03	14.32	15.42	15.93	19.43
Oct 2026	5.07	3.96	12.55	13.54	14.36	15.11	18.41
Nov 2026	5.32	3.86	12.41	13.60	14.94	15.91	18.91
Dec 2026	5.92	3.96	12.03	13.34	14.82	15.61	18.31
Jan 2027	6.28	3.88	12.56	13.86	14.85	15.61	18.61
Feb 2027	6.45	4.00	13.32	14.62	16.21	17.11	20.11
Mar 2027	6.41	4.18	14.04	15.34	17.03	17.71	20.71
Apr 2027	4.07	4.26	14.60	15.94	18.11	19.11	21.11
May 2027	4.26	4.30	14.30	15.84	17.61	18.61	21.11
Jun 2027	5.30	4.28	13.70	15.12	16.51	17.51	20.11
Jul 2027	5.16	4.34	13.92	15.24	16.31	17.41	20.51
Aug 2027	5.22	4.18	13.10	14.34	15.41	15.71	17.71
Sep 2027	5.02	4.20	13.74	15.02	16.07	16.53	20.03
Oct 2027	5.52	4.02	13.26	14.24	15.01	15.71	19.01
Nov 2027	5.80	3.92	13.12	14.30	15.59	16.51	19.51
Dec 2027	6.46	4.02	12.74	14.04	15.47	16.21	18.91

ANNEXURE – XIV

Water quality (WT, DO, BOD) and AT data at Hanuman Sethu and calculated BWQI (1998 – 2017)

Date	AT	WT	DO	BOD	BWQI
Jan-1998	14.13	16.50	6.60	2.03	93.33
Feb-1998	18.11	19.00	6.40	2.03	91.67
Mar-1998	22.48	21.50	6.27	1.89	86.67
Apr-1998	31.65	23.00	5.95	2.03	76.67
May-1998	36.15	32.50	5.62	1.89	45.00
Jun-1998	36.26	34.00	5.69	2.03	43.33
Jul-1998	30.21	32.50	5.62	1.89	45.00
Aug-1998	28.94	31.50	6.40	1.83	53.33
Sep-1998	27.98	32.50	6.60	1.83	48.33
Oct-1998	25.96	32.00	6.14	1.83	53.33
Nov-1998	21.24	26.50	6.27	2.02	65.00
Dec-1998	16.79	23.00	6.60	1.83	81.67
Jan-1999	15.40	16.00	6.40	2.09	91.67
Feb-1999	20.38	18.50	6.60	2.09	93.33
Mar-1999	26.22	23.50	5.95	2.16	76.67
Apr-1999	32.70	25.50	5.62	2.22	70.00
May-1999	36.40	28.50	5.69	2.22	56.67
Jun-1999	36.50	32.50	6.01	1.83	46.67
Jul-1999	33.67	33.00	6.01	2.03	45.00
Aug-1999	30.31	32.10	5.88	1.83	45.00
Sep-1999	27.73	32.00	6.08	2.02	51.67
Oct-1999	24.84	30.00	6.40	1.83	60.00
Nov-1999	21.07	28.00	6.27	1.83	66.67
Dec-1999	17.12	21.00	6.54	2.02	93.33
Jan-2000	16.33	18.50	6.60	2.03	93.33
Feb-2000	17.67	19.50	6.40	2.03	91.67
Mar-2000	24.62	20.50	6.27	1.89	93.33
Apr-2000	32.57	26.50	5.95	2.03	63.33
May-2000	35.83	31.00	5.62	1.89	51.67
Jun-2000	33.06	32.00	5.69	2.03	50.00
Jul-2000	30.72	33.00	5.62	1.89	45.00
Aug-2000	30.19	31.00	6.40	1.83	53.33
Sep-2000	27.34	30.50	6.60	1.83	55.00
Oct-2000	24.84	32.00	6.14	1.83	53.33
Nov-2000	21.31	27.50	6.27	2.02	65.00
Dec-2000	16.39	20.50	6.60	1.83	95.00
Jan-2001	14.98	18.50	6.40	2.09	91.67

