

A

Major Project Report

on

**ASSESSMENT OF TEMPORAL PATTERNS AND TRENDS OF AMBIENT AIR QUALITY
AROUND LANDFILLS USING LINEAR REGRESSION ANALYSIS**

submitted in the partial fulfilment of the requirement for the award of degree of

MASTER OF TECHNOLOGY

(Environmental Engineering)

by

ADARSH KHARE

(2K20/ENE/01)

under supervision of

Mr. ANUNAY A. GOUR

(Assistant Professor)



DEPARTMENT OF ENVIRONMENTAL ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

2020-2022

Acknowledgement

*On the submission of this thesis, I would like to express my sincere gratitude towards my mentor **Mr. Anunay A. Gour** for his guidance and constant support in completing my thesis. Also, I would like to extend my gratitude to **DELHI TECHNOLOGICAL UNIVERSITY** for giving me this opportunity. We truly appreciate and value his esteemed guidance and encouragement from the very beginning till the very end. At last I also like to thank my friends and staff of the Department of Environmental Engineering, who directly or indirectly helped me in completing this thesis.*

Adarsh Khare

Certificate

This is to certify that Mr. ADARSH KHARE, M.Tech. student in the Department of Environmental Engineering has submitted a thesis on “ASSESSMENT OF TEMPORAL PATTERNS AND TRENDS OF AMBIENT AIR QUALITY AROUND LANDFILL USING LINEAR REGRESSION ANALYSIS” in partial fulfilment of the requirement for award of degree of Master of Technology in Environmental Engineering, during the academic year 2020-21.

It is a record of the student’s research work prepared under my supervision and guidance.

Mr. ANUNAY A. GOUR

Asst. Professor

Department of Environmental Engineering,

Delhi Technological University

Declaration of Originality

I hereby undertake that I am the sole author of this report. I undertake that this report neither infringes upon anyone's copyright nor violates any proprietary rights to the best of my knowledge. Any ideas, techniques, quotations, or any other material form of work of other people included in this report, published or otherwise, are fully acknowledged in accordance with the standard referencing practices.

I declare that this is the true copy of my report, including all revisions, as approved by my advisor and supervisor, and that this report has not been submitted for any other degree to any other University or Institution.

Signature

Adarsh Khare
(2K20/ENE/01)

Abstract

Landfill is responsible for methane and carbon dioxide generation and the ground level emission like PM_{2.5}, PM₁₀, NO, NO_x, NO₂, SO₂, NH₃, CO, Ozone, Benzene, Toluene responsible for what we call pollution. Due to COVID-19 outbreak whole world faces lockdown which lead to the shutdown of industries, construction activities which eventually lead to decrease in pollution. Lockdown started from 24th March 2020 in four phases and then unlock from June till November, which lead to decrease in air and water pollution. In this study, concentrations of major pollutants like PM_{2.5}, PM₁₀, NO, NO_x, NO₂, SO₂, NH₃, CO, Ozone, Benzene, Toluene within the proximity of landfill were analysed during lockdown and unlock period and the seasonal variation of the particle has also been discussed, their regression model has been estimated to know the good fit curve. Descriptive statistics and correlation have also been estimated to know the variation of particles with each other, also how they vary with the meteorological parameter like wind speed (WS), wind direction (WD) solar radiation (SR), barometric pressure (BP), ambient temperature (AT) and rainfall (RF). Maximum PM_{2.5} value near Ghazipur, Narela and Okhla was 632.63 µg/m³ in 2020, 689.1 µg/m³ in 2019 and 551.19 µg/m³ in 2019 respectively, and for PM₁₀ maximum emission for Ghazipur, Narela and Okhla was 692.3 µg/m³ in 2020, 717.35 µg/m³ in 2020 and 740.19 µg/m³ in 2020 respectively, the common thing between these emissions was that peak occurred during winter season. Even though the lockdown was there PM₁₀ still peaked in 2020 during winter, same is the case for most of the pollutants that the emission peaked during winter season. The linear regression model has been generated using MATLAB between PM_{2.5} vs PM₁₀, NO vs NO_x and NO₂ vs NO_x, graph has shown how much error has been there between true and predicted value and how much deviation is there from regression line. The model has given RMSE, MSE, MAE and R-Squared value for each regression model with their governing linear equation, model between NO₂ vs NO_x has given negative intercept meaning that the oxide of nitrogen (NO_x) decreases as the nitrogen dioxide (NO₂) increases, other model has given positive intercept. study gives governing bodies that during crisis of air pollution certain measures can be taken to improve the condition of air quality otherwise detrimental effect of these can be seen every year to the people.

Contents

List of figures.....	vii
List of Tables.....	x
Chapter 1 INTRODUCTION.....	1
1.1 IMPACT OF AIR POLLUTANTS AROUND LANDFILL	2
1.1.1 Sulphur Dioxide (SO ₂).....	3
1.1.2 Nitrogen Oxides (NO _x)	3
1.1.3 Carbon Monoxide (CO).....	3
1.1.4 Ozone (O ₃)	3
1.1.5 Particulate Matter (PM)	3
1.1.6 Ammonia (NH ₃).....	4
1.1.7 Benzene.....	4
1.1.8 Toluene	4
1.2 OBJECTIVE	5
Chapter 2 LITERATURE REVIEW.....	6
2.1 Models of methane and LFG emission estimation	8
2.1.1 First order decay (FOD) model.....	8
2.1.2 IPCC Model	8
2.1.3 LandGEM model	9
2.1.4 Multi-phase model (Afvalzorg)	9
2.1.5 EPER Model Germany (Umwelt Bundesamt).....	10
2.1.6 The atmospheric dispersion model – ISC3-LT.....	11
2.1.7 The stoichiometric model	12
2.2 REGRESSION ANALYSIS	14
2.2.1 Linear regression.....	14
2.3 REGRESSION USING MATLAB.....	14
Chapter 3 METHODOLOGY	16
3.1 STUDY AREA	16
3.2 DATA	16
Chapter 4 RESULT AND DISCUSSION	36

4.1	AIR POLLUTANTS VARIATION.....	36
4.1.1	Ghazipur landfill.....	36
4.1.2	Narela Landfill.....	43
4.1.3	Okhla landfill.....	50
4.2	REGRESSION ANALYSIS.....	57
4.2.1	Ghazipur 2019.....	57
4.2.2	Ghazipur 2020.....	60
4.2.3	Narela 2019.....	65
4.2.4	Narela 2020.....	69
4.2.5	Okhla 2019.....	74
4.2.6	Okhla 2020.....	78
Chapter 5	CONCLUSION.....	85
5.1	FUTURE SCOPE.....	86
REFERENCES	87
VITAE	90

List of Figures

Figure 3.1: Landfill and monitoring station location.....	16
Figure 4.1: PM _{2.5} Variation around Ghazipur landfill.....	36
Figure 4.2: PM ₁₀ variation around Ghazipur landfill.....	37
Figure 4.3: NO Variation around Ghazipur landfill.....	37
Figure 4.4: NO ₂ variation around Ghazipur landfill.	38
Figure 4.5: NO _x Variation around Ghazipur landfill.....	39
Figure 4.6: NH ₃ Variation around Ghazipur landfill.....	39
Figure 1.7: SO ₂ Variation around Ghazipur landfill.....	40
Figure 4.8: CO Variation around Ghazipur landfill.....	40
Figure 4.9: Ozone Variation around Ghazipur landfill.....	41
Figure 4.10: Benzene variation around Ghazipur landfill.....	42
Figure 4.11: Toluene Variation around Ghazipur landfill.....	42
Figure 4.12: PM _{2.5} Variation of Narela landfill.....	43
Figure 4.13: PM ₁₀ Variation of Narela landfill.....	44
Figure 4.14: NO variation of Narela landfill.....	45
Figure 4.15: NO ₂ variation of Narela landfill.....	45
Figure 4.16: NO _x Variation of Narela landfill.....	46
Figure 4.17: NH ₃ Variation around Narela landfill.....	46
Figure 4.18: SO ₂ Variation of Narela landfill.....	47
Figure 4.19: CO Variation of Narela landfill.....	48
Figure 4.20: Ozone Variation of Narela landfill.....	49
Figure 4.21: Benzene variation of Narela landfill.....	49
Figure 4.22: Toluene Variation of Narela landfill.....	50
Figure 4.23: PM _{2.5} Variation of Okhla landfill.....	51
Figure 4.24: PM ₁₀ Variation of Okhla landfill.....	51

Figure 4.25: NO Variation of Okhla landfill.....	52
Figure 4.26: NO ₂ Variation of Okhla landfill.....	52
Figure 4.27: NO _x Variation of Okhla landfill.....	53
Figure 4.28: NH ₃ Variation around Okhla landfill.....	53
Figure 4.29: SO ₂ variation of Okhla landfill.....	54
Figure 4.30: CO Variation of Okhla landfill.....	54
Figure 4.31: Ozone Variation of Okhla landfill.....	54
Figure 4.32: Benzene variation of Okhla landfill.....	56
Figure 4.33: Toluene Variation of Okhla landfill.....	57
Figure 4.34: Regression model between PM _{2.5} and PM ₁₀	58
Figure 4.35: Predicted vs True response.....	58
Figure 4.36: Regression model between NO and NO _x	59
Figure 4.37: Predicted vs True response.....	60
Figure 4.38: Regression model between PM _{2.5} and PM ₁₀	61
Figure 4.39: Predicted vs True response.....	61
Figure 4.40: Regression model between NO and NO _x	62
Figure 4.41: Predicted vs True response.....	63
Figure 4.42: Regression model between NO ₂ and NO _x	64
Figure 4.43: Predicted vs True response.....	64
Figure 4.44: Regression model between PM _{2.5} and PM ₁₀	65
Figure 4.45: Predicted vs True response.....	66
Figure 4.46: Regression model between NO and NO _x	67
Figure 4.47: Predicted vs True response.....	67
Figure 4.48: Regression model between NO ₂ and NO _x	68
Figure 4.49: Predicted vs True response.....	69
Figure 4.50: Regression model between PM _{2.5} and PM ₁₀	70
Figure 4.51: Predicted vs True response.....	70
Figure 4.52: Regression between NO and NO _x	71

Figure 4.53: Predicted vs True response.....	72
Figure 4.54: Regression model between NO ₂ and NO _x	73
Figure 4.55: Predicted vs True response.....	73
Figure 4.56: Regression model between PM _{2.5} and PM ₁₀	74
Figure 4.57: Predicted vs True response.....	75
Figure 4.58: Regression model between NO and NO _x	76
Figure 4.59: Predicted vs True response.....	76
Figure 4.60: Regression model between NO ₂ and NO _x	77
Figure 4.61: Predicted vs True response.....	78
Figure 4.62: Regression model between PM _{2.5} and PM ₁₀	79
Figure 4.63: Predicted vs True response.....	79
Figure 4.64: Regression model between NO and NO _x	80
Figure 4.65: Predicted vs True response.....	81
Figure 4.66: Regression model between NO ₂ and NO _x	82
Figure 4.67: Predicted vs True response.....	82

List of Tables

Table 2.1: Features of landfill sites of Delhi.....	2
Table 3.1: Correlation of Ghazipur monitoring station 2019.....	17
Table 3.2: Descriptive statistics of Ghazipur landfill 2019.....	18
Table 3.3: Correlation of Ghazipur monitoring station 2020.....	19
Table 3.4: Descriptive statistics of Ghazipur landfill 2020.....	20
Table 3.5: Correlation of Ghazipur monitoring station 2021.....	21
Table 3.6: Descriptive statistics of Ghazipur landfill 2021.....	22
Table 3.7: Correlation of Narela monitoring station 2019.....	23
Table 3.8: Descriptive statistics of Narela landfill 2019.....	24
Table 3.9: Correlation of Narela monitoring station 2020.....	25
Table 3.10: Descriptive statistics of Narela landfill 2020.....	26
Table 3.11: Correlation of Narela monitoring station 2021.....	27
Table 3.12: Descriptive statistics of Narela landfill 2021.....	28
Table 3.13: Correlation of Okhla monitoring station 2019.....	29
Table 3.14: Descriptive statistics of Okhla landfill 2019.....	30
Table 3.15: Correlation of Okhla monitoring station 2020.....	31
Table 3.16: Descriptive statistics of Okhla landfill 2020.....	32
Table 3.17: Correlation of Okhla monitoring station 2021.....	33
Table 3.18: Descriptive statistics of Okhla landfill 2021.....	34
Table 4.1: Summary of Regression model of PM _{2.5} vs PM ₁₀	83
Table 4.2: Summary of Regression model of NO ₂ vs NO _x	83
Table 4.3: Summary of Regression model of NO vs NO _x	84

Chapter 1

INTRODUCTION

The production of hazardous greenhouse gases (GHG) from solid waste disposal dumps and landfill sites is one of the key elements posing a threat to the environment. The tremendous population and economic progress development as a consequence of a rise in the amount of municipal solid trash (MSW). Management of municipal solid waste (MSW) has become one of India's and other developing countries' most pressing issues in recent years, as a result of rising urbanisation. According to Census 2011, India creates roughly 100000 tonnes of municipal solid waste (MSW) each day, with a population of 1.21 billion. In major cities around the country, daily per capita garbage creation rates range from 200 to 600 grams, depending on the people's lifestyles and the natural environment. A few years ago, community bin collection was employed, but after the MSW (Management and Handling) rules went into effect in 2000, several municipalities adopted a collection, segregation, and containerized – based system. Unfortunately, around 70-90 percent of MSW is dumped openly, which is the most common and least expensive disposal technique for all Indian towns (Das et al., 2016) and widely preferred.

The discarding of MSW in landfills may contribute in hazards such as soil pollution and ground water contamination due to the generation of greenhouse gases, contamination, and air pollution. Due to the government's lack of attention, a large volume of methane gas is released into the environment. Methane is a key component of greenhouse gases (GHGs), which are the primary cause of global warming. It is crucial to estimate the energy generating capacity of MSW in order to use new technologies.

Currently, Delhi generate almost 10,000 tonnes of MSW every day, which is thrown away in three landfill sites throughout the city, namely Bhalswa (BL), Okhla (OL), and Ghazipur (GL). Each of the three dump sites is at capacity in terms of height and weight, having exceeded the height limit and accumulating more than 40 million metric tonnes of garbage. However, the municipal council of Delhi (MCD) continues to dump rubbish in these sites due to a lack of land.(A. N. Srivastava & Chakma, 2020) Due to overcrowding at the three existing landfill sites, the Municipal Corporation of Delhi (MCD) opened the Narela-Bawana garbage site in May 2011. This is the city's first scientific landfill, where about 1300 metric tonnes of solid waste will be separated and processed to produce refuse derived fuel (RDF) for industrial use, manure, recyclable materials, and other products. Total area of Narela-Bawana landfill is 100 Acres and its capacity is 4000 Metric Tonnes.

Table 1.1: Features of landfill sites of Delhi

Features	Ghazipur Landfill	Bhalswa Landfill	Okhla Landfill
Location	28° 37' 22.4" N, 77° 19' 25.7" E	28°44' 27.16" N, 77° 9' 27.92" E	28°3' 42" N, 77°16' 59" E
Commissioned year	1984	1994	1996
Year of closure	2012	2010	2011
Current status	Oversaturated	Oversaturated	Oversaturated
Area (m ²)	29.62 × 10 ⁴	26.22 × 10 ⁴	16.89 × 10 ⁴
Waste receiving quantity (TPD) collection	1200	1650	1700
Areas of waste	Shahdara (North & West), City zone, Sadar Pahargunj, NDMC	Civil Lines, Karol Bagh, Rohini, Narela, Najafgarh and West	Central, Najafgarh, South and Cantonment Board
Average depth (m)	7	7	9
Supervising authority	EDMC	NDMC	SDMC
Average height (m)	25.5–30.5	18.0	27.0–40.0
Density (tons/m ³) Annual	1.2	1.2	1.2
precipitation (mm/year)	706	706	706
Gas collection system	NO	NO	NO

Apart from the pollution due to landfill, other major pollutants like PM_{2.5}, PM₁₀, NO, NO_x, NO₂, SO₂, CO, ozone, benzene and toluene also responsible for the pollution in the environment and their study, behaviour and origin are important to know the effect and risks to human, animals and the environment. The section 1.1 describes the major pollutants and their effects.

1.1 IMPACT OF AIR POLLUTANTS AROUND LANDFILL

The principal components of the classic primary air pollutants are briefly described in this section - SO₂, NO_x, CO, Ozone, Benzene, Toluene, Ammonia and PM (Murk, 1955) (Nathanson, 2020).

1.1.1 Sulphur Dioxide (SO₂)

Sulphur dioxide is largely produced in power plants by the combustion of sulphur-containing fossil fuels like coal and heavy fuel oil. Natural gas, gasoline, and diesel fuels have very low sulphur levels. The maximum acceptable concentration in the atmosphere is 0.03 ppm (1-year period); 0.14 ppm (24-hour period). Environmental risks are cause of haze, contributes to acid rain formation, which in turn damages the foliage, buildings and monuments. It also causes breathing difficulties in human particularly people suffering from asthma.

1.1.2 Nitrogen Oxides (NO_x)

Because nitrogen oxides produce high quantities of nitrogen dioxide and are a precursor to ozone generation in the troposphere, they are a serious pollutant. Nitrogen oxides (NO_x) are formed in the atmosphere by lightning, forest fires and bacterial activity in soils. The common source of NO and NO₂ is emissions from automobiles, power generation and industrial processes. The maximum acceptable concentration in the atmosphere is 0.053 ppm (1-year period). Environmental risks are the damage to foliage; contributes to smog formation. It also irritates and inflames the respiratory passages.

1.1.3 Carbon Monoxide (CO)

The majority of anthropogenic carbon monoxide is produced during combustion. Internal combustion engines are the primary sources, both in on-road vehicles and in a variety of off-road applications. The maximum acceptable concentration in the atmosphere is 35 ppm (1-hour period); 9 ppm (8-hour period). Its environmental risk is that it contributes to smog formation. Human health impacts are exacerbating symptoms of heart disease, such as chest pain; may cause vision problems and reduce physical and mental capabilities in healthy people.