Date	AT	WT	DO	BOD	BWQI
Feb-2001	19.66	18.00	6.60	2.09	93.33
Mar-2001	25.38	23.00	5.95	2.16	76.67
Apr-2001	31.59	25.00	5.62	2.22	70.00
May-2001	35.61	28.50	5.69	2.22	56.67
Jun-2001	34.24	30.00	5.36	2.22	56.67
Jul-2001	31.50	29.50	6.47	2.02	58.33
Aug-2001	29.82	29.50	6.54	2.15	60.00
Sep-2001	30.03	31.00	6.60	2.16	53.33
Oct-2001	25.88	29.50	6.08	2.22	58.33
Nov-2001	21.55	26.50	6.21	2.16	65.00
Dec-2001	16.76	18.00	6.73	2.29	93.33
Jan-2002	15.12	15.00	6.54	2.35	86.67
Feb-2002	18.69	16.50	6.14	2.42	91.67
Mar-2002	25.87	19.50	6.14	2.42	91.67
Apr-2002	32.54	25.00	5.42	2.42	70.00
May-2002	36.30	31.00	5.49	2.42	50.00
Jun-2002	36.28	32.00	5.23	2.55	50.00
Jul-2002	36.69	29.50	5.69	2.42	56.67
Aug-2002	30.53	30.00	5.95	2.22	56.67
Sep-2002	27.06	30.50	5.56	1.96	51.67
Oct-2002	25.37	29.50	6.21	1.64	60.00
Nov-2002	21.50	24.00	6.54	2.22	80.00
Dec-2002	17.14	18.00	6.73	2.35	93.33
Jan-2003	14.07	14.00	6.60	2.28	80.00
Feb-2003	18.85	16.50	6.40	2.28	91.67
Mar-2003	24.58	22.00	6.14	2.42	85.00
Apr-2003	32.16	25.50	5.82	2.49	70.00
May-2003	34.77	28.00	5.56	2.35	63.33
Jun-2003	37.15	30.50	7.45	0.65	56.67
Jul-2003	31.83	30.50	5.10	0.98	51.67
Aug-2003	29.83	28.50	6.01	3.46	56.67
Sep-2003	27.73	31.00	6.60	3.92	51.67
Oct-2003	23.61	29.00	6.47	4.71	55.00
Nov-2003	18.55	25.00	6.86	3.46	71.67
Dec-2003	15.75	17.00	7.12	3.53	93.33
Jan-2004	14.09	14.50	7.91	3.86	81.67
Feb-2004	18.10	15.50	7.58	3.60	88.33
Mar-2004	26.43	20.50	7.19	2.81	95.00
Apr-2004	33.10	25.50	6.80	1.96	75.00
May-2004	35.54	26.50	6.86	1.37	68.33
Jun-2004	33.30	30.50	5.69	2.61	50.00

Date	AT	WT	DO	BOD	BWQI
Jul-2004	29.73	31.50	6.14	2.29	51.67
Aug-2004	29.45	29.50	6.67	2.16	60.00
Sep-2004	28.90	30.50	6.86	3.52	51.67
Oct-2004	24.99	29.50	5.88	2.36	56.67
Nov-2004	20.65	22.50	7.84	1.17	85.00
Dec-2004	16.73	20.00	7.06	1.96	96.67
Jan-2005	15.02	14.50	7.25	1.37	83.33
Feb-2005	19.44	16.50	4.31	14.50	76.67
Mar-2005	26.59	20.00	3.33	11.76	75.00
Apr-2005	30.57	23.50	2.55	9.39	61.67
May-2005	34.19	26.00	6.47	9.42	63.33
Jun-2005	37.58	29.50	2.35	11.75	40.00
Jul-2005	29.82	29.50	2.35	9.99	41.67
Aug-2005	29.92	31.00	4.70	7.65	41.67
Sep-2005	28.02	31.50	7.25	3.52	53.33
Oct-2005	25.15	29.50	4.70	7.46	48.33
Nov-2005	19.91	22.00	4.51	7.06	75.00
Dec-2005	15.62	19.50	1.37	8.22	71.67
Jan-2006	15.79	16.00	4.90	10.59	78.33
Feb-2006	22.79	17.00	4.51	14.10	76.67
Mar-2006	24.97	21.50	1.76	8.32	65.00
Apr-2006	31.20	25.00	1.96	9.99	51.67
May-2006	35.69	31.00	2.16	9.42	35.00
Jun-2006	33.25	29.50	3.92	9.40	45.00
Jul-2006	30.32	29.00	1.76	9.39	38.33
Aug-2006	28.88	30.00	5.29	6.28	50.00
Sep-2006	29.05	28.00	2.94	6.28	50.00
Oct-2006	27.56	31.00	2.16	7.46	36.67
Nov-2006	21.90	25.00	2.35	7.06	56.67
Dec-2006	17.44	17.00	2.16	8.22	75.00
Jan-2007	15.90	16.00	1.18	10.59	70.00
Feb-2007	18.88	17.50	0.98	14.10	70.00
Mar-2007	23.62	21.00	1.18	8.32	71.67
Apr-2007	32.69	26.00	0.98	11.19	51.67
May-2007	34.33	28.50	0.98	11.19	38.33
Jun-2007	36.08	30.00	0.78	14.70	36.67
Jul-2007	31.53	31.00	2.34	12.52	31.67
Aug-2007	28.90	29.00	5.88	8.82	48.33
Sep-2007	28.06	29.50	7.06	4.32	58.33
Oct-2007	24.56	28.00	6.28	4.20	61.67
Nov-2007	20.99	25.00	5.68	4.32	66.67

Date	AT	WT	DO	BOD	BWQI
Dec-2007	15.88	18.00	2.68	5.88	78.33
Jan-2008	15.73	14.00	2.35	4.72	66.67
Feb-2008	18.06	14.00	3.14	3.52	70.00
Mar-2008	27.01	20.50	0.98	7.08	75.00
Apr-2008	31.25	25.00	0.78	8.80	53.33
May-2008	34.74	28.50	0.98	9.80	40.00
Jun-2008	31.34	30.00	0.98	9.80	40.00
Jul-2008	28.62	28.00	5.10	9.80	55.00
Aug-2008	28.20	31.00	7.06	8.80	46.67
Sep-2008	27.12	32.00	7.13	1.56	56.67
Oct-2008	24.47	29.00	7.06	1.72	63.33
Nov-2008	18.96	24.00	7.45	2.74	81.67
Dec-2008	15.92	19.50	7.06	3.51	93.33
Jan-2009	15.37	16.50	7.45	4.72	91.67
Feb-2009	18.93	18.00	6.27	8.62	83.33
Mar-2009	25.02	20.50	3.74	8.32	78.33
Apr-2009	31.80	24.50	3.92	11.19	56.67
May-2009	35.58	29.00	3.33	11.19	41.67
Jun-2009	37.04	29.00	3.41	14.70	40.00
Jul-2009	33.28	31.00	3.43	12.52	33.33
Aug-2009	30.38	32.00	3.44	8.82	36.67
Sep-2009	27.65	31.00	3.54	4.32	43.33
Oct-2009	22.53	30.50	3.50	4.20	41.67
Nov-2009	18.46	23.50	3.55	4.32	70.00
Dec-2009	14.85	18.00	3.52	5.88	81.67
Jan-2010	13.94	14.00	3.54	4.72	70.00
Feb-2010	18.44	16.00	3.54	8.62	78.33
Mar-2010	26.54	23.00	3.54	8.32	65.00
Apr-2010	33.85	27.00	1.22	11.19	43.33
May-2010	36.56	29.00	1.24	11.19	36.67
Jun-2010	37.27	31.00	0.98	14.70	30.00
Jul-2010	32.16	32.50	1.28	12.52	21.67
Aug-2010	29.23	30.00	4.31	8.82	46.67
Sep-2010	26.84	31.00	4.33	4.32	45.00
Oct-2010	24.42	29.00	6.22	4.20	55.00
Nov-2010	20.53	23.50	6.14	4.32	75.00
Dec-2010	14.71	20.00	4.31	5.88	83.33
Jan-2011	13.23	15.50	3.92	4.72	76.67
Feb-2011	18.63	9.05	3.33	3.52	50.00
Mar-2011	25.47	8.28	2.16	7.08	43.33
Apr-2011	31.12	25.50	1.96	8.80	51.67