1.1.4 Ozone (O₃)

Nitrogen oxides (NO_x) and volatile organic compounds (VOCs) from industries and car emissions, gasoline vapours, chemical solvents, and electrical utilities are by far the most prominent sources of ozone. The maximum acceptable concentration is 0.075 ppm (8-hour period). Environmental risk is that it interferes with the ability of certain plants to respire, leading to increased susceptibility to other environmental stressors (e.g., disease, harsh weather). Its impact on human health is reduced lung function; irritation and inflammation of breathing passages.

1.1.5 Particulate Matter (PM)

Particulate matter is made up of particles of various sizes and chemical compositions that originate from a variety of natural and anthropogenic sources. Tiny droplets of liquid, dry solid fragmentation, and solid nuclei with liquid coatings make up this complicated blend of solids and aerosols (CALIFORNIA AIR RESOURCE BOARD, 2022). And these sources are fires,

smokestacks, construction sites, and unpaved roads; sources of secondary particles include reactions between gaseous chemicals emitted by power plants and automobiles. The maximum concentration in the atmosphere that can be tolerated is $150 \mu\text{g}/\text{m}^3$ (24-hour period for particles $<10 \mu\text{m}$); $35 \mu\text{g}/\text{m}^3$ (24-hour period for particles $<2.5 \mu\text{m}$). The environmental risk contributes to formation of haze as well as acid rain, which changes the pH balance of waterways and damages foliage, buildings, and monuments. Irritation of breathing passages, aggravation of asthma, irregular heartbeat are some impacts on human.

1.1.6 Ammonia (NH_3)

Agriculture is believed to be the primary source, with animal manure and fertiliser application playing a minor role. A large source is also likely to be industrial processes. Uncultivated soils, human respiration, and vehicles are all considered minor contributors of pollution. Exposure to high concentrations of ammonia in air causes immediate burning of the nose, throat and respiratory tract.

1.1.7 Benzene

The manufacture, distribution, and use of automobile fuels are the primary sources of benzene in the environment. Smog is created when benzene reacts with other compounds in the atmosphere. Human contact to benzene has been linked to a number of short- and long-term health problems, including cancer and haematological consequences. It has an effect on the bone marrow and can lead to a reduction in red blood cells, resulting in anaemia.

1.1.8 Toluene

The largest source of toluene in the urban environment is motor vehicle emissions, although other sources include evaporative losses from gasoline storage facilities and service stations, as well as the usage of toluene-based solvents and thinners. Toluene has caused membrane damage to the leaves in plants. Toluene has effects on animals that are similar to those seen in humans. Toluene's main effect is on the brain and nervous system, although animals exposed to moderate or high amounts of toluene have negative effects on their liver, kidneys, and lungs, as well as reduced immune function.

In the present study Methane emission from landfill by different researcher has been studied future prediction of emission has been estimated by various models and ground level concentration of air pollutants (including Particulate Matter $\text{PM}_{2.5}$ and PM_{10} ; Carbon Monoxide CO; oxides of nitrogen NO_x ; sulphur dioxide SO_2 ; Ozone O_3 ; Benzene and Toluene) data collected from CPCB website for the year 2019, 2020 and 2021 to know the impact of lockdown on the air quality before and after the lockdown because of the halt of Industrial, Construction and transportation activities etc. Also, the correlation between these parameters with the wind speed, relative humidity, atmospheric temperature, wind direction, solar radiation and rainfall

were observed. Linear regression performed using MATLAB for major air pollutants of Delhi, predicted vs actual response has been plotted shows the variation of error in the value and their governing equation has been estimated.

1.2 OBJECTIVE

The objective of this study is:

- ▶ To ascertain the ground level emissions in air pollution caused by landfills in ambient air at Delhi.
- ▶ To analyse temporal variation of major air pollutants in steps of monthly, seasonal and annual variation.
- ▶ To appraise the variation in air quality around landfills before, during and after the COVID-19 imposed lockdown and subsequent unlock phases.
- ▶ To formulate linear regression models for various air quality parameters.

Chapter 2

LITERATURE REVIEW

One of the studies conducted in Northern China landfill revealed that Students who are from non-exposure area showed high concentration of lysozyme and SIgA than who are from exposure area which suggested that farther the distance from landfill better the condition of people. Air quality also have a major impact on the lung capacity of the people, people who were in proximity of the landfill have poor lung quality than those of who are outside the exposure area of 5 km (Yu et al., 2018). (Liu et al., 2016) studied the ACs emissions from the working face of a landfill in Beijing were studied from 2014 to 2015 and study showed that the top five emission constituents were toluene, 1,3,5- trimethylbenzene, m p-xylene, o-xylene, and styrene, which accounted for 21.5 percent, 18.2 percent, 17.1 percent, 12.4 percent, and 10.6 percent of total emissions (by mass concentration), respectively. Temperature and season can play important role in CH₄ and CO₂ emission from landfill, in summer CH₄ and CO₂ fluxes were high as compared to winter, study also showed that all models (Modified Triangular Method (MTM), the IPCC model, and the USEPA Landfill gas emissions) overestimated the CH₄ emission (Gollapalli & Kota, 2018). The concentrations of C2–C8 NMVOCs were detected at 21 distinct sites in the downwind of Ahmedabad's largest landfill (Pirana) and it was observed that the concentrations of NMVOCs vary significantly between sites, and the shift in concentrations with distance may be seen clearly (Dave et al., 2020). One study revealed that the amount of methane emitted from the landfill increases as the landfill's life and the amount of waste produced grow by FOD, IPCC, and Land GEM models (Chakraborty et al., 2011).

The analysis of emission potential of the Saliyar open dump site in Roorkee shows that the FOD method is the most suitable method for quantifying GHG emissions from the Saliyar open dumpsite because detailed data on waste quantity and composition were used as parameters, and the method captures site specific circumstances better than the other methods, reducing uncertainties in the results. The contribution of garbage burning to air pollution was explored by Bihaowicz et al., the annual pollution (CO, NO_x, PM₁₀, SO₂) and greenhouse gas (CH₄, CO₂) emissions were assessed in Poland landfill, without any threshold value, an increase in PM₁₀ concentration has a discernible health impact. This emphasises the need of comprehending and assessing the dispersion of contaminants from all trash burns in terms of environmental and health concerns (Bihałowicz et al., 2021). The LFG estimation based on the Multi-phase model is the lowest for all cities, but the EPER model Germany calculates the highest emission, which is almost 300-500 percent more than the lowest estimate for Bangalore, Chennai, Delhi, Hyderabad, Kolkata and Mumbai (Das et al., 2016). Paraskaki et. al. measured fugitive pollutant emissions

and conduct a dispersion analysis downwind of a specific dump site. The research was carried out at the Ano Liosia dump site, which is located in the greater Athens area, with the help of model that Land-GEM model provides the most conservative and proximate estimates to the field measurements to predict human exposure from priority to health risk contaminants emitted from landfill, such as vinyl chloride and benzene (Paraskaki & Lazaridis, 2005). Farideh Atabi et. al. used the Land GEM 3.02 model to calculate CH₄ (Methane) and CO₂ (Dioxide carbon) emissions and assess the carbon reduction potential at the Kahrizak landfill site, he used the value of 'k' is a function of the refuse moisture content, availability of the nutrients for methanogens, pH, and the temperature. The value of 'k' obtained from the data collected for the emission guidelines ranges from 0.003 to 0.21 (Atabi et al., 1994). Saeid Fallahizadeh et. al. used Land GEM software to estimate the amount of methane emissions from the municipal solid waste dump in Yasuj MSW landfill in Iran, the results revealed that the highest rate of methane production occurred from 2010 to 2012, and then gradually decreased from 2012 onwards with a soft slope (Fallahizadeh et al., 2019).

MSW characterisation and energy recovery from Kakia Landfill Makkah, it showed that the organic matter (48%), plastics (25%), paper and cardboard (20%), metals (4%), glass (2%), textiles (1%), and wood make up the average makeup of solid waste in Makkah. The Gas Generation Model (Land GEM) was used to assess the possibilities for energy recovery from solid waste in the Kakia open dumpsite landfill (Osra et al., 2021). The environmental benefits and practicality of using landfill gas as an alternative energy source from two landfill sites in Bangalore and Mysore are assessed, U.S. EPA's landfill gas energy cost model, LFG cost-Web (version 3.2), was used to conduct the economic analysis of various landfill gas energy recovery projects (Sughosh et al., n.d.). Only 78 percent of the 9,600 tonnes of municipal solid waste (MSW) generated in Delhi is collected, 9 percent is composted, and the rest is deposited in one of three publicly accessible landfills on the outskirts of Delhi (Okhla, Ghazipur, and Bhalswa).

India and many developing countries are using a number of methodologies to ascertain GHG emissions, such as stoichiometric method, IPCC 1996 default method, IPCC 2006 first order decay (FOD) method, triangular method (TM), modified triangular method (MTM), in-situ closed flux chamber method. Protocol like First Order model (TNO), Multi-phase model, Land GEM model (US-EPA), EPER Model Germany (Umwelt Bundesamt), Gas SIM, EPER Model France (ADEME) are used by European Union and other developed nation also for estimation LFG emission from landfills.(Wedaa et al., 2021).

2.1 Models of methane and LFG emission estimation

2.1.1 First order decay (FOD) model

This model incorporates statistics on solid waste creation and disposal in landfills, as well as IPCC waste removal data. The FOD equation is based on only three variables: methane generation potential, degradable organic carbon content, and methane generation rate. Only methane-generating parameters are used in the FOD equation: the methane generation potential (L_0) (m^3/kg) and the methane generation rate (k) ($1/year$). The potential for methane generation (L_0) and methane production can be computed as follows:

$$L_0 = DOC * DDOCF * MCF * F * (16/12) \quad \text{Eq. (1.1)}$$

$$CH_4 \text{ generated} = W * L_0 * (1 - e^{-K}) \quad \text{Eq. (1.2)}$$

Where,

CH_4 generated is CH_4 emitted in year (kg/year),

DOC stands for degradable organic carbon,

$DDOC_F$ stands for dissimilated degradable organic carbon fraction,

MCF stands for methane correction factor,

F stands for fraction of CH_4 in landfill gas,

16/12 stands for molecular weight ratio between CH_4 and carbon,

W stands for mass of waste deposited (kg).

2.1.2 IPCC Model

It's a basic method based on theoretical gas output that operates on the mass balance concept, as shown below.

$$CH_4 \text{ generated} = MSWT * MSWF * MCF * DOC * DDOCF * F * [(16/12) - R] * (1 - OX) \quad \text{Eq. (1.3)}$$

Where,

MSW is total MSW generated (kg/year),

MSWF is the fraction of buried urban waste,

'R' is recovered CH_4 (kg/year),

OX is oxidation factor.

2.1.3 LandGEM model

The model was developed by the US Environmental Protection Agency and is based on a first-order breakdown rate, as shown in the equation below.

$$\text{CH}_4\text{generated} = \sum_{i=1}^n \sum_{j=0.1}^1 \left(K L_0 \left[\frac{M_i}{1.0} \right] e^{-k t_{ij}} \right) \quad \text{Eq. (1.4)}$$

Where,

i = 1-year time increment,

n = (year of the calculation) = (initial year of waste acceptance),

j = 0.1-year time increment,

M_i is mass of waste accepted in the i^{th} year (Mg),

t_{ij} is age of the j^{th} section of waste mass M_i accepted in the i^{th} year.

2.1.4 Multi-phase model (Afvalzorg)

In the first order multi-phase model different fraction of waste are considered. All types of waste contain typical fraction of slow, moderate and fast degradable. Here three waste fractions are taken and for that LFG productions are calculated separately the model was developed by Agricultural University of Wageningen in the year 1996.

$$\alpha_t = \zeta * \sum_{i=1}^3 c * A * C_0 * k_{1,i} * e^{-k_{1,i} * t} \quad \text{Eq. (1.5)}$$

Where,

α_t = landfill gas production at a given time [$\text{m}^3 \text{LFG} \cdot \text{y}^{-1}$]

ζ = dissimilation factor, 0.58

i = waste fraction with degradation rate $k_{1,i}$ [$\text{kg}_i \text{kg}^{-1} \text{waste}$]

c = conversion factor [$\text{m}^3 \text{LFG} \cdot \text{kgC}^{-1} \text{degraded}$]

A = amount of waste in place [Mg]

C_0 = amount of organic carbon in waste [$\text{kgC} \cdot \text{Mg Waste}^{-1}$]

$k_{1,i}$ = degradation rate constant of fraction i [y^{-1}]

t = time elapsed since depositing [y]

Here the values of 'k' were reported as 0.1, 0.03 and 0.009 per year for fast decaying (e.g. food and garden waste), medium decaying (e.g. paper, wood, textiles) and slow decaying organic waste (e.g. leather, rubber) respectively.

2.1.5 EPER Model Germany (Umwelt Bundesamt)

This is a Germany based zero order model and can be mathematically describes as:

$$Me = M * BDC * BDC_f * F * D * C \quad \text{Eq. (1.6)}$$

Where,

Me = amount of diffuse methane emission [Mg CH₄. y⁻¹]

M = annual amount of landfilled waste [Mg waste. y⁻¹]

BDC = proportion of biodegradable carbon [MgC. Mg Waste⁻¹]

BDC_f = proportion of biodegradable C converted 0.5 [-]

F = calculation factor of carbon converted into CH₄, 1.33 [Mg CH₄. MgC⁻¹]

D = collection efficiency:

active degassing 0.4 [-]

no recovery 0.9 [-]

active LFG recovery and cover 0.1 [-]

C = methane concentration 50 [%]

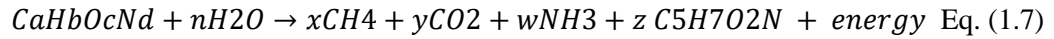
For the present case study, it has been considered that the total waste generated in the city was landfilled and not recovered for other use. So here we took 0.9 as collection efficiency for all the metro cities.

2.1.6 The atmospheric dispersion model – ISC3-LT

The ISC3-LT dispersion model (Industrial Source Complex 3-Long Term) developed by the US Environmental Protection Agency is a screening modelling tool for analysing the possible environmental and health consequences of continuous emissions to the atmosphere. The ISC3-LT model, which operates in long-term mode, is a steady-state Gaussian plume model that may be used to estimate pollutant concentrations downwind from a source, including point, area, volume, and open pit source types.

2.1.7 The stoichiometric model

The chemical reaction that represents the total volatilization process of the mass of decomposable dumped waste into methane and carbon dioxide is given by the equation (Tchobanoglous et al. 1993)



Where,

CaH_bOcNd is an empirical formula of biodegradable organic matter from which the municipal waste is consisted

$C_5H_7O_2N$ is the chemical formula of microbial mass.

Rapid decomposable material (RDM) and slow decomposable material (SDM) are two types of organic matter that provides the stoichiometric coefficients of C, H, O, and N.

Due to the increasing number in the cases of novel coronavirus in several countries, COVID-19 has triggered complete lockdown in various countries throughout the world, forcing people to stay in their homes. The disease has spread to practically every area of the globe, prompting the World Health Organization to designate it a global pandemic in March 2020. (WHO). Because there were fewer human activities, the lockdown reduced pollutant levels in the environment and improved air and water quality in a short period of time. Several studies have been conducted throughout the world to know the level of air pollutants that has varied pre and post lockdown and after the lockdown.

Sudhakar Srivastava et.al. in 2020 studied the data for principal air pollutants (PM_{2.5}, NO₂, SO₂, and CO) from two major Indian cities, Lucknow and New Delhi, scientifically. The analysis was based on air quality data for 21-day periods before and after the lockdown (first phase of 21 days). The findings revealed a significant decrease in the analysed air pollution indices as well as improved air quality in both cities. PM_{2.5}, NO₂, and CO levels were all affected significantly. During the lockdown, the levels of SO₂ decreased less dramatically (S. Srivastava et al., 2020). Several research tried to determine the effect of meteorological conditions such as temperature, relative humidity, dew point, wind speed, and rainfall in the spread of COVID-19 based on this reasoning (Pani et al., 2020) (Sahoo et al., 2020).

Some studies have found out that during the lockdown and unlock periods, atmospheric pollutants such as PM_{2.5}, PM₁₀, NO_x, and CO were significantly reduced, with the highest reduction in places with higher traffic levels. Due to the additional impact of weather (rainfall and temperature) paired with the lockdown conditions, these values continued to decrease by up to 80% throughout the unlock periods. Higher temperature and dew point cannot prevent

COVID-19 transmission, according to the association between COVID-19 and environmental parameters incidences. In Maharashtra, population density was discovered to be a major factor in the virus's rapid spread (Sahoo et al., 2021).

Some studies have been conducted to know the AQI of 22 cities of India during lockdown period and comparing with the past AQI, in India, PM_{2.5}, PM₁₀, CO, and NO₂ levels decreased by 43, 31, 10, and 18 percent respectively during the shutdown period compared to previous years. While O₃ levels increased by 17%, SO₂ levels remained same. In north, south, east, central, and western India, the air quality index (AQI) decreased by 44, 33, 29, 15, and 32 percent, respectively (Sharma et al., 2020). The results of study done in Kolkata demonstrate that pollutants including CO, NO₂, and SO₂ have fallen dramatically, whereas the average level of O₃ has increased somewhat in 2020 due to the shutdown of all industrial and transportation activity. Meanwhile, due to a complete halt in vehicle movement, biomass burning, and dust particles from construction projects, the average reduction of PM₁₀ and PM_{2.5} during lockdown was roughly 17.5 percent compared to prior years (Bera et al., 2021). The findings suggest that the new coronavirus may be a blessing in disguise. Although the current state of air quality may be transient, we (scientists/researchers/students/individuals) have a great opportunity to learn/understand from applied lockdown activities how to reduce air pollution concentrations over time (Gautam, 2020).

Every day, India generates additionally 145,000 metric tonnes of municipal solid waste (MSW), which is greater than many other countries' total daily garbage creation. Delhi is predicted to produce 9,600 tonnes of CO₂ (Central Pollution Control Board 2017 of MSW daily) (Nagar et al., 2017). Unfortunately, only 70–80 percent of MSW produced is collected, and only 9% of collected MSW is composted; the rest is dumped on the streets or in small open dumps and unsupervised public landfills on the outskirts of town. The study shows that decentralisation, capacity building, and access to MSW management information sharing are critical drivers for long-term MSW management. As a result of the data analysis and observation, it is clear that Delhi produces a massive quantity of metric tonnes of MSW per day, far exceeding the entire daily MSW production of many countries (Jolly & Ahmad, 2021).

Regression analysis was also conducted to know the concentration of air pollutants O₃, NO, NO₂, SO₂, PM₁₀ and CO. Researcher have used the artificial neural network as a regression tool, study was conducted in Poland. To assess the approximation accuracy, the predicted concentrations were compared to the observed ones. Measures like MAE, MSE, and RMSE accurately reflect the challenges of modelling concentrations across the whole range as well as in different subranges (Hoffman, 2021). The link between the concentration of PM_{2.5} (response variable) in a building and external element such as PM₁₀ and PM_{2.5} particulate concentrations, air

temperature, and relative humidity was studied using a linear regression model (independent variables). On the basis of data on atmospheric dust concentration, a linear regression model was developed that permits calculation of PM_{2.5} concentration inside the building. The model's statistical and substantive verification shows that the concentration of dangerous PM_{2.5} in indoor air is most heavily influenced by the concentration of PM₁₀ in outdoor air. As a result of the model, data on the concentration of PM₁₀ outside the tested object may be used to estimate the concentration of PM_{2.5} in the building, which can be beneficial for monitoring indoor air quality without needing a measuring tool within the structure (Załoska & Gładyszewska-Fiedoruk, 2020).

One study was conducted to better understand the current status of ambient air quality in Jakarta, Indonesia, seasonal experiments on rainwater chemistry and particulate matter pollution (SPM, PM₁₀, and PM_{2.5}) was undertaken. The concentrations of chemical constituents in precipitation, such as anion and cation concentrations, are dropping from 2006 onwards. Meteorological elements such as wind speed, wind direction, and rainfall affect the removal of SPM, PM₁₀, and PM_{2.5}. Additionally, during the feast of Ied Al Fitr in 2016 and 2017, a study demonstrated a further reduction in PM_{2.5} due to significantly reduced internal traffic. The PM_{2.5} concentration in Jakarta was drastically reduced as a result of these incidents (Dewi et al., 2018). Another study was conducted in a Turkey, where the current study uses data from Turkey to examine the impact of temperature, dew point, humidity, and wind speed on COVID-19 cases over the span of one day, three days, seven days, and fourteen days. The frequency of COVID-19 instances is proportional to the day's temperature, temperature has the most impact. The influence of the dew point on the COVID-19 cases is same on first and the third day. During the day of the COVID-19 cases, the impact of humidity is greatest. The COVID-19 cases' wind speed 14 days earlier shows the strongest association with COVID-19. The findings of the study could help officials and decision-makers develop specialised solutions for cities (Mehmet, 2020).

2.2 REGRESSION ANALYSIS

Regression analysis is a reliable method for studying which variables have an impact on a certain situation. You can use regression analysis to determine which components are most important, which factors can be ignored, and how these factors interact effectively. The most popular type of regression analysis is linear regression, which involves determining which line best fits the data based on a set of mathematical constraints. Regression can be of two types linear or non-linear. One must first comprehend the following terms in order to fully understand regression analysis:

- **Dependent variable:** The key aspect you're trying to understand or forecast is known as the dependent variable.

- Independent Variables: These are the variables that you believe influence your dependent variable.

2.2.1 Linear regression

Linear regression analysis is a mathematical approach for estimating one variable's value based on the value of another. The dependent variable is the element you want to forecast. The independent variable is the one that is used to predict the other variable's value. Linear regression decreases the difference between expected and actual output values by creating a straight line or surface. Simple linear regression calculators that employ the "least squares" method to get the best-fit line for a set of paired data can be found. You then use Y to calculate the value of X (dependent variable) (independent variable). We can perform the linear regression method in a variety of programs and environments, including:

- R linear regression
- MATLAB linear regression
- Sklearn linear regression
- Linear regression Python
- Excel linear regression

2.3 REGRESSION USING MATLAB

MATLAB can be a multi useful tool to determine the regression analysis of using numerous regression model. The regression models that can be obtained in the MATLAB are: (a) Linear regression model i.e., simple linear regression model, interaction linear, robust linear and stepwise linear, (b) Regression trees i.e., Fine tree, Coarse tree, Medium tree and Optimizable tree, (c) Support Vector Machine i.e., Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian and Optimizable SVM, (d) Gaussian Process regression Models i.e., Rational Quadratic, Squared exponential, Matern 5/2, Exponential and Optimizable GPR, (e) Ensembles of Trees i.e., Boosted Trees, Bagged Trees and Optimizable Ensemble, (f) Neural Networks i.e., Narrow Neural Network, Wide Neural Network, Medium Neural Network, Bilayered Neural Network and Trilayered Neural Network.

Check the Models window after training a model in Regression Learner to determine which model has the best aggregate score. The best RMSE (Validation) is highlighted in a box. This score is the root mean square error (RMSE) on the validation set. The score assesses the trained model 's performance on raw data. Use the score to assist you in selecting the best model. Three different types of Validation used by MATLAB for regression are: (a) Cross-Validation: Protect against overfitting by segregating the data set into folds and estimating accuracy on each fold. (b) Holdout validation: Suggested for large data set. (c) Resubstitution Validation: No fortification against overfitting. The app uses all the data for training and validation.

Chapter 3

METHODOLOGY

3.1 STUDY AREA

To assess the air quality around landfill, data from 3 monitoring stations (in yellow) namely Okhla Phase-2, Delhi - DPCC, Narela, Delhi - DPCC and Patparganj, Delhi - DPCC were collected which is within the proximity of 5km and 10km from the landfill (in blue) – Okhla landfill, Narela Bawana landfill and Ghazipur landfill respectively. In Delhi, three municipal corporations, the Delhi Municipal Corporation (MCD), the New Delhi Municipal Corporation (NDMC), and the Delhi Cantonment, are authorized for the disposal of MSW. All of the Waste produced in the city is sent to landfill sites in Ghazipur, East Delhi, Bhalswa, North Delhi, and Okhla, South East Delhi.

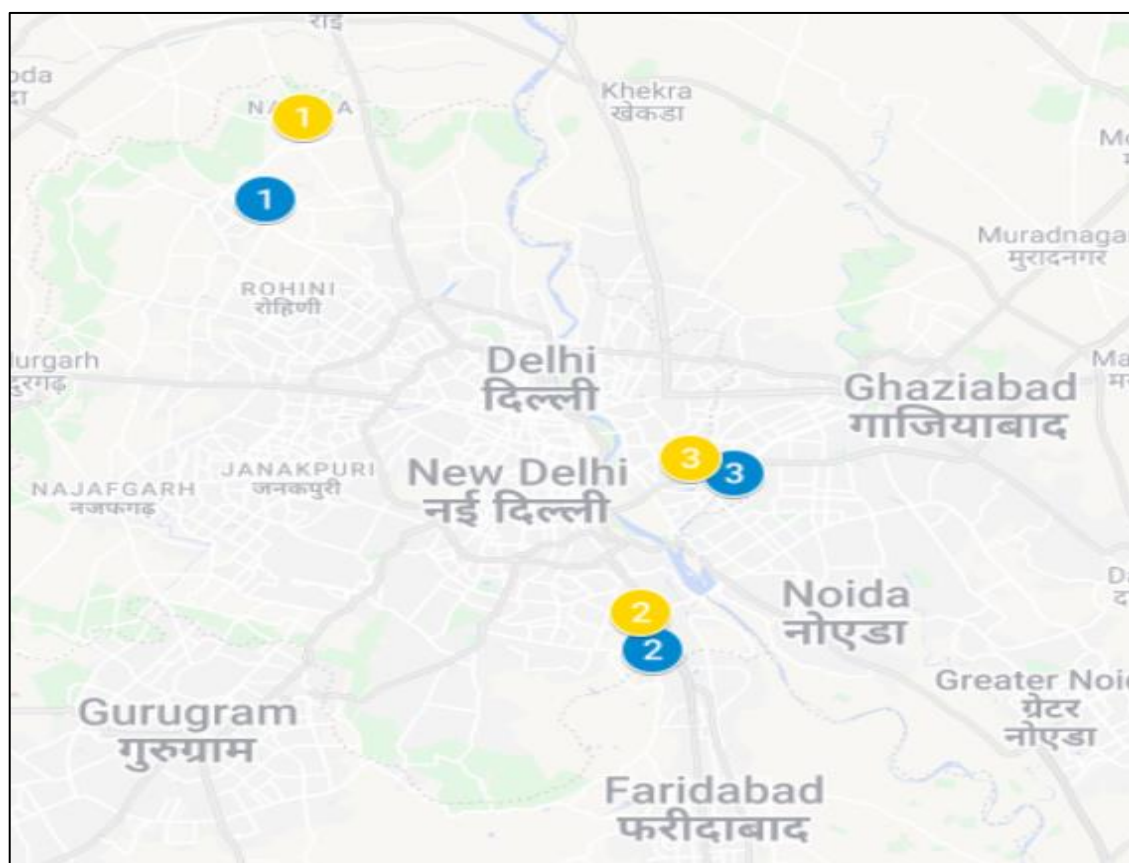


Figure 3.1: Landfill and Monitoring station location

3.2 DATA

The parameters that has been used to study are Particulate Matter (PM_{2.5}) in $\mu\text{g}/\text{m}^3$, Particulate Matter (PM₁₀) in $\mu\text{g}/\text{m}^3$, various oxides of Nitrogen (NO_x) in ppb, Nitrogen oxide and Nitrogen dioxide NO and NO₂ in $\mu\text{g}/\text{m}^3$, Sulphur Dioxide (SO₂) in $\mu\text{g}/\text{m}^3$, Carbon Monoxide (CO) in

mg/m³, Ozone (O₃) in µg/m³, Ammonia (NH₃) in µg/m³, Benzene in µg/m³ and Toluene in µg/m³. The meteorological parameters such as ambient temperature (AT) in degree C, rainfall (RF) in mm, relative humidity (RH) in %, solar radiation (SR) in W/mt², barometric pressure (BP) in mm/Hg and wind speed (WS) in m/s and wind direction (WD) in degree have been used to evaluate the deviation of air quality in lockdown period. The data pertain to 2019, 2020 and 2021 has been taken for the analysis, from Central Control Room for Air Quality Management by Central Pollution Control Board (CPCB). Lockdown has been imposed nationwide in 4 phases from 24th March 2020 to 31st May 2020 and unlock phase from 1st June 2020 to 30th November 2020. And for the emission of CH₄ and CO₂ from the landfill studies conducted to estimate the emission of Methane and Carbon Dioxide, various models have been used to determine the emission for that particular year and for the future prediction.

Descriptive statistics and correlation matrix for each year and for each landfill have been presented which is shown from the table 3.1 to 3.18. To estimate the ordinal connection between variables such as air pollution and weather factors, Pearson correlation was used and its value ranged from -1 to +1, showing that whether the variables are positively correlated or negatively correlated. All statistical treatments were performed using MS-Excel 2019.

Table 3.1: Correlation of Ghazipur monitoring station 2019

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
PM2.5	1.00																			
PM10	0.91	1.00																		
NO	0.65	0.66	1.00																	
NO2	0.62	0.70	0.75	1.00																
NOx	0.68	0.71	0.98	0.85	1.00															
NH3	0.16	0.25	0.36	0.33	0.36	1.00														
SO2	0.08	0.28	0.18	0.40	0.24	0.45	1.00													
CO	0.83	0.77	0.78	0.65	0.79	0.17	0.15	1.00												
Ozone	-0.33	-0.11	-0.17	-0.02	-0.15	0.23	0.55	-0.28	1.00											
Benzene	-0.13	-0.01	0.06	0.08	0.08	0.20	0.17	0.03	0.32	1.00										
Toluene	0.07	0.19	0.28	0.27	0.31	0.14	0.23	0.30	0.21	0.86	1.00									
RH	0.23	-0.07	0.07	-0.21	0.00	-0.20	-0.65	0.18	-0.64	-0.26	-0.23	1.00								
WS	-0.24	-0.20	-0.24	-0.26	-0.27	0.04	0.00	-0.33	0.14	-0.06	-0.20	0.00	1.00							
WD	0.21	0.22	0.20	0.41	0.27	-0.05	0.06	0.18	-0.11	-0.03	0.05	-0.25	-0.38	1.00						
SR	-0.52	-0.29	-0.29	-0.15	-0.27	0.09	0.37	-0.42	0.70	0.37	0.24	-0.75	0.04	0.12	1.00					
BP	0.56	0.41	0.39	0.41	0.42	0.00	-0.03	0.40	-0.45	-0.63	-0.42	0.33	-0.14	0.29	-0.57	1.00				
AT	-0.47	-0.26	-0.26	-0.26	-0.26	-0.11	0.19	-0.20	0.47	0.53	0.50	-0.49	0.04	-0.14	0.60	-0.78	1.00			
RF	-0.15	-0.20	-0.09	-0.15	-0.11	0.05	-0.12	-0.09	-0.05	0.24	0.14	0.22	0.05	-0.14	-0.10	-0.18	0.00	1.00		
TOT-RF	-0.15	-0.20	-0.09	-0.15	-0.11	0.05	-0.12	-0.08	-0.05	0.24	0.15	0.22	0.05	-0.14	-0.10	-0.18	0.01	1.00	1.00	

Table 3.2: Descriptive statistics of Ghazipur landfill 2019

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
Mean	101.04	191.2	21.26	19.97	40.58	49.00	3.98	1.09	22.60	2.06	4.53	57.20	1.14	198.7	131.1	986.8	27.13	0.01	1.35	
Standard Error	4.52	6.30	1.56	0.51	1.92	0.97	0.12	0.04	0.65	0.09	0.16	0.96	0.04	3.65	3.08	0.39	0.38	0.00	0.33	
Median	73.01	166.6	9.92	19.42	29.22	49.16	3.40	0.85	19.59	1.50	4.08	61.76	0.99	195.3	130.17	988.2	29.46	0.00	0.00	
Mode	55.42	195.2	2.72	14.28	40.24	55.69	2.22	0.66	9.15	0.46	1.38	61.76	0.89	135.2	74.93	994.4	29.99	0.00	0.00	
Standard Deviation	85.17	118.6	29.33	9.61	36.09	18.27	2.20	0.71	12.18	1.77	3.02	18.16	0.70	68.72	58.01	7.27	7.16	0.06	6.19	
Sample Variance	7254	1408	860.4	92.36	1302.	333.8	4.82	0.50	148.4	3.15	9.13	329.8	0.49	4722	3365	52.86	51.28	0.00	38.26	
Range	491.5	557.7	211.1	50.83	212.0	110.8	14.18	4.06	60.91	8.99	13.70	76.42	7.07	284.9	286.0	26.68	29.77	0.70	67.00	
Minimum	4.53	8.33	0.38	1.99	3.32	4.50	0.45	0.20	2.75	0.19	0.54	13.88	0.38	36.06	16.22	972.8	8.98	0.00	0.00	
Maximum	496.1	566.0	211.4	52.82	215.3	115.3	14.63	4.26	63.66	9.18	14.24	90.30	7.45	320.9	302.2	999.5	38.75	0.70	67.00	
Count	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0	355.0
Confidence Level (95.0%)	8.89	12.39	3.06	1.00	3.77	1.91	0.23	0.07	1.27	0.19	0.32	1.90	0.07	7.17	6.06	0.76	0.75	0.01	0.65	

Table 3.3: Correlation of Ghazipur monitoring station 2020

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>
PM2.5	1.00																
PM10	0.96	1.00															
NO	0.80	0.82	1.00														
NO2	0.86	0.88	0.82	1.00													
NOx	0.85	0.87	0.97	0.90	1.00												
NH3	0.59	0.59	0.52	0.41	0.51	1.00											
SO2	0.27	0.33	0.26	0.35	0.28	0.01	1.00										
CO	0.89	0.90	0.94	0.86	0.94	0.60	0.22	1.00									
Ozone	-0.58	-0.59	-0.55	-0.63	-0.62	-0.37	-0.02	-0.62	1.00								
Benzene	0.62	0.65	0.64	0.54	0.65	0.56	-0.05	0.74	-0.56	1.00							
Toluene	0.10	0.10	0.15	0.09	0.14	0.07	-0.02	0.13	-0.10	0.20	1.00						
RH	0.27	0.18	0.21	0.12	0.20	0.33	-0.46	0.30	-0.37	0.40	-0.01	1.00					
WS	-0.52	-0.53	-0.51	-0.60	-0.56	-0.26	-0.29	-0.56	0.53	-0.43	-0.07	0.01	1.00				
WD	0.24	0.30	0.24	0.44	0.32	0.01	0.15	0.25	-0.41	0.16	-0.03	-0.14	-0.59	1.00			
SR	-0.43	-0.38	-0.34	-0.33	-0.36	-0.34	0.24	-0.43	0.41	-0.53	-0.02	-0.63	0.12	0.05	1.00		
BP	0.55	0.55	0.47	0.56	0.52	0.38	-0.02	0.56	-0.50	0.65	-0.01	0.41	-0.34	0.31	-0.43	1.00	
AT	-0.22	-0.21	-0.16	-0.16	-0.19	-0.23	0.27	-0.27	0.38	-0.62	-0.03	-0.52	0.14	-0.10	0.42	-0.75	1.00

Table 3.4: Descriptive statistics of Ghazipur landfill 2020

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>
Mean	106.09	177.86	27.92	21.76	47.30	53.95	6.54	1.03	17.62	0.52	3.39	61.22	1.05	214.73	125.30	987.49	25.50	0.00
Standard Error	5.32	7.06	2.41	0.83	2.81	0.95	0.16	0.04	0.42	0.02	0.43	0.58	0.03	3.66	2.89	0.37	0.54	0.00
Median	71.66	143.41	7.48	18.45	26.26	50.18	6.21	0.74	17.25	0.37	2.14	61.33	0.94	225.00	116.79	988.19	29.79	0.00
Mode	48.94	230.68	1.29	21.19	22.50	58.75	6.49	0.49	17.28	0.10	1.46	66.86	0.99	256.31	-	996.28	30.23	0.00
Standard Deviation	94.96	126.05	42.96	14.87	50.27	16.91	2.84	0.77	7.55	0.43	7.74	10.31	0.48	65.34	51.64	6.54	9.65	0.00
Sample Variance	9016.47	15888.3	1845.56	221.05	2527.44	285.87	8.06	0.59	57.07	0.18	59.88	106.39	0.23	4269.25	2666.97	42.72	93.17	0.00
Range	621.30	671.19	209.47	70.66	229.42	129.22	16.13	3.80	35.22	2.31	99.61	52.26	2.71	267.82	280.14	23.88	31.06	0.00
Minimum	11.33	21.11	0.43	1.77	2.61	28.74	1.77	0.23	3.91	0.02	0.34	35.23	0.36	71.35	3.02	974.34	9.82	0.00
Maximum	632.63	692.30	209.90	72.43	232.03	157.96	17.90	4.03	39.13	2.33	99.95	87.49	3.07	339.17	283.16	998.22	40.88	0.00
Count	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00	319.00
Confidence Level (95.0%)	10.46	13.89	4.73	1.64	5.54	1.86	0.31	0.08	0.83	0.05	0.85	1.14	0.05	7.20	5.69	0.72	1.06	0.00