Date	AT	WT	DO	BOD	BWQI
May-2011	36.55	29.50	1.76	9.80	38.33
Jun-2011	34.38	30.00	1.57	9.80	38.33
Jul-2011	29.48	28.50	1.57	9.80	38.33
Aug-2011	28.32	29.50	1.76	8.80	38.33
Sep-2011	27.48	32.50	4.70	1.56	43.33
Oct-2011	24.24	26.50	3.92	1.72	61.67
Nov-2011	20.21	23.50	4.31	2.74	75.00
Dec-2011	15.51	20.00	3.72	3.51	85.00
Jan-2012	13.70	14.50	3.92	2.94	73.33
Feb-2012	17.21	16.50	3.72	3.54	85.00
Mar-2012	23.94	20.00	3.33	3.51	83.33
Apr-2012	31.44	25.00	8.70	5.37	71.67
May-2012	36.05	28.00	2.74	5.68	51.67
Jun-2012	38.86	31.50	2.35	7.65	36.67
Jul-2012	31.55	32.00	2.16	7.05	36.67
Aug-2012	28.75	31.00	5.88	2.74	50.00
Sep-2012	26.72	30.50	5.68	3.54	48.33
Oct-2012	23.43	30.50	5.10	3.92	48.33
Nov-2012	18.19	23.50	4.90	3.54	73.33
Dec-2012	14.88	18.50	4.70	4.32	85.00
Jan-2013	13.41	13.00	4.51	5.31	63.33
Feb-2013	17.56	14.50	6.66	3.52	78.33
Mar-2013	24.40	21.00	4.90	4.11	85.00
Apr-2013	31.40	24.00	1.76	6.48	60.00
May-2013	36.47	29.50	1.57	7.85	40.00
Jun-2013	33.01	30.00	1.76	9.80	38.33
Jul-2013	29.54	28.50	5.29	12.75	45.00
Aug-2013	28.67	31.50	3.72	16.65	33.33
Sep-2013	28.02	29.00	4.31	17.65	41.67
Oct-2013	24.95	25.00	4.70	12.75	56.67
Nov-2013	18.84	27.50	4.90	15.70	48.33
Dec-2013	15.62	20.00	3.53	10.75	76.67
Jan-2014	14.90	12.00	3.33	8.25	56.67
Feb-2014	17.25	10.50	2.74	7.65	50.00
Mar-2014	23.51	17.00	2.55	8.25	75.00
Apr-2014	31.08	23.00	2.74	8.85	61.67
May-2014	35.90	30.00	2.55	12.75	38.33
Jun-2014	38.79	33.00	0.98	15.65	21.67
Jul-2014	32.32	25.00	0.00	10.80	51.67
Aug-2014	31.13	32.50	0.98	9.80	26.67
Sep-2014	29.32	32.50	1.96	12.75	21.67