Table 3.5: Correlation of Ghazipur monitoring station 2021

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
PM2.5	1.00																			
PM10	0.94	1.00																		
NO	0.73	0.71	1.00																	
NO2	0.71	0.70	0.82	1.00																
NOx	0.77	0.77	0.98	0.85	1.00															
NH3	0.27	0.24	0.07	-0.07	0.11	1.00														
SO2	0.63	0.59	0.71	0.78	0.71	-0.05	1.00													
CO	0.82	0.76	0.86	0.83	0.87	0.10	0.73	1.00												
Ozone	0.19	0.16	0.32	0.48	0.27	-0.33	0.42	0.38	1.00											
Benzene	0.78	0.74	0.87	0.90	0.87	-0.02	0.81	0.86	0.51	1.00										
Toluene	0.64	0.60	0.79	0.81	0.76	-0.10	0.70	0.75	0.56	0.90	1.00									
RH	0.32	0.09	0.24	0.14	0.19	0.18	0.21	0.30	0.08	0.25	0.31	1.00								
WS	-0.03	-0.06	-0.24	-0.36	-0.25	0.11	-0.31	-0.22	-0.34	-0.31	-0.23	0.10	1.00							
WD	0.04	0.19	0.10	0.23	0.18	-0.03	0.14	0.05	-0.10	0.07	0.04	-0.41	-0.25	1.00						
SR	-0.41	-0.31	-0.46	-0.53	-0.44	-0.05	-0.59	-0.51	-0.26	-0.55	-0.51	-0.48	0.26	0.15	1.00					
BP	0.67	0.62	0.57	0.60	0.61	0.11	0.64	0.61	0.08	0.64	0.53	0.24	-0.03	0.18	-0.40	1.00				
AT	-0.48	-0.47	-0.34	-0.23	-0.39	-0.26	-0.28	-0.34	0.35	-0.32	-0.22	-0.11	-0.16	-0.18	0.23	-0.74	1.00			
RF	-0.10	-0.11	-0.07	-0.08	-0.08	0.00	-0.05	-0.08	-0.02	-0.07	-0.04	0.10	-0.08	-0.10	-0.01	-0.08	0.08	1.00		
TOT-RF	-0.09	-0.11	-0.07	-0.08	-0.08	0.00	-0.05	-0.07	-0.02	-0.07	-0.04	0.10	-0.08	-0.10	-0.01	-0.08	0.08	1.00	1.00	

Table 3.6: Descriptive statistics of Ghazipur landfill 2021

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>
Mean	120.61	201.95	36.68	36.43	59.83	53.44	7.05	1.28	26.24	0.57	4.63	61.50	1.93	193.69	164.83	985.85	24.45	0.02	2.08
Standard Error	5.20	6.34	2.46	1.46	2.79	1.47	0.33	0.05	0.91	0.03	0.29	0.81	0.09	3.88	3.76	0.37	0.39	0.01	0.96
Median	79.34	178.68	15.59	27.70	40.47	49.45	4.96	0.89	20.23	0.36	2.19	61.98	1.53	205.90	168.47	985.82	24.70	0.00	0.00
Mode	-	215.72	1.51	26.26	85.33	58.71	2.16	0.61	16.10	0.12	0.86	60.90	7.40	135.39	144.13	990.32	16.94	0.00	0.00
Standard Deviation	95.51	116.38	45.07	26.72	51.26	27.05	6.02	0.95	16.74	0.59	5.27	14.92	1.74	71.17	69.09	6.71	7.17	0.18	17.67
Sample Variance	9121.8	13544	2031.1	713.96	2627.5	731.95	36.22	0.90	280.08	0.35	27.73	222.62	3.04	5065.7	4773.3	45.05	51.43	0.03	312.36
Range	465.20	562.26	244.94	123.80	265.67	216.82	27.72	5.91	84.03	2.97	36.22	63.86	15.18	281.18	397.36	27.52	25.36	3.09	296.50
Minimum	15.43	24.12	0.59	3.41	4.78	22.37	1.14	0.35	3.39	0.00	0.26	29.00	0.23	60.38	18.77	971.53	13.58	0.00	0.00
Maximum	480.63	586.38	245.53	127.21	270.45	239.19	28.86	6.26	87.42	2.97	36.48	92.86	15.41	341.56	416.13	999.05	38.94	3.09	296.50
Count	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00	337.00
Confidence Level (95.0%)	10.23	12.47	4.83	2.86	5.49	2.90	0.64	0.10	1.79	0.06	0.56	1.60	0.19	7.63	7.40	0.72	0.77	0.02	1.89

Table 3.7: Correlation of Narela monitoring station 2019

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
PM2.5	1.00																			
PM10	0.88	1.00																		
NO	0.54	0.53	1.00																	
NO2	0.48	0.56	0.62	1.00																
NOx	0.57	0.59	0.95	0.82	1.00															
NH3	0.46	0.31	0.34	0.18	0.31	1.00														
SO2	0.17	0.32	0.14	0.28	0.21	-0.01	1.00													
CO	0.42	0.39	0.37	0.46	0.44	0.27	0.01	1.00												
Ozone	-0.03	0.20	-0.10	0.24	0.01	-0.26	0.43	-0.01	1.00											
Benzene	0.82	0.80	0.64	0.64	0.70	0.37	0.27	0.38	0.07	1.00										
Toluene	0.10	0.27	0.29	0.34	0.33	0.09	0.26	0.12	0.20	0.34	1.00									
RH	0.06	-0.28	0.11	-0.21	0.00	0.35	-0.49	0.07	-0.76	-0.04	-0.29	1.00								
WS	-0.27	-0.19	-0.27	-0.19	-0.26	-0.10	-0.05	-0.14	0.08	-0.26	-0.04	-0.21	1.00							
WD	0.24	0.20	-0.15	-0.07	-0.13	-0.04	0.20	-0.13	0.15	0.04	-0.26	-0.20	-0.09	1.00						
SR	-0.28	-0.08	-0.26	-0.14	-0.24	-0.25	0.21	-0.16	0.47	-0.23	0.07	-0.56	0.00	0.15	1.00					
BP	0.52	0.31	0.35	0.27	0.36	0.32	0.07	0.06	-0.24	0.56	0.06	0.34	-0.19	0.33	-0.37	1.00				
AT	-0.47	-0.20	-0.37	-0.17	-0.33	-0.46	0.08	-0.10	0.42	-0.45	0.08	-0.57	0.17	-0.26	0.46	-0.88	1.00			
RF	-0.14	-0.20	-0.06	-0.07	-0.07	0.00	-0.14	-0.01	-0.12	-0.12	-0.05	0.22	0.02	-0.13	-0.21	-0.16	0.03	1.00		
TOT-RF	-0.14	-0.20	-0.06	-0.07	-0.07	0.00	-0.13	-0.01	-0.12	-0.12	-0.05	0.22	0.02	-0.12	-0.21	-0.16	0.03	1.00	1.00	

Table 3.8: Descriptive statistics of Narela landfill 2019

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>
Mean	108.25	231.02	18.09	40.10	36.14	35.67	15.43	1.43	40.31	2.85	75.65	63.21	1.17	207.06	165.94	985.84	24.98	0.01	1.31
Standard Error	4.45	6.64	1.25	0.93	1.39	0.70	0.57	0.02	1.29	0.10	2.45	1.02	0.04	4.28	2.90	0.38	0.43	0.00	0.25
Median	85.29	207.46	10.01	36.94	27.82	34.54	12.99	1.47	38.28	2.49	66.77	67.95	1.09	206.32	165.31	986.46	27.20	0.00	0.00
Mode	46.79	213.51	10.89	27.59	25.54	61.16	12.99	1.63	9.31	2.56	68.77	82.68	0.76	300.40	91.81	994.58	30.89	0.00	0.00
Standard Deviation	84.03	125.42	23.60	17.65	26.27	13.23	10.77	0.47	24.35	1.85	46.35	19.21	0.70	80.88	54.85	7.19	8.05	0.05	4.79
Sample Variance	7060.2	15728	556.73	311.47	690.31	175.03	116.09	0.22	592.70	3.41	2148.4	369.04	0.48	6541.4	3008.4	51.74	64.81	0.00	22.91
Range	682.48	628.57	167.73	158.67	164.56	76.52	130.19	2.94	96.21	8.59	256.68	80.96	9.24	271.06	309.13	26.34	33.24	0.47	45.00
Minimum	6.62	20.48	0.87	8.08	5.02	1.22	0.30	0.36	3.66	0.13	7.72	14.23	0.37	54.61	13.32	972.31	5.86	0.00	0.00
Maximum	689.10	649.05	168.60	166.75	169.58	77.74	130.49	3.30	99.87	8.72	264.40	95.19	9.61	325.67	322.45	998.65	39.10	0.47	45.00
Count	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00
Confidence Level (95.0%)	8.75	13.05	2.46	1.84	2.73	1.38	1.12	0.05	2.53	0.19	4.82	2.00	0.07	8.42	5.71	0.75	0.84	0.01	0.50

Table 3.9: Correlation of Narela monitoring station 2020

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
PM2.5	1.00																			
PM10	0.94	1.00																		
NO	0.58	0.62	1.00																	
NO2	0.78	0.83	0.71	1.00																
NOx	0.69	0.73	0.97	0.86	1.00															
NH3	0.40	0.48	0.29	0.40	0.35	1.00														
SO2	0.16	0.23	0.09	0.19	0.13	0.41	1.00													
CO	0.62	0.60	0.47	0.57	0.54	0.13	-0.02	1.00												
Ozone	0.07	0.13	-0.09	0.12	-0.03	0.31	0.56	-0.04	1.00											
Benzene	0.81	0.84	0.62	0.75	0.71	0.50	0.27	0.45	0.12	1.00										
Toluene	0.41	0.50	0.53	0.53	0.57	0.18	-0.08	0.31	-0.22	0.49	1.00									
RH	-0.13	-0.27	-0.05	-0.19	-0.10	-0.11	-0.02	-0.09	-0.13	-0.06	-0.27	1.00								
WS	-0.52	-0.52	-0.46	-0.45	-0.48	-0.20	0.02	-0.38	0.17	-0.46	-0.44	0.23	1.00							
WD	0.20	0.21	-0.06	0.08	-0.02	0.25	0.19	-0.01	0.01	0.09	0.01	-0.20	-0.32	1.00						
SR	-0.48	-0.48	-0.29	-0.37	-0.33	-0.26	0.18	-0.37	0.30	-0.35	-0.37	0.20	0.36	-0.25	1.00					
BP	0.43	0.41	0.33	0.42	0.38	0.35	0.20	0.06	0.20	0.44	0.16	0.02	-0.17	0.15	-0.03	1.00				
AT	-0.53	-0.42	-0.40	-0.42	-0.44	-0.44	-0.16	-0.20	0.08	-0.50	-0.10	-0.41	0.24	-0.34	0.36	-0.48	1.00			
RF	-0.18	-0.24	-0.08	-0.15	-0.11	-0.19	-0.15	-0.01	-0.12	-0.17	-0.02	0.14	0.11	-0.20	0.10	-0.12	0.05	1.00		
TOT-RF	-0.18	-0.23	-0.08	-0.14	-0.11	-0.19	-0.15	-0.01	-0.12	-0.17	-0.02	0.14	0.11	-0.20	0.10	-0.12	0.05	1.00	1.00	

Table 3.10: Descriptive statistics of Narela landfill 2020

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>
Mean	110.36	224.18	19.20	40.77	37.31	31.22	11.43	1.12	38.76	3.29	99.86	49.29	1.11	198.95	151.52	983.19	23.83	0.02	2.14
Standard Error	4.96	7.37	1.49	1.04	1.65	0.77	0.38	0.03	1.17	0.11	3.70	1.65	0.02	4.15	4.18	0.48	0.43	0.01	0.57
Median	80.34	190.02	9.40	35.26	25.92	34.03	10.84	0.95	35.11	2.96	88.60	60.59	1.03	224.74	162.75	983.26	25.24	0.00	0.00
Mode	-	129.81	10.78	58.69	15.86	31.71	6.54	0.77	16.39	1.65	45.24	0.34	1.01	167.32	-	977.38	12.51	0.00	0.00
Standard Deviation	89.34	132.59	26.79	18.63	29.71	13.89	6.82	0.59	21.10	1.93	66.67	29.78	0.39	74.64	75.24	8.65	7.73	0.11	10.31
Sample Variance	7981.8	17580	717.44	347.25	882.63	192.92	46.54	0.35	445.30	3.71	4445.1	887.09	0.15	5570.7	5661.1	74.89	59.82	0.01	106.27
Range	587.91	675.21	162.07	117.46	161.63	62.96	37.33	4.48	98.66	9.45	400.30	94.36	2.15	266.30	435.14	72.87	29.35	1.43	137.00
Minimum	15.10	42.14	1.70	12.10	8.27	5.60	0.78	0.00	8.00	0.32	3.47	0.30	0.46	59.40	4.20	924.84	8.43	0.00	0.00
Maximum	603.01	717.35	163.77	129.56	169.90	68.56	38.11	4.48	106.66	9.77	403.77	94.66	2.61	325.70	439.34	997.71	37.78	1.43	137.00
Count	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00	324.00
Confidence Level (95.0%)	9.76	14.49	2.93	2.04	3.25	1.52	0.75	0.06	2.31	0.21	7.29	3.26	0.04	8.16	8.22	0.95	0.85	0.01	1.13

Table 3.11: Correlation of Narela monitoring station 2021

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
PM2.5	1.00																		
PM10	0.91	1.00																	
NO	0.63	0.59	1.00																
NO2	0.75	0.74	0.79	1.00															
NOx	0.70	0.67	0.98	0.90	1.00														
NH3	0.60	0.54	0.38	0.49	0.43	1.00													
SO2	0.44	0.61	0.20	0.45	0.29	0.30	1.00												
CO	0.00	-0.12	0.13	0.01	0.10	-0.26	-0.30	1.00											
Ozone	-0.26	-0.15	-0.36	-0.22	-0.33	-0.06	0.21	-0.11	1.00										
Benzene	0.86	0.79	0.77	0.80	0.82	0.54	0.38	0.01	-0.37	1.00									
Toluene	0.25	0.23	0.41	0.37	0.42	0.14	0.17	0.10	-0.17	0.43	1.00								
RH	0.26	0.00	0.28	0.14	0.25	0.18	-0.47	0.33	-0.49	0.25	0.10	1.00							
WS	0.09	0.07	0.08	0.07	0.08	-0.09	0.03	-0.05	-0.20	0.22	0.02	0.02	1.00						
SR	-0.23	-0.08	-0.27	-0.20	-0.26	-0.07	0.14	-0.07	0.41	-0.29	-0.05	-0.29	-0.04	1.00					
BP	0.70	0.55	0.49	0.58	0.54	0.53	0.26	-0.10	-0.41	0.74	0.30	0.29	0.10	-0.21	1.00				
AT	-0.70	-0.47	-0.52	-0.56	-0.55	-0.52	-0.06	-0.07	0.55	-0.71	-0.25	-0.56	-0.11	0.31	-0.88	1.00			
RF	-0.06	-0.12	-0.05	-0.09	-0.07	-0.08	-0.10	0.15	-0.10	-0.05	-0.03	0.17	0.00	-0.20	-0.05	-0.03	1.00		
TOT-RF	-0.06	-0.13	-0.06	-0.12	-0.08	-0.10	-0.11	0.11	-0.16	-0.02	0.03	0.20	0.03	-0.23	-0.02	-0.06	0.90	1.00	

Table 3.12: Descriptive statistics of Narela landfill 2021

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	TOT-RF
Mean	101.09	220.97	19.08	35.55	34.42	35.28	12.96	1.12	49.00	2.58	125.24	62.88	1.21	152.50	983.03	25.28	0.07	4.76
Standard Error	5.77	8.05	1.54	1.08	1.74	1.05	0.53	0.03	0.92	0.11	4.21	0.97	0.10	4.13	0.40	0.47	0.03	1.43
Median	62.68	195.72	10.27	30.30	24.66	31.33	10.83	1.16	47.60	2.09	112.58	66.88	1.00	166.20	981.75	28.34	0.00	0.00
Mode	76.83	-	4.28	26.25	24.42	22.74	7.72	1.10	76.71	0.93	124.93	30.29	0.93	177.18	984.84	29.35	0.00	0.00
Standard Deviation	94.17	131.24	25.09	17.68	28.43	17.17	8.58	0.43	14.95	1.78	68.65	15.74	1.60	67.37	6.60	7.64	0.49	23.38
Sample Variance	8867.33	17223.4	629.52	312.74	808.28	294.65	73.61	0.18	223.41	3.17	4712.49	247.72	2.56	4538.24	43.57	58.32	0.24	546.80
Range	420.89	567.05	144.27	105.37	158.73	83.48	46.23	3.36	78.53	9.18	352.42	83.01	14.77	344.33	28.29	28.70	6.97	223.00
Minimum	14.73	37.07	3.18	4.13	6.57	8.46	3.16	0.00	12.92	0.35	8.78	7.68	0.22	1.60	970.58	8.48	0.00	0.00
Maximum	435.62	604.12	147.45	109.50	165.30	91.94	49.39	3.36	91.45	9.53	361.20	90.69	14.99	345.93	998.87	37.18	6.97	223.00
Count	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00	266.00
Confidence Level (95.0%)	11.37	15.84	3.03	2.13	3.43	2.07	1.04	0.05	1.80	0.21	8.29	1.90	0.19	8.13	0.80	0.92	0.06	2.82

Table 3.13: Correlation of Okhla monitoring station 2019

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT- RF</i>	
PM2.5	1.00																			
PM10	0.92	1.00																		
NO	0.61	0.65	1.00																	
NO2	0.65	0.71	0.77	1.00																
NOx	0.64	0.69	0.99	0.84	1.00															
NH3	0.71	0.66	0.44	0.43	0.46	1.00														
SO2	0.33	0.46	0.44	0.63	0.49	0.06	1.00													
CO	0.70	0.74	0.85	0.75	0.86	0.53	0.42	1.00												
Ozone	-0.19	-0.05	-0.08	0.05	-0.06	-0.29	0.44	0.02	1.00											
Benzene	0.69	0.69	0.67	0.62	0.69	0.32	0.41	0.66	0.01	1.00										
Toluene	0.30	0.35	0.53	0.39	0.53	0.11	0.36	0.42	0.11	0.73	1.00									
RH	0.20	-0.05	-0.07	-0.33	-0.12	0.28	-0.61	-0.02	-0.60	0.07	-0.03	1.00								
WS	-0.26	-0.24	-0.28	-0.15	-0.27	-0.06	-0.01	-0.36	0.09	-0.33	-0.28	-0.25	1.00							
WD	0.15	0.09	-0.01	0.00	-0.01	-0.03	-0.02	0.06	-0.05	0.22	0.04	0.24	-0.10	1.00						
SR	-0.48	-0.29	-0.19	-0.06	-0.18	-0.41	0.27	-0.24	0.55	-0.35	-0.16	-0.78	0.24	-0.30	1.00					
BP	0.63	0.49	0.44	0.48	0.47	0.62	0.17	0.41	-0.39	0.39	0.13	0.28	0.12	-0.02	-0.50	1.00				
AT	-0.64	-0.45	-0.35	-0.31	-0.36	-0.67	0.07	-0.34	0.57	-0.34	-0.06	-0.57	0.00	-0.07	0.68	-0.88	1.00			
RF	-0.09	-0.13	-0.08	-0.14	-0.10	-0.12	-0.21	-0.06	-0.08	-0.05	-0.05	0.19	-0.12	0.07	-0.08	-0.15	0.05	1.00		
TOT-RF	-0.09	-0.13	-0.08	-0.14	-0.09	-0.12	-0.21	-0.06	-0.08	-0.05	-0.05	0.18	-0.11	0.07	-0.07	-0.14	0.05	1.00	1.00	

Table 3.14: Descriptive statistics of Okhla landfill 2019

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>
Mean	114.65	222.08	43.56	40.10	56.96	34.88	12.61	1.54	27.19	4.68	32.83	62.53	1.03	192.84	79.67	985.08	25.34	0.01	0.61
Standard Error	5.35	7.06	2.40	0.87	2.36	0.79	0.18	0.03	0.75	0.13	0.73	1.02	0.02	3.51	2.14	0.38	0.43	0.00	0.20
Median	76.03	193.95	26.81	38.64	43.54	30.48	12.20	1.35	24.21	4.05	30.13	65.40	0.97	191.46	68.15	986.04	27.51	0.00	0.00
Mode	77.25	103.69	25.95	23.15	31.24	30.64	15.30	1.15	10.57	0.00	0.00	60.93	0.92	231.95	49.34	989.47	27.70	0.00	0.00
Standard Deviation	100.86	133.24	45.29	16.50	44.47	14.83	3.37	0.65	14.19	2.48	13.80	19.30	0.44	66.23	40.36	7.23	8.13	0.04	3.74
Sample Variance	10173	17752	2050.9	272.21	1977.7	219.79	11.37	0.42	201.45	6.15	190.47	372.51	0.19	4386.2	1629.0	52.34	66.07	0.00	13.96
Range	543.04	636.51	240.29	91.14	240.09	87.22	20.52	3.86	66.72	12.92	79.51	80.95	3.01	267.31	213.89	26.17	32.25	0.35	33.50
Minimum	8.15	15.52	1.85	10.53	8.07	12.01	6.43	0.49	6.00	0.00	0.00	16.32	0.16	63.94	4.42	971.31	6.90	0.00	0.00
Maximum	551.19	652.03	242.14	101.67	248.16	99.23	26.95	4.35	72.72	12.92	79.51	97.27	3.17	331.25	218.31	997.48	39.15	0.35	33.50
Count	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00	356.00
Confidence Level (95.0%)	10.51	13.89	4.72	1.72	4.64	1.55	0.35	0.07	1.48	0.26	1.44	2.01	0.05	6.90	4.21	0.75	0.85	0.00	0.39

Table 3.15: Correlation of Okhla monitoring station 2020

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
PM2.5	1.00																			
PM10	0.94	1.00																		
NO	0.76	0.81	1.00																	
NO2	0.81	0.88	0.82	1.00																
NOx	0.79	0.85	0.99	0.89	1.00															
NH3	0.23	0.25	0.15	0.07	0.14	1.00														
SO2	0.56	0.66	0.61	0.62	0.63	0.13	1.00													
CO	0.77	0.81	0.86	0.80	0.87	0.14	0.65	1.00												
Ozone	-0.20	-0.18	-0.17	-0.24	-0.18	-0.06	0.13	-0.10	1.00											
Benzene	0.86	0.86	0.84	0.81	0.86	0.23	0.53	0.75	-0.25	1.00										
Toluene	0.55	0.64	0.73	0.72	0.75	0.04	0.43	0.60	-0.07	0.63	1.00									
RH	-0.12	-0.29	-0.17	-0.25	-0.19	0.04	-0.66	-0.28	-0.36	-0.05	-0.08	1.00								
WS	-0.20	-0.25	-0.27	-0.36	-0.30	0.07	-0.08	-0.28	0.01	-0.19	-0.50	-0.04	1.00							
WD	0.22	0.27	0.22	0.38	0.25	-0.15	0.28	0.27	-0.14	0.26	-0.03	-0.38	0.14	1.00						
SR	-0.56	-0.51	-0.48	-0.61	-0.53	0.09	-0.09	-0.44	0.45	-0.63	-0.49	-0.36	0.27	-0.10	1.00					
BP	0.63	0.57	0.51	0.55	0.53	-0.01	0.51	0.50	-0.23	0.60	0.17	-0.15	0.21	0.44	-0.46	1.00				
AT	-0.62	-0.51	-0.47	-0.51	-0.49	-0.07	-0.30	-0.40	0.39	-0.62	-0.14	-0.13	-0.21	-0.34	0.62	-0.90	1.00			
RF	-0.18	-0.23	-0.14	-0.15	-0.15	-0.11	-0.29	-0.17	-0.11	-0.16	-0.02	0.34	-0.06	-0.17	-0.14	-0.23	0.07	1.00		
TOT-RF	-0.18	-0.22	-0.14	-0.15	-0.14	-0.11	-0.28	-0.17	-0.11	-0.16	-0.02	0.34	-0.06	-0.17	-0.14	-0.22	0.07	1.00	1.00	

Table 3.16: Descriptive statistics of Okhla landfill 2020

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
Mean	101.88	199.93	41.87	43.86	57.99	32.61	15.08	1.56	28.43	3.18	42.59	61.42	0.56	228.21	77.16	985.40	24.45	0.01	1.38	
Standard Error	5.14	7.49	2.92	1.38	3.09	0.80	0.27	0.05	0.75	0.12	1.36	0.92	0.02	4.04	2.09	0.39	0.39	0.00	0.37	
Median	66.47	171.61	18.77	38.04	36.24	30.54	15.19	1.34	26.96	2.57	35.89	61.20	0.45	241.64	66.45	986.51	25.86	0.00	0.00	
Mode	131.25	249.02	3.74	42.72	23.04	31.41	15.19	1.07	11.38	1.03	61.18	62.71	0.29	171.49	58.03	996.31	15.31	0.00	0.00	
Standard Deviation	91.40	133.19	51.88	24.44	54.93	14.13	4.88	0.83	13.32	2.19	24.18	16.36	0.30	71.76	37.14	6.89	6.92	0.07	6.64	
Sample Variance	8353.5	17739	2692.0	597.52	3017.7	199.73	23.83	0.68	177.35	4.79	584.90	267.50	0.09	5148.9	1379.6	47.41	47.90	0.00	44.15	
Range	541.27	711.98	234.44	104.50	245.60	88.77	23.96	4.04	67.89	10.00	132.46	76.64	2.07	268.47	156.43	26.69	28.68	0.83	80.00	
Minimum	6.29	28.21	0.81	7.56	5.73	5.46	6.05	0.37	0.30	0.54	7.62	20.61	0.25	67.25	8.72	970.00	9.82	0.00	0.00	
Maximum	547.56	740.19	235.25	112.06	251.33	94.23	30.01	4.41	68.19	10.54	140.08	97.25	2.32	335.72	165.15	996.69	38.50	0.83	80.00	
Count	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00	316.00
Confidence Level (95.0%)	10.12	14.74	5.74	2.71	6.08	1.56	0.54	0.09	1.47	0.24	2.68	1.81	0.03	7.94	4.11	0.76	0.77	0.01	0.74	

Table 3.17: Correlation of Okhla monitoring station 2021

	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>	
PM2.5	1.00																			
PM10	0.92	1.00																		
NO	0.75	0.77	1.00																	
NO2	0.71	0.75	0.77	1.00																
NOx	0.78	0.80	0.99	0.87	1.00															
NH3	0.62	0.58	0.53	0.49	0.55	1.00														
SO2	0.16	0.27	0.08	0.03	0.06	-0.07	1.00													
CO	0.66	0.63	0.67	0.51	0.66	0.33	0.13	1.00												
Ozone	-0.25	-0.15	-0.24	-0.22	-0.24	0.00	0.37	-0.16	1.00											
Benzene	0.84	0.78	0.86	0.78	0.88	0.62	-0.10	0.64	-0.34	1.00										
Toluene	0.62	0.53	0.70	0.51	0.69	0.49	-0.17	0.50	-0.35	0.81	1.00									
RH	0.25	-0.01	0.14	-0.06	0.09	0.16	-0.48	0.17	-0.53	0.30	0.38	1.00								
WS	0.15	0.09	0.22	0.35	0.26	0.11	-0.55	0.10	-0.30	0.40	0.34	0.22	1.00							
WD	-0.03	0.08	-0.05	0.04	-0.03	-0.14	0.29	0.02	-0.05	-0.18	-0.16	-0.36	-0.26	1.00						
SR	-0.50	-0.33	-0.36	-0.27	-0.35	-0.34	0.10	-0.35	0.48	-0.51	-0.47	-0.58	-0.12	0.18	1.00					
BP	0.69	0.65	0.62	0.64	0.65	0.36	0.19	0.53	-0.31	0.67	0.45	0.10	0.35	0.07	-0.43	1.00				
AT	-0.76	-0.61	-0.61	-0.53	-0.61	-0.41	-0.01	-0.54	0.50	-0.71	-0.55	-0.48	-0.31	0.04	0.67	-0.85	1.00			
RF	0.00	-0.04	0.07	0.00	0.06	0.07	-0.10	-0.04	-0.13	0.09	0.11	0.11	0.09	-0.08	-0.17	0.10	-0.13	1.00		
TOT-RF	-0.02	-0.07	0.06	-0.02	0.04	0.06	-0.11	-0.05	-0.14	0.07	0.11	0.14	0.09	-0.08	-0.19	0.08	-0.12	0.98	1.00	

Table 3.18: Descriptive statistics of Okhla landfill 2021

Descriptive Statistics	<i>PM2.5</i>	<i>PM10</i>	<i>NO</i>	<i>NO2</i>	<i>NOx</i>	<i>NH3</i>	<i>SO2</i>	<i>CO</i>	<i>Ozone</i>	<i>Benzene</i>	<i>Toluene</i>	<i>RH</i>	<i>WS</i>	<i>WD</i>	<i>SR</i>	<i>BP</i>	<i>AT</i>	<i>RF</i>	<i>TOT-RF</i>
Mean	104.93	223.66	46.65	54.68	67.66	35.23	15.15	1.44	31.40	4.05	55.84	57.36	0.51	199.67	75.98	984.14	25.76	0.06	4.95
Standard Error	5.12	6.91	2.66	1.51	2.93	0.79	0.30	0.04	0.76	0.13	1.76	0.97	0.02	3.66	1.60	0.34	0.36	0.02	1.57
Median	61.02	205.15	24.82	50.48	47.50	31.34	14.89	1.22	27.60	3.37	50.25	60.51	0.32	180.69	78.28	983.44	27.67	0.00	0.00
Mode	105.94	#N/A	5.40	37.06	12.30	32.06	17.75	0.97	24.58	3.25	87.34	82.84	0.27	305.34	47.27	979.22	29.60	0.00	0.00
Standard Deviation	96.73	130.56	50.31	28.58	55.29	14.85	5.68	0.72	14.41	2.44	33.31	18.37	0.34	69.19	30.27	6.35	6.74	0.42	29.66
Sample Variance	9355.7	17044	2531.4	816.81	3057.2	220.54	32.25	0.52	207.61	5.93	1109.8	337.63	0.12	4787.2	916.40	40.28	45.44	0.18	879.83
Range	505.36	677.81	235.22	206.39	271.23	86.11	31.99	3.98	69.77	10.70	214.57	85.04	1.92	285.04	179.90	27.71	29.13	6.39	380.50
Minimum	12.33	26.06	1.09	12.64	9.03	9.29	3.96	0.42	4.64	0.80	9.08	11.38	0.18	45.65	9.17	970.58	10.25	0.00	0.00
Maximum	517.69	703.87	236.31	219.03	280.26	95.40	35.95	4.40	74.41	11.50	223.65	96.42	2.10	330.69	189.07	998.29	39.38	6.39	380.50
Count	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00	357.00
Confidence Level (95.0%)	10.07	13.59	5.24	2.97	5.76	1.55	0.59	0.07	1.50	0.25	3.47	1.91	0.04	7.20	3.15	0.66	0.70	0.04	3.09

Chapter 4

RESULT AND DISCUSSION

4.1 AIR POLLUTANTS VARIATION

4.1.1 Ghazipur landfill

Major pollution in Delhi is basically due to Particulates Matter (PM_{2.5}), if compare 2020 data of PM_{2.5} with 2019 and 2021 in fig. 4.1. After the implementation of lockdown value of PM_{2.5} have been falling till September, as the restrictions were lifted off its value begin to increase and reached the all-time maximum value of 632.63 $\mu\text{g}/\text{m}^3$ on 9th November 2020 during the lockdown and unlock period and minimum value of 7.78 $\mu\text{g}/\text{m}^3$ on 31st August 2020. And with the maximum value of 496.1 $\mu\text{g}/\text{m}^3$ on 03rd November 2019 and minimum value of 4.53 $\mu\text{g}/\text{m}^3$ on 17th August 2019. And maximum value of 461.7 $\mu\text{g}/\text{m}^3$ on 12th November 2021 and minimum value of 15.43 $\mu\text{g}/\text{m}^3$ on 18th October 2021.

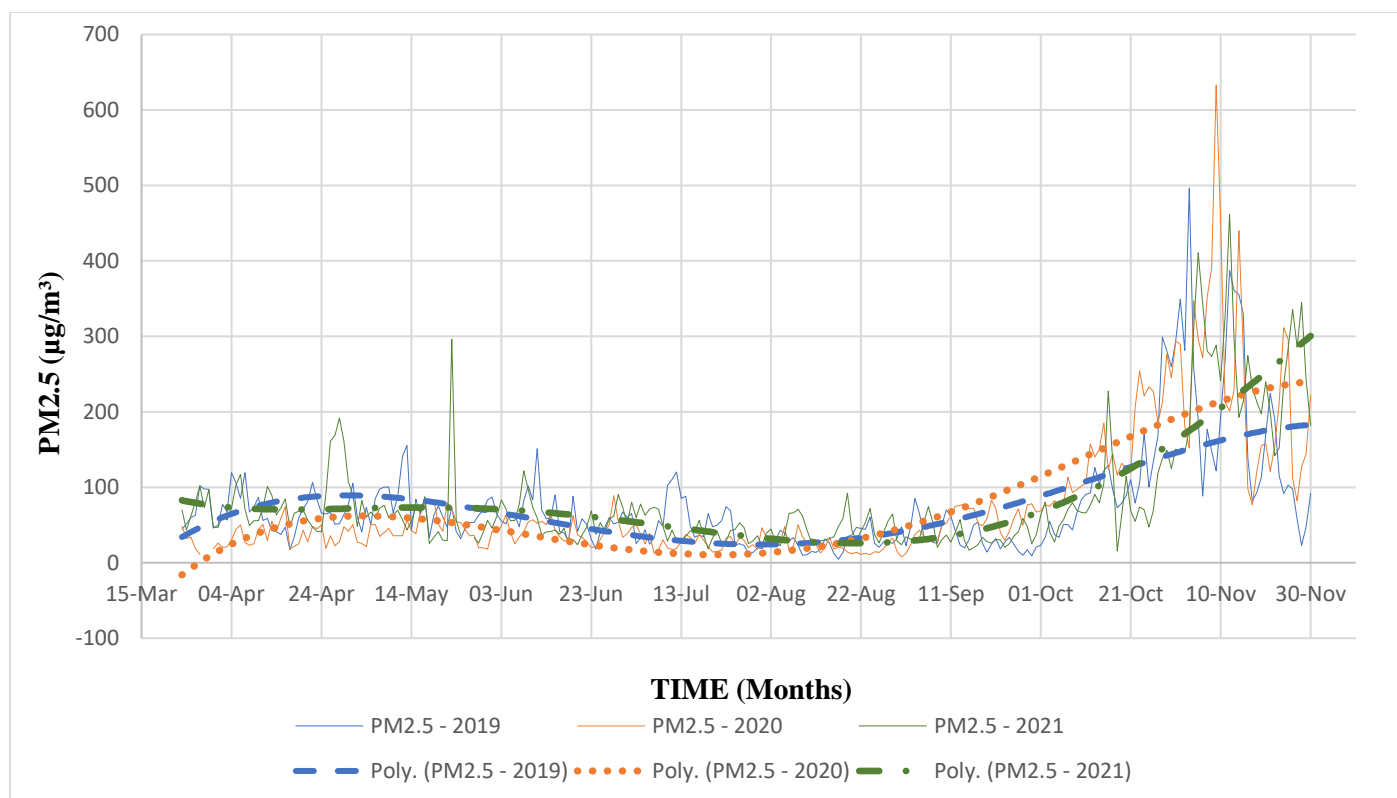


Figure 4.1: PM_{2.5} Variation around Ghazipur landfill

Variation of PM₁₀ at the start of lockdown was 100.56 $\mu\text{g}/\text{m}^3$ on 24th of March 2020 which was lowest compared to 2019 and 2021 data shown in fig. 4.2. PM₁₀ remained lowest till mid-September, as the restrictions were lifted off PM₁₀ starts increasing and reached the maximum value of 692.3 $\mu\text{g}/\text{m}^3$ on 09th November 2020. Since the start of the 2020 NO had the least value of 2.62 $\mu\text{g}/\text{m}^3$ on 24th March 2020 compare to 2019 and 2021.