Date	AT	WT	DO	BOD	BWQI
Oct-2014	26.37	30.00	0.00	17.60	35.00
Nov-2014	20.55	29.00	0.00	18.12	35.00
Dec-2014	14.90	21.00	1.76	24.50	66.67
Jan-2015	14.31	12.00	2.35	19.60	50.00
Feb-2015	19.74	14.00	1.96	39.20	53.33
Mar-2015	23.00	20.00	2.35	19.80	70.00
Apr-2015	29.06	21.00	0.00	7.84	75.00
May-2015	35.82	23.00	0.00	29.10	55.00
Jun-2015	36.92	30.00	0.98	26.40	35.00
Jul-2015	30.86	26.50	0.00	20.04	41.67
Aug-2015	30.58	29.50	1.57	15.70	33.33
Sep-2015	30.55	31.50	0.59	25.50	28.33
Oct-2015	27.91	27.50	0.78	23.60	41.67
Nov-2015	23.96	22.50	0.98	27.40	55.00
Dec-2015	17.08	22.00	0.98	29.40	61.67
Jan-2016	17.11	16.50	0.00	21.60	68.33
Feb-2016	21.01	24.00	0.00	23.50	55.00
Mar-2016	27.06	28.00	0.00	18.90	41.67
Apr-2016	33.82	30.00	1.96	13.70	35.00
May-2016	35.87	29.00	0.39	39.20	35.00
Jun-2016	35.61	32.50	0.78	11.60	25.00
Jul-2016	29.65	29.00	1.37	15.70	33.33
Aug-2016	28.76	31.50	3.72	11.80	36.67
Sep-2016	28.01	33.00	1.76	9.80	25.00
Oct-2016	25.54	30.50	3.92	4.00	43.33
Nov-2016	20.20	27.50	1.57	5.90	48.33
Dec-2016	16.67	21.50	0.00	7.80	68.33
Jan-2017	15.83	16.50	0.00	21.60	68.33
Feb-2017	19.73	24.00	0.00	23.50	55.00
Mar-2017	25.44	28.00	0.00	18.90	41.67
Apr-2017	33.58	30.00	1.96	13.70	35.00
May-2017	36.57	29.00	0.39	39.20	35.00
Jun-2017	35.96	32.50	0.78	11.60	25.00
Jul-2017	29.23	29.00	1.37	15.70	33.33
Aug-2017	28.91	31.50	3.72	11.80	36.67
Sep-2017	28.23	33.00	1.76	9.80	25.00
Oct-2017	26.26	30.50	3.92	4.00	43.33
Nov-2017	20.07	27.50	1.57	5.90	48.33
Dec-2017	16.98	21.50	0.00	7.80	68.33

ANNEXURE – XV

Drinking Water Specifications (IS 10500: 2012)

S. No.	Parameters	Permissible Limit	Maximum Limit
1	Odor	Agreeable	Agreeable
2	Taste	Agreeable	Agreeable
3	pH	6.5 to 8.5	No relaxation
4	TDS (mg/l)	500	2000
5	Hardness (as $CaCO_3$) (mg/l)	200	600
6	Alkalinity (as $CaCO_3$) (mg/l)	200	600
7	Nitrate (mg/l)	45	No relaxation
8	Sulfate (mg/l)	200	400
9	Fluoride (mg/l)	1	1.5
10	Chloride (mg/l)	250	1000
11	Turbidity (NTU)	5	10
12	Arsenic (mg/l)	0.01	0.05
13	Copper (mg/l)	0.05	1.5
14	Cadmium (mg/l)	0.003	No relaxation
15	Chromium (mg/l)	0.05	No relaxation
16	Lead (mg/l)	0.01	No relaxation
17	Iron (mg/l)	0.3	No relaxation
18	Zinc (mg/l)	5	15
19	Fecal Coliform (CFU)	0	0
20	E. Coli (CFU)	0	0

Water Quality Standards in India (Source IS 2296:1992)

Characteristics	Designated best use				
	A	B	C	D	E
Dissolved Oxygen (DO) mg/l, min.	6	5	4	4	-
Biochemical Oxygen demand (BOD) mg/l, max.	2	3	3	-	-
Total coliform organisms MPN/100 ml, max.	50	500	5,000	-	-
pH value	6.5-8.5	6.5-8.5	6.0-9.0	6.5-8.5	6.0-8.5
Color, Hazen units, max.	10	300	300	-	-
Odor	Un-objectionable			-	-
Taste	Tasteless	-	-	-	-

Characteristics	Designated best use				
	A	B	C	D	E
Total dissolved solids, mg/l, max.	500	-	1,500	-	2,100
Total hardness (as $CaCO_3$), mg/l, max.	200	-	-	-	-
Calcium hardness (as $CaCO_3$), mg/l, max.	200	-	-	-	-
Magnesium hardness (as $CaCO_3$), mg/l, max.	200	-	-	-	-
Copper (as Cu), mg/l, max.	1.5	-	1.5	-	-
Iron (as Fe), mg/l, max.	0.3	-	0.5	-	-
Manganese (as Mn), mg/l, max.	0.5	-	-	-	-
Chlorides (as Cu), mg/l, max.	250	-	600	-	600
Sulphates (as SO_4), mg/l, max.	400	-	400	-	1,000
Nitrates (as NO_3), mg/l, max.	20	-	50	-	-
Fluorides (as F), mg/l, max.	1.5	1.5	1.5	-	-
Phenolic compounds (as C_2H_5OH), mg/l, max.	0.002	0.005	0.005	-	-
Mercury (as Hg), mg/l, max.	0.001	-	-	-	-
Cadmium (as Cd), mg/l, max.	0.01	-	0.01	-	-
Selenium (as Se), mg/l, max.	0.01	-	0.05	-	-
Arsenic (as As), mg/l, max.	0.05	0.2	0.2	-	-
Cyanide (as Pb), mg/l, max.	0.05	0.05	0.05	-	-
Lead (as Pb), mg/l, max.	0.1	-	0.1	-	-
Zinc (as Zn), mg/l, max.	15	-	15	-	-
Chromium (as Cr^{6+}), mg/l, max.	0.05	-	0.05	-	-
Anionic detergents (as MBAS), mg/l, max.	0.2	1	1	-	-
Barium (as Ba), mg/l, max.	1	-	-	-	-
Free Ammonia (as N), mg/l, max.	-	-	-	1.2	-
Electrical conductivity, micromhos/cm, max.	-	-	-	-	2,250
Sodium absorption ratio, max.	-	-	-	-	26
Boron, mg/l, max.	-	-	-	-	2

Designated Best Uses of Water (Source: CPCB)

Designated Best Use	**Class**	**Criteria**
Drinking Water Source without conventional treatment but after disinfection	A	1.Total Coliforms Organism MPN/100 ml shall be 50 or less 2. pH between 6.5 and 8.5 3. Dissolved Oxygen 6 mg/l or more 4. Biochemical Oxygen Demand 5 days 20°C, 2 mg/l or less
Outdoor bathing (Organized)	B	1.Total Coliforms Organism MPN/100 ml shall be 500 or less 2. pH between 6.5 and 8.5 3. Dissolved Oxygen 5 mg/l or more 4. Biochemical Oxygen Demand 5 days 20°C, 3 mg/l or less
Drinking water source after conventional treatment and disinfection	C	1.Total Coliforms Organism MPN/100 ml shall be 5000 or less 2. pH between 6 and 9 3. Dissolved Oxygen 4 mg/l or more 4. Biochemical Oxygen Demand 5 days 20°C, 3 mg/l or less
Propagation of Wild life and Fisheries	D	1. pH between 6.5 and 8.5 2. Dissolved Oxygen 4 mg/l or more 3. Free Ammonia (as N) 4. Biochemical Oxygen Demand 5 days 20°C, 2 mg/l or less
Irrigation, Industrial Cooling, Controlled Waste disposal	E	1. pH between 6.0 and 8.5 2. Electrical Conductivity at 25°C micro mhos/cm, maximum 2250 3. Sodium absorption Ratio Max. 26 4. Boron Max. 2mg/l
	Below-E	Not meeting any of the A, B, C, D & E criteria