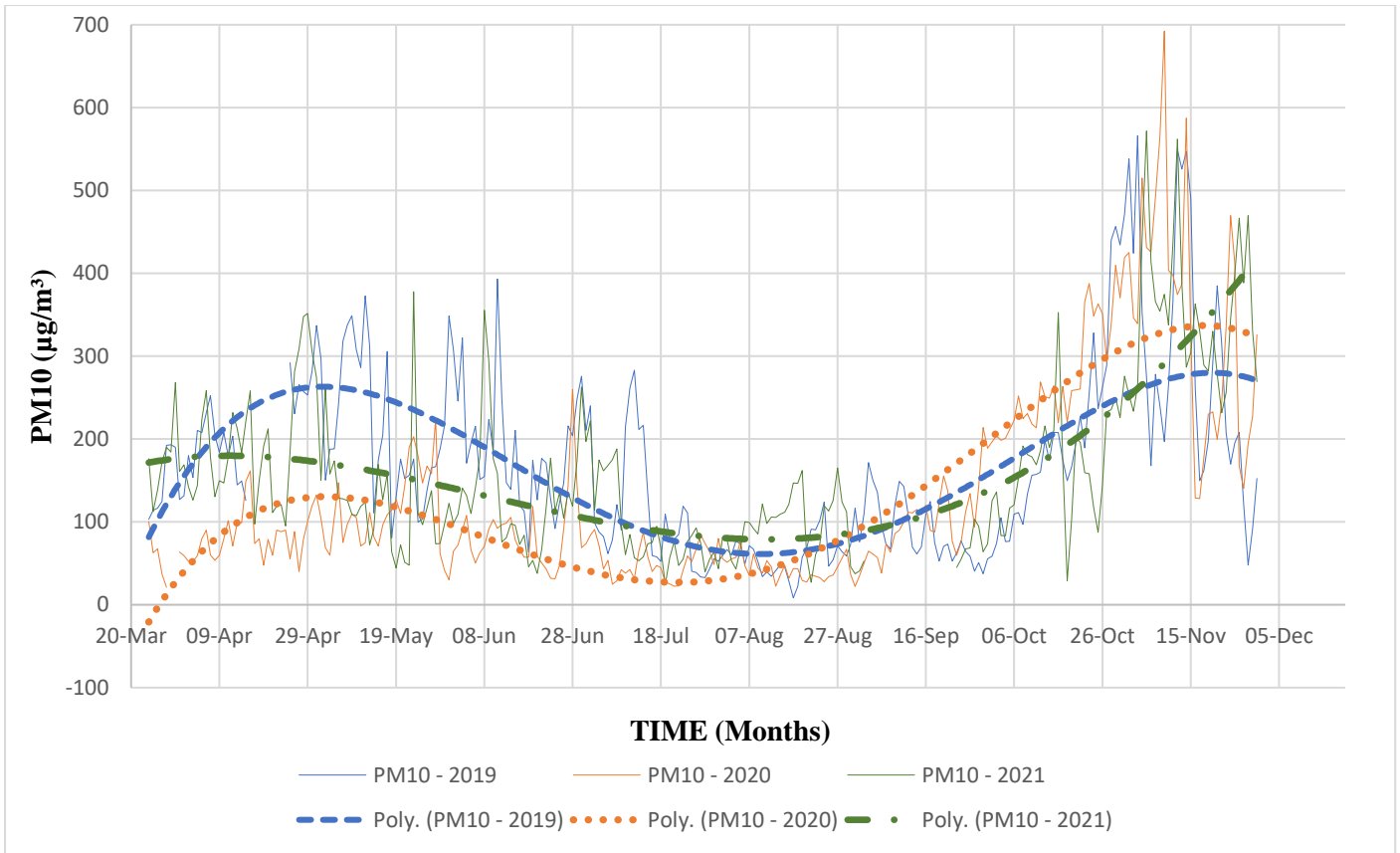


Figure 4.2: PM10 variation around Ghazipur landfill

NO starts increasing during the mid-September during the unlock phase and they reached the maximum value of 198.82 $\mu\text{g}/\text{m}^3$ on 11th November 2020, and 245.53 $\mu\text{g}/\text{m}^3$ maximum value after the first wave on 26th November 2021, exceeding the prescribed standards (0-80 $\mu\text{g}/\text{m}^3$) shown in fig. 4.3.

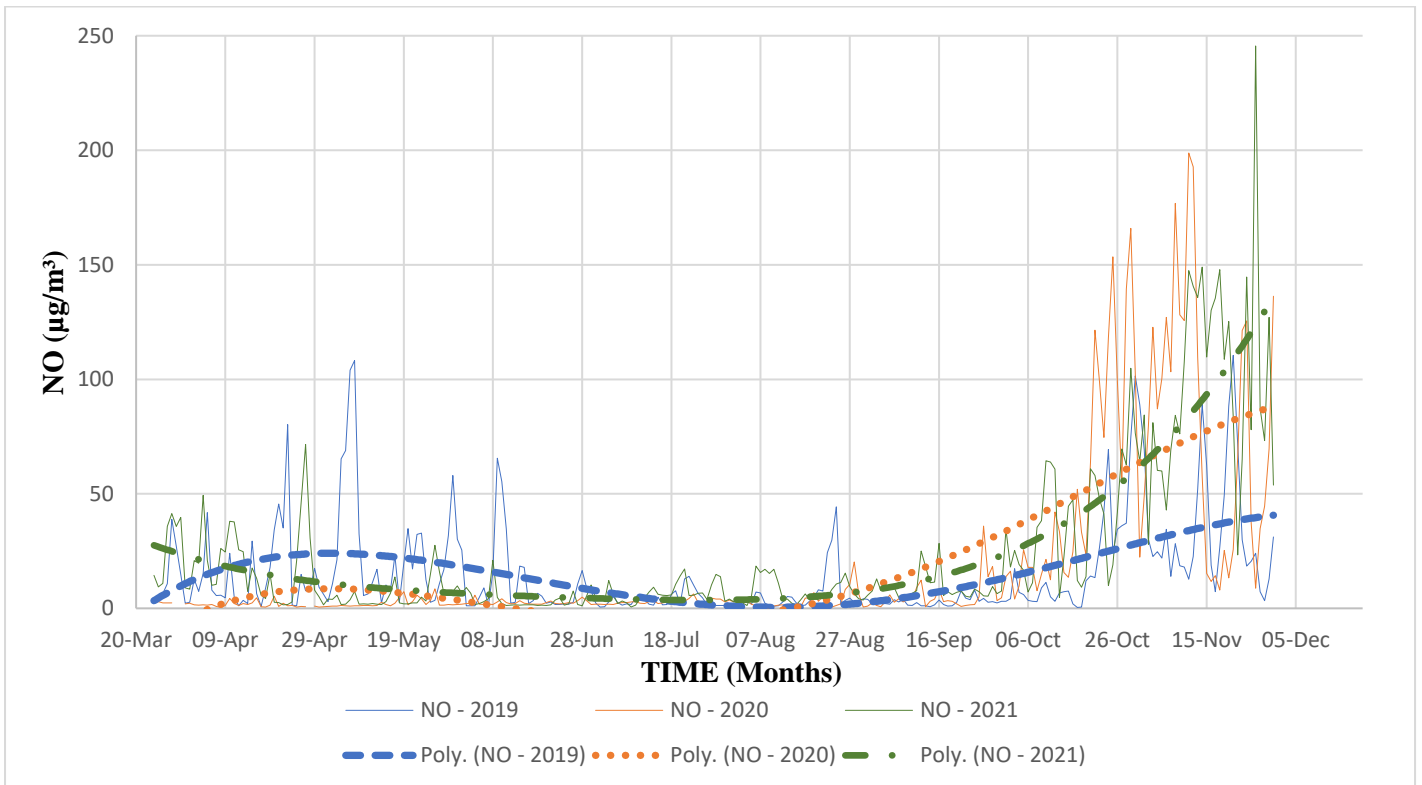


Figure 4.3: NO Variation around Ghazipur landfill

During the lockdown period till end of August NO_2 has been the lowest in 2020 compared to 2019 and 2021 shown in fig. 4.4. The maximum value of NO_2 in 2019, 2020 and 2021 is $52.82 \mu\text{g}/\text{m}^3$, $72.43 \mu\text{g}/\text{m}^3$, $127.21 \mu\text{g}/\text{m}^3$ on 14th November 2019, 09th November 2020 and 19th November 2021 respectively.

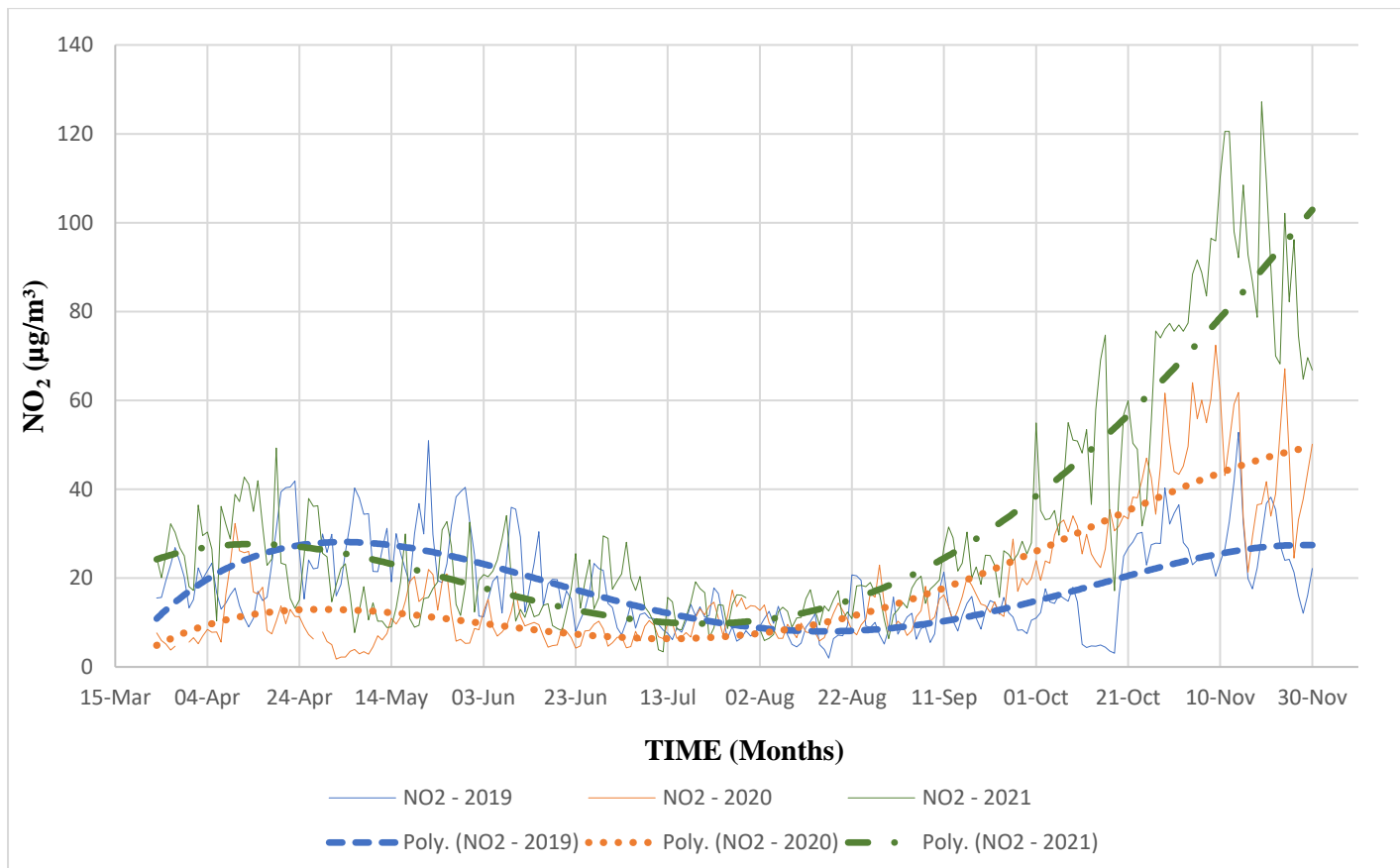


Figure 4.4: NO₂ variation around Ghazipur landfill

NO_x had the highest emission from 24th March 2019 till 23rd June 2019, for 2020 NO_x had the lowest emission and started increasing from mid-September and for 2021 on average had the highest emission from 24th March till 30th November shown in fig. 4.5. Unlike other pollutants SO_2 has the highest emission during lockdown period till August 2020, after August till November SO_2 peaked in 2021 with value of $27.55 \mu\text{g}/\text{m}^3$ shown in fig. 4.7. CO has been the lowest in 2020, 2019 has the highest CO emission $4.26 \text{ mg}/\text{m}^3$ on 01 November 2019. On 29th November 2021 CO has the peak of $6.26 \text{ mg}/\text{m}^3$ crossing the prescribed standard of $0\text{-}6 \text{ mg}/\text{m}^3$. NH_3 variation during summer and monsoon season was lowest in 2020 and increased in winter season of 2020 with the value of $111.12 \mu\text{g}/\text{m}^3$. In 2021 variation was high in summer and monsoon season and lowest in winter shown in fig. 4.6.

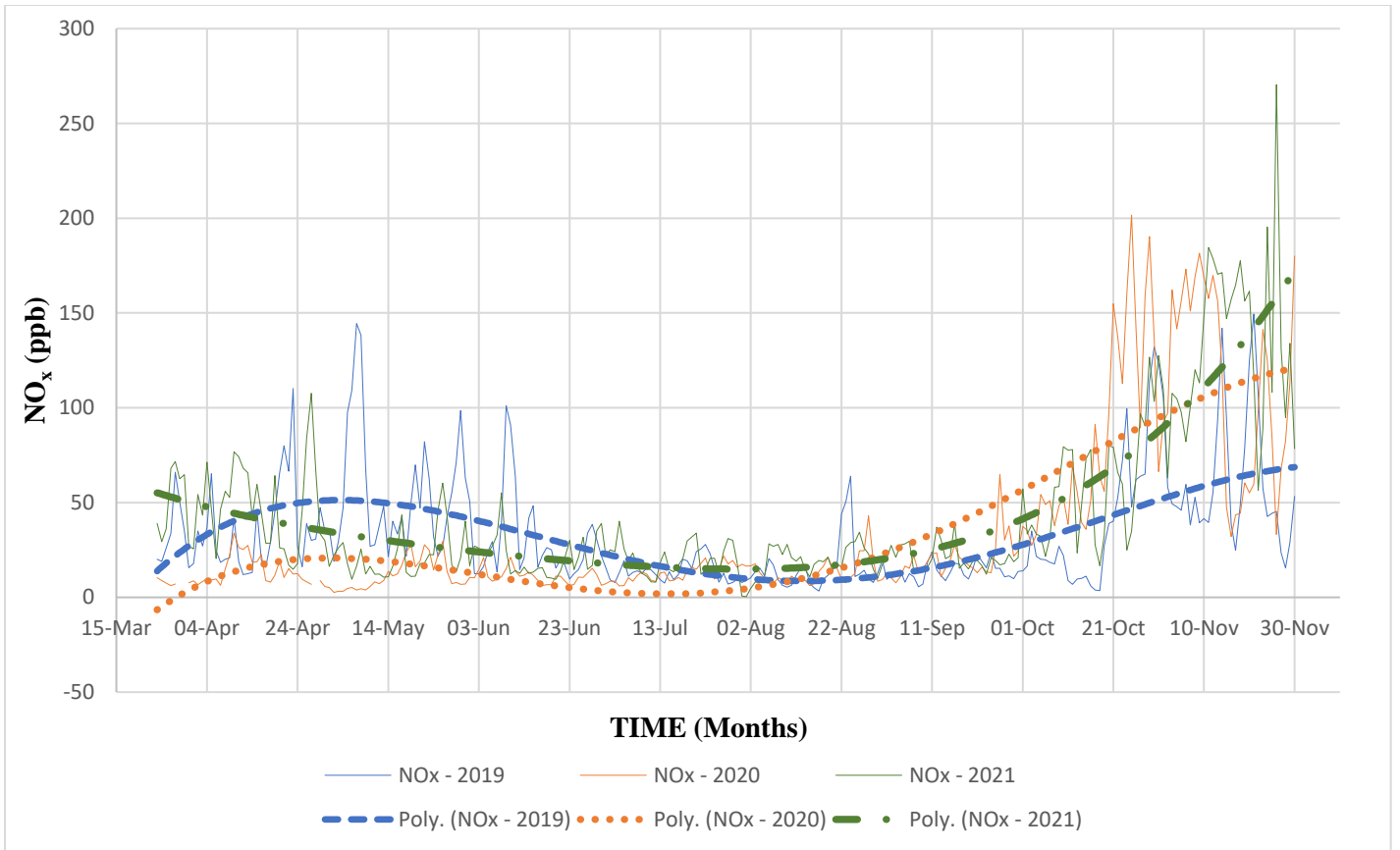


Figure 4.5: NO_x Variation around Ghazipur landfill

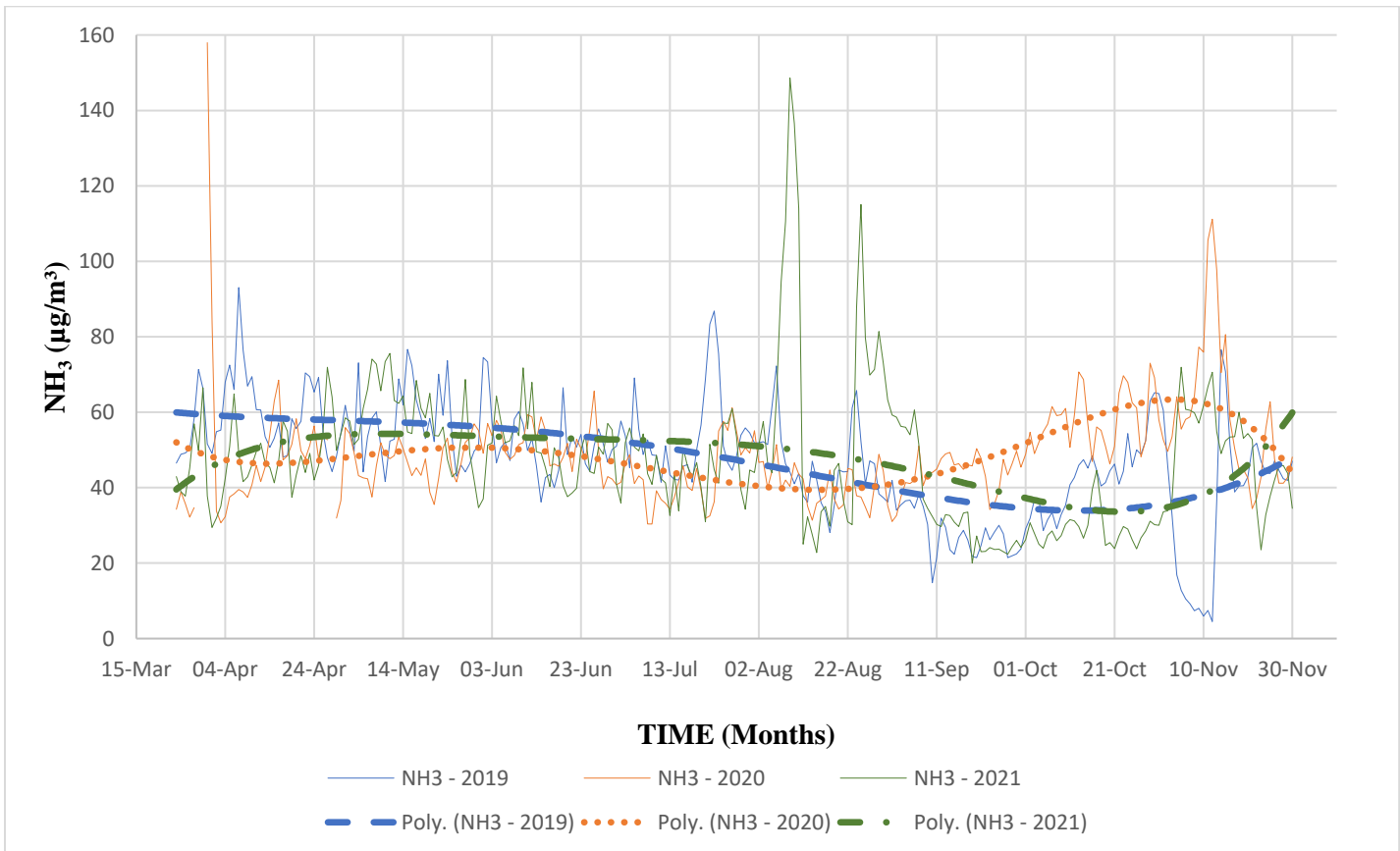


Figure 4.6: NH₃ Variation around Ghazipur landfill

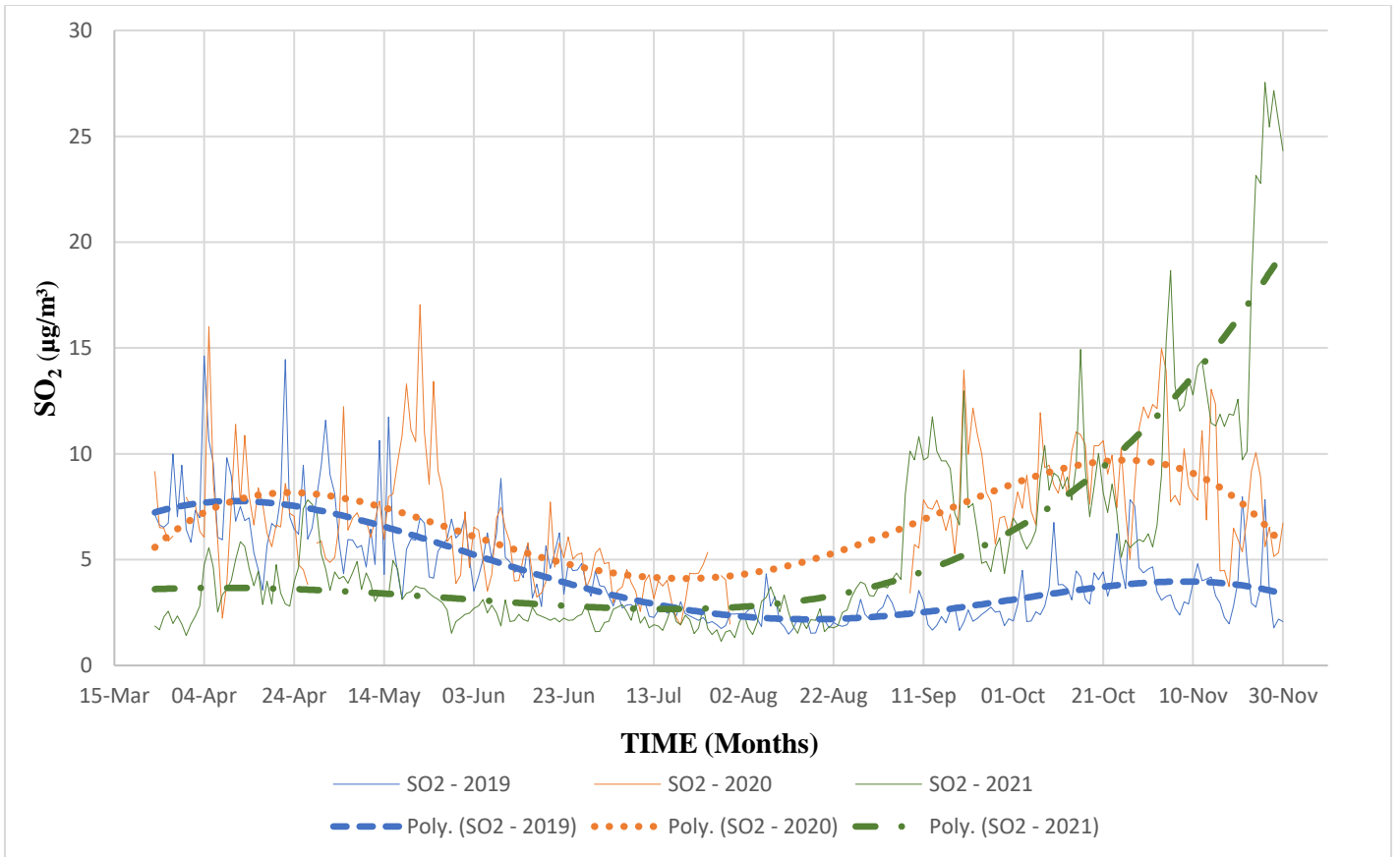


Figure 4.7: SO₂ Variation around Ghazipur landfill

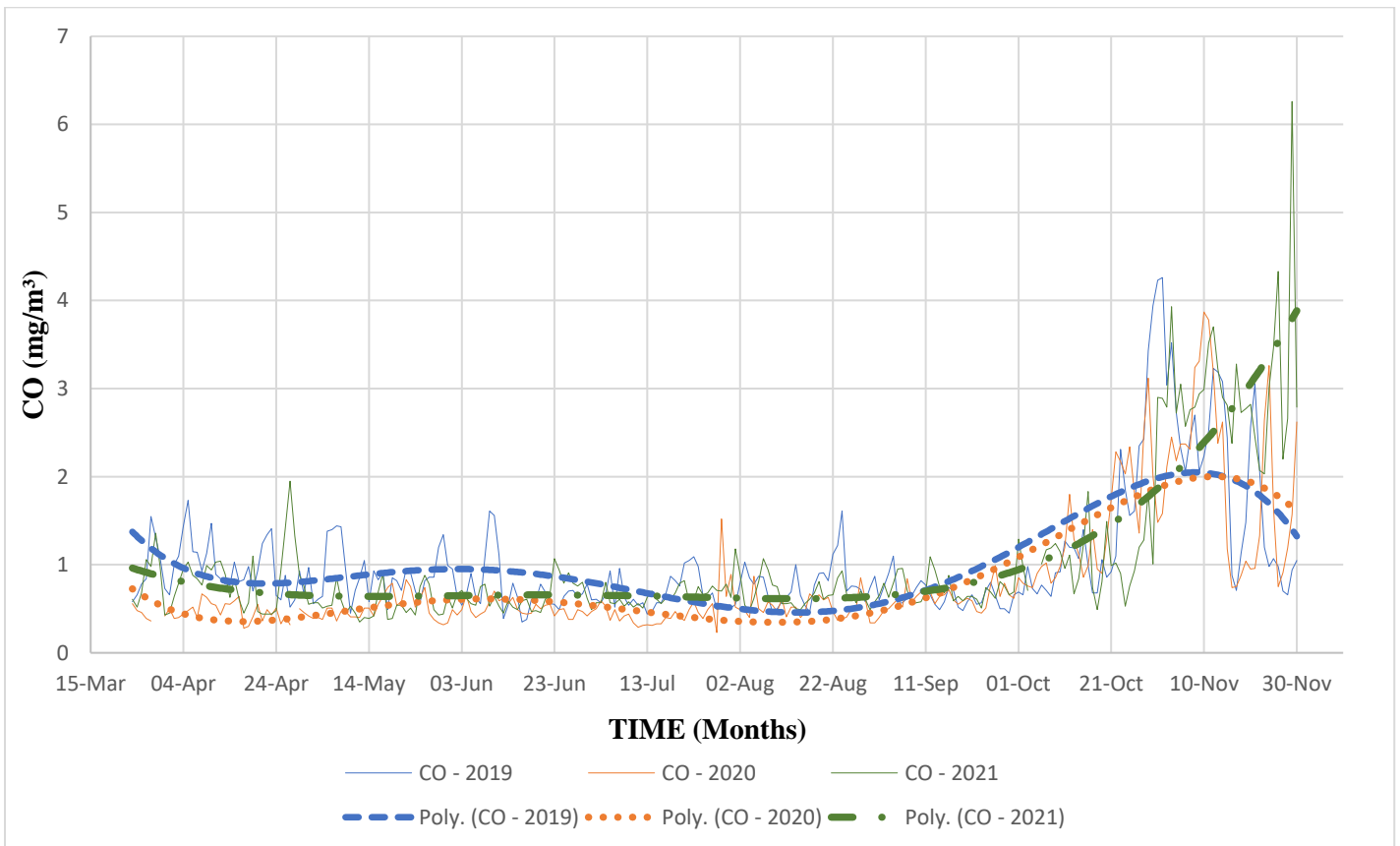


Figure 4.8: CO Variation around Ghazipur landfill

In 2019 Ozone has the peak emission in June but as the time increases its ozone variation decreases reached the minimum value of 5.09 $\mu\text{g}/\text{m}^3$ on 19th November 2019 and maximum 63.66 $\mu\text{g}/\text{m}^3$ on 03rd October 2019. During 2020 the maximum value was 39.13 $\mu\text{g}/\text{m}^3$ on 05th July 2020, ozone had the highest emission of during summer and the lowest during winter and the case was opposite during 2021 ozone has the lowest emission during summer 3.39 $\mu\text{g}/\text{m}^3$ on 24th August 2021 and maximum 79.35 $\mu\text{g}/\text{m}^3$ on 13th October 2021.

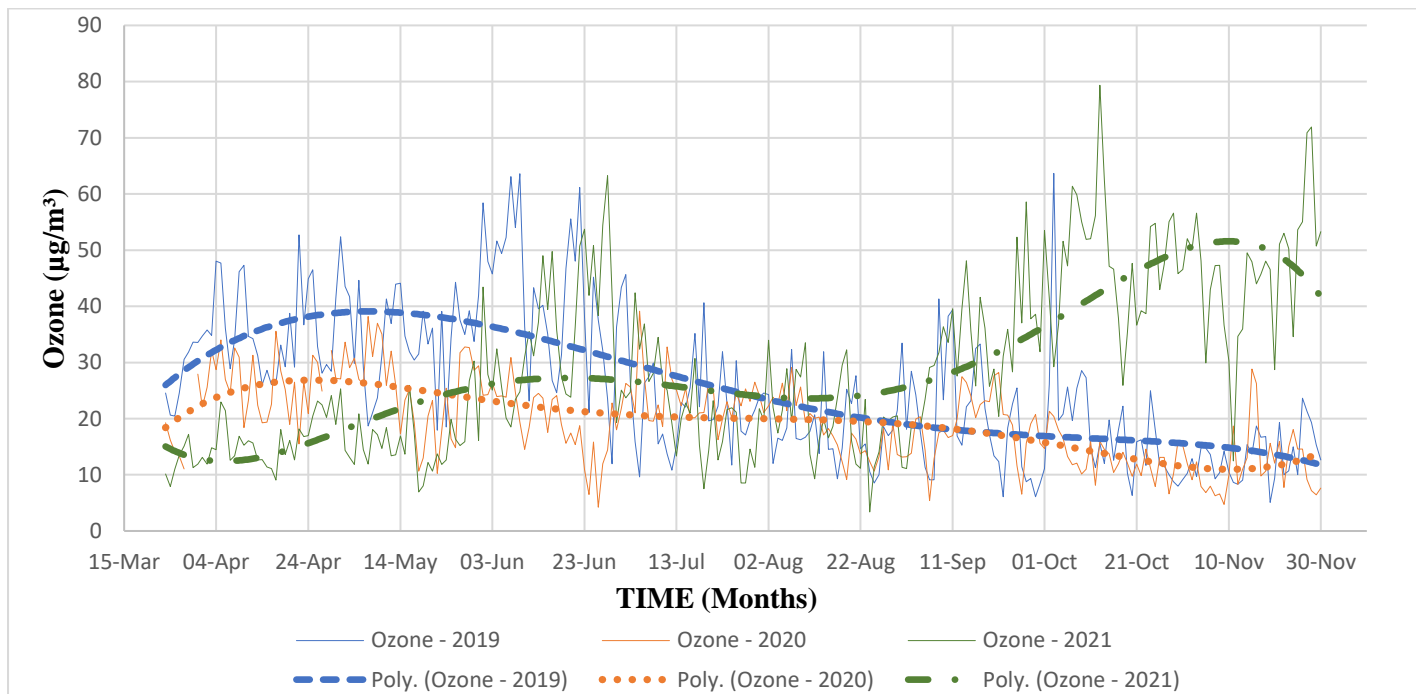


Figure 4.9: Ozone Variation around Ghazipur landfill

Benzene has the highest emission during summer reaching the value of 9.18 $\mu\text{g}/\text{m}^3$ on 24th August 2019 exceeding the prescribed standard value of 0-5 $\mu\text{g}/\text{m}^3$, and 2020 and 2021 had the lowest emission during summer value of .02 and 0 $\mu\text{g}/\text{m}^3$ respectively. Toluene had the lowest emission in 2021 during summer and it increases during winter reaching maximum value of 22.25 $\mu\text{g}/\text{m}^3$ on 26th November 2021 and minimum value of .26 $\mu\text{g}/\text{m}^3$ on 29th May 2021. In 2019 summer and monsoon Toluene emission was more than 2020 and 2021 summer and monsoon but during winter 2021 had the high Toluene emission.

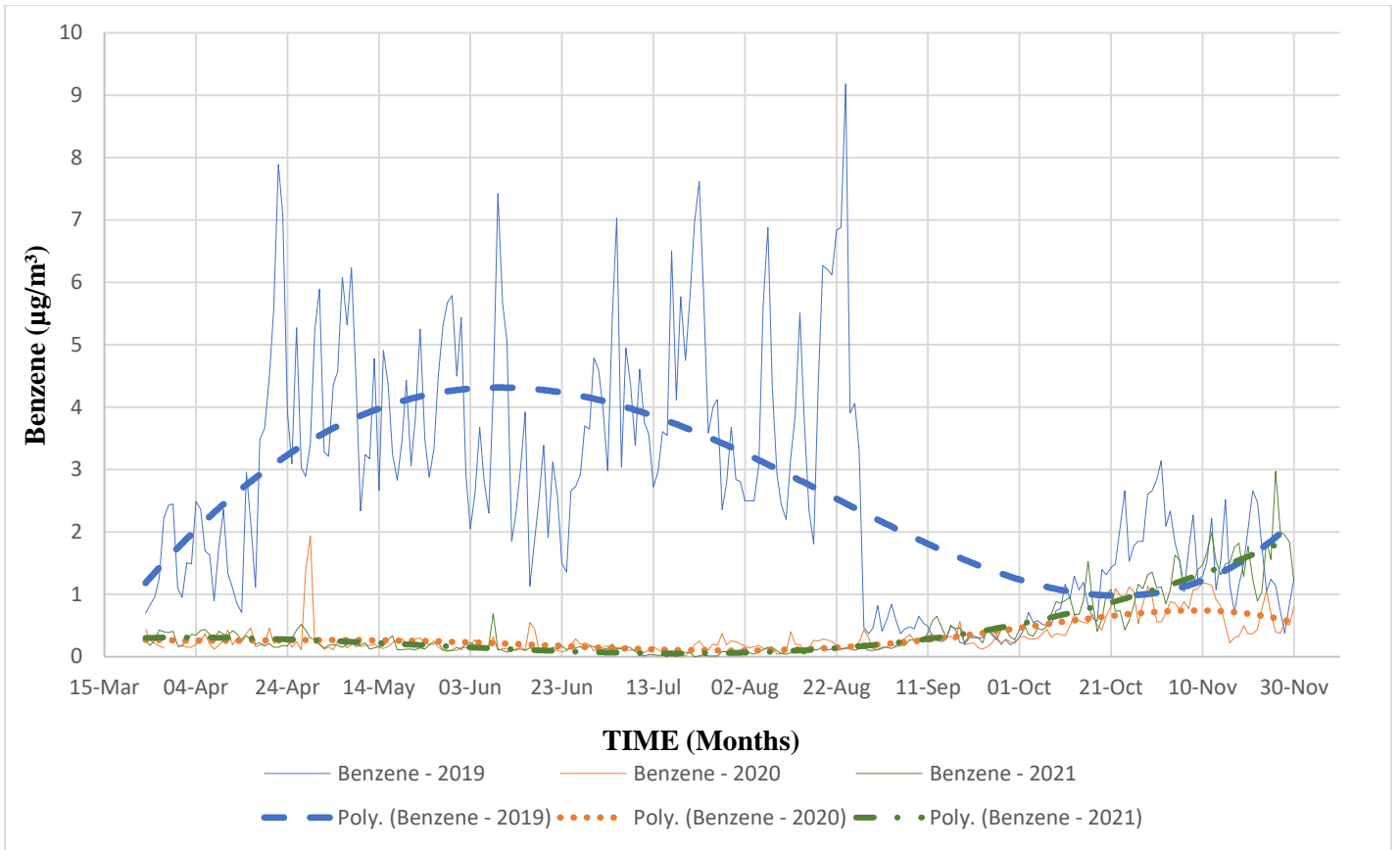


Figure 4.10: Benzene variation around Ghazipur landfill

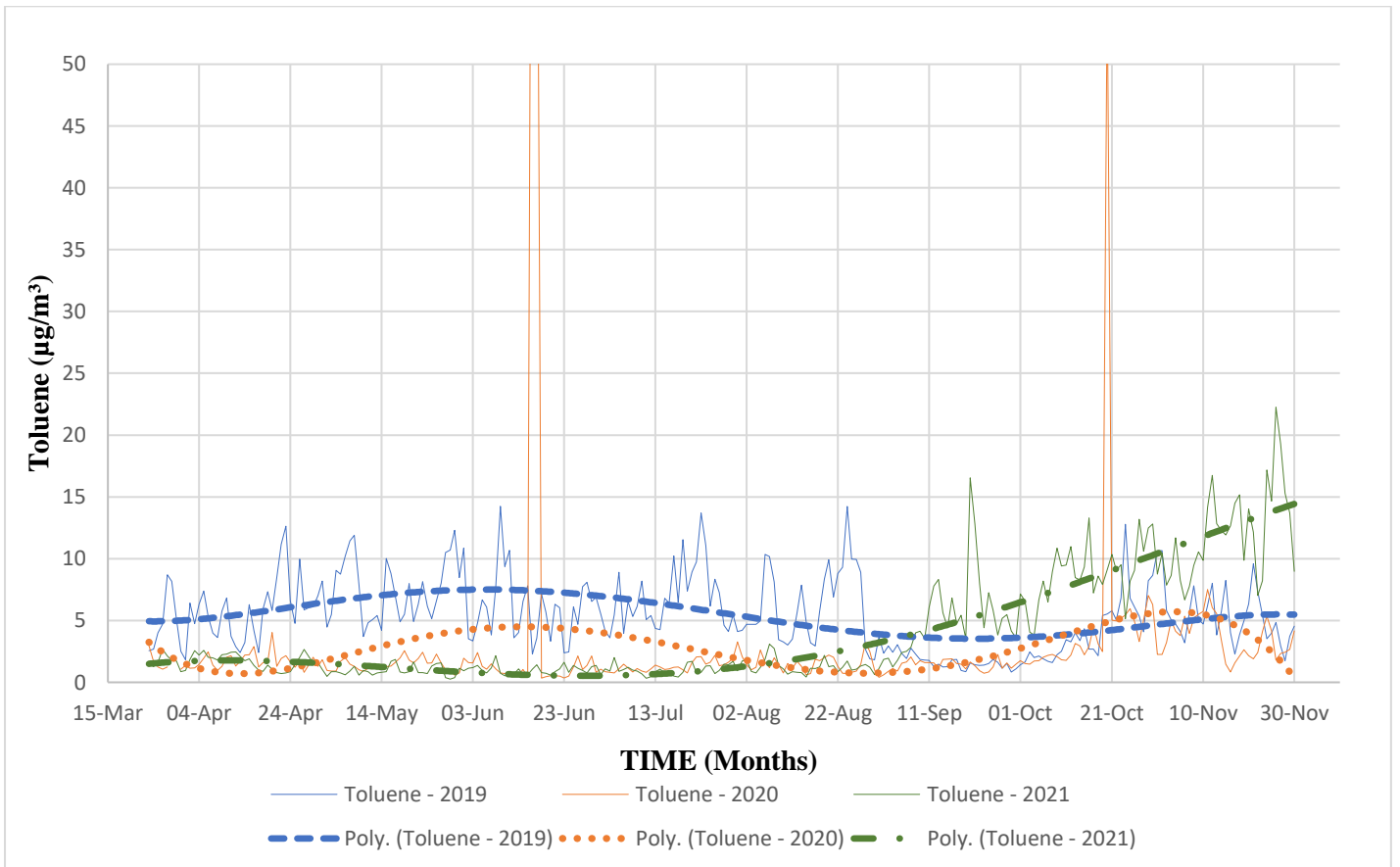


Figure 4.11: Toluene Variation around Ghazipur landfill

4.1.2 Narela Landfill

In summer and monsoon season the PM_{2.5} particles were highest during 2019 summer and 2019 monsoon season and reached maximum value of 689.1 $\mu\text{g}/\text{m}^3$ during winter of 03rd November 2019. And PM_{2.5} were lowest during summer and monsoon season of 2020 and its value start increasing from mid-September and reached the maximum value of 603.01 $\mu\text{g}/\text{m}^3$ on 09th November 2020.

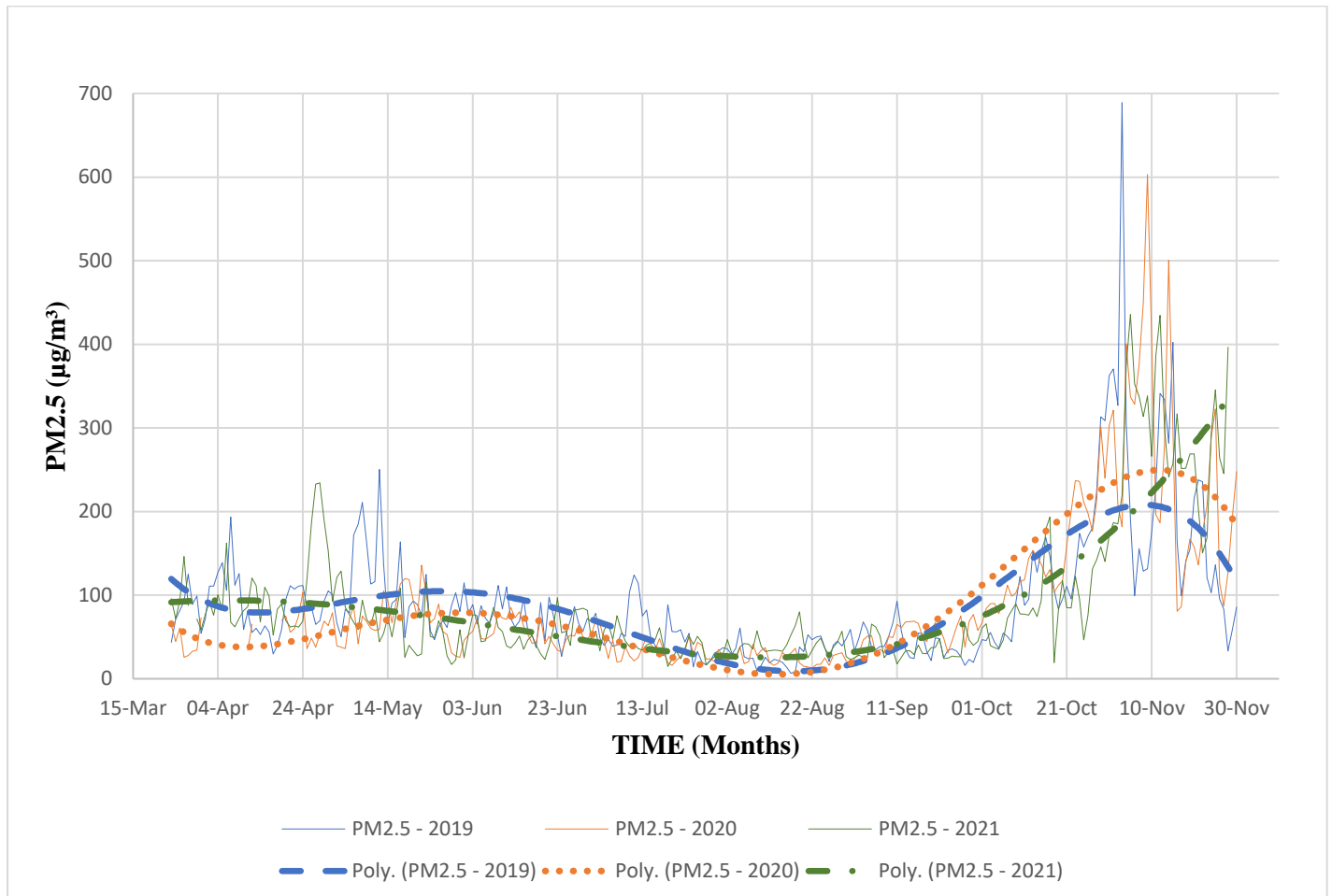


Figure 4.12: PM_{2.5} Variation around Narela landfill

During summer and monsoon season of 2020 PM₁₀ were lowest compared to 2019 and 2021 and increased during winter and on 09th November 2020 reached the maximum value of 717.35 $\mu\text{g}/\text{m}^3$. During summer and monsoon of 2019 PM₁₀ was at peak compared to 2020 and 2021 but reached maximum value of 649.05 $\mu\text{g}/\text{m}^3$ on 03rd November 2019.

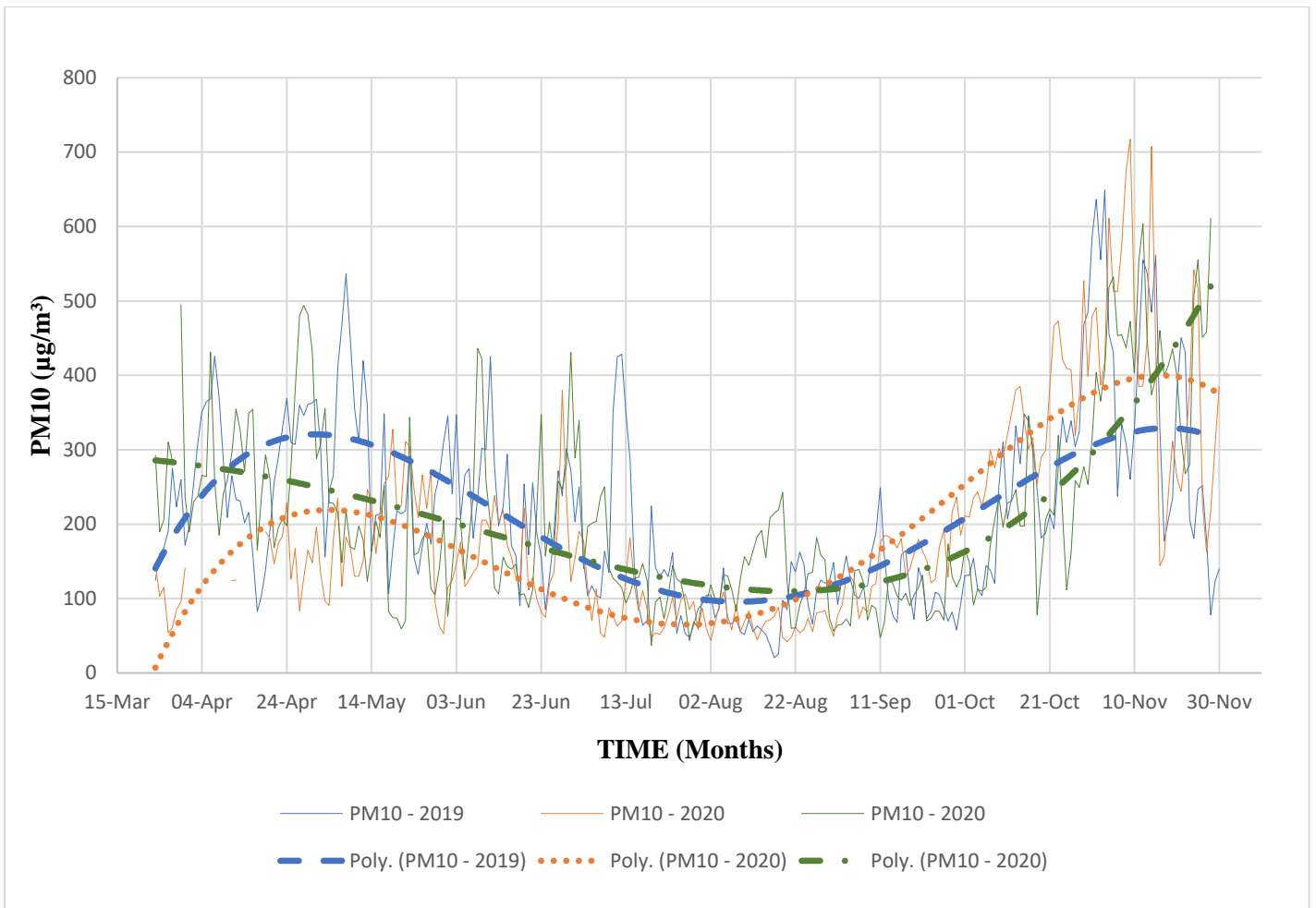


Figure 4.13: PM10 Variation around Narela landfill

NO variation for 2020 was lowest during summer and monsoon and maximum during winter reached the value of 163.77 $\mu\text{g}/\text{m}^3$ on 11th November 2020. 2019 had the high emission during summer and average during monsoon and winter, but reached the peak value 128.07 $\mu\text{g}/\text{m}^3$ on 20th November 2019. During summer season of 2019 NO_2 emission were at peak reached the maximum value of 166.75 $\mu\text{g}/\text{m}^3$ on 16th April and lowest in winter compared to 2020 and 2021, during lockdown NO_2 were lowest in summer with value of 12.1 $\mu\text{g}/\text{m}^3$ on 29th March 2020 as restriction lifted off value soar up to the value of 105.77 $\mu\text{g}/\text{m}^3$ on 24th November 2020. NO_x variation in 2019 were at peak all season with value of 157.48 ppb on 20th November. In 2020 NO_x emission were lower in summer and monsoon season, post October its value begins to increase and reached up to 169.9 ppb on 11th November. NH_3 variation in 2020 was maximum in winter with value of 68.56 $\mu\text{g}/\text{m}^3$ minimum in monsoon and average in summer. In 2021 value peaked all time in winter as well in summer season with maximum value of 91.94 $\mu\text{g}/\text{m}^3$.

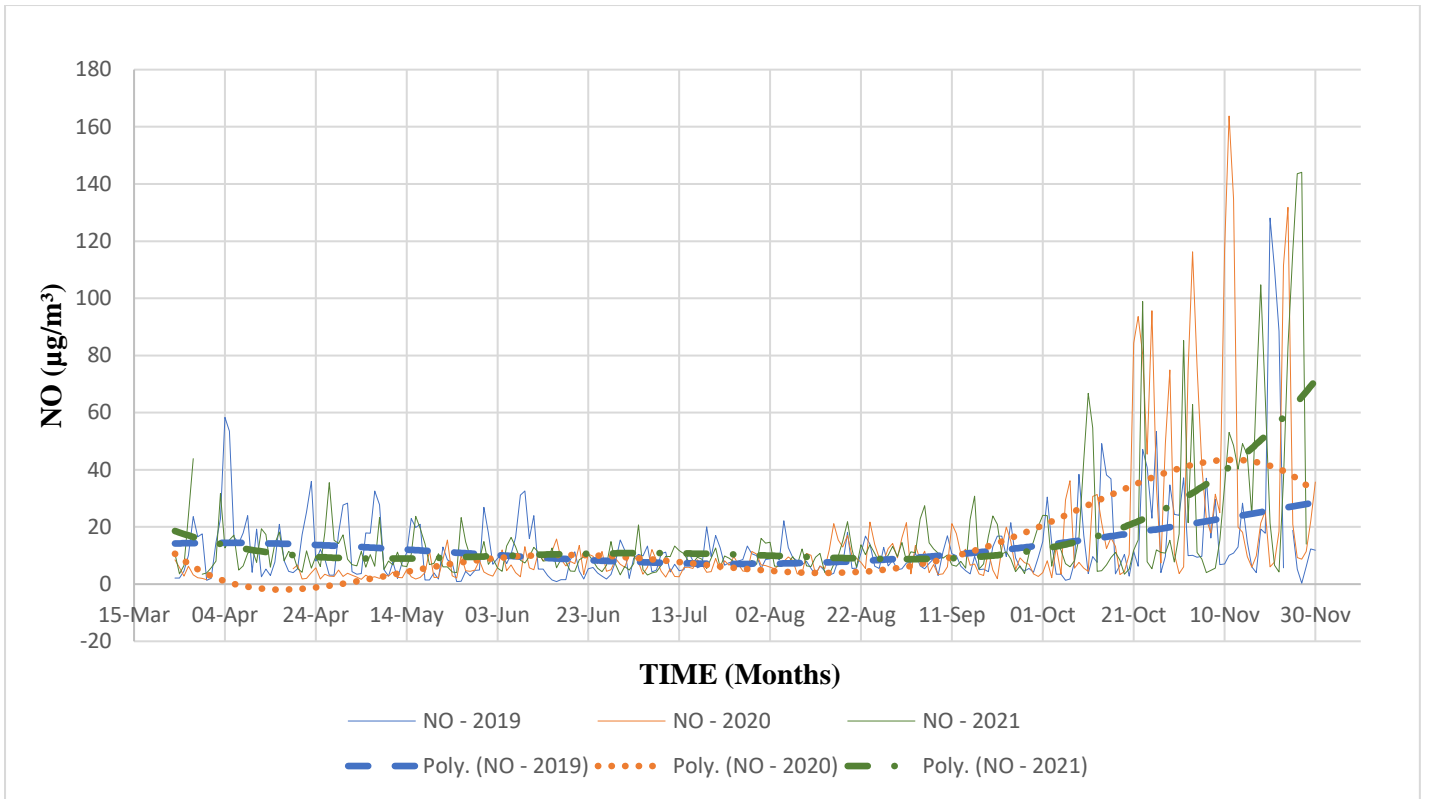


Figure 4.14: NO variation around Narela landfill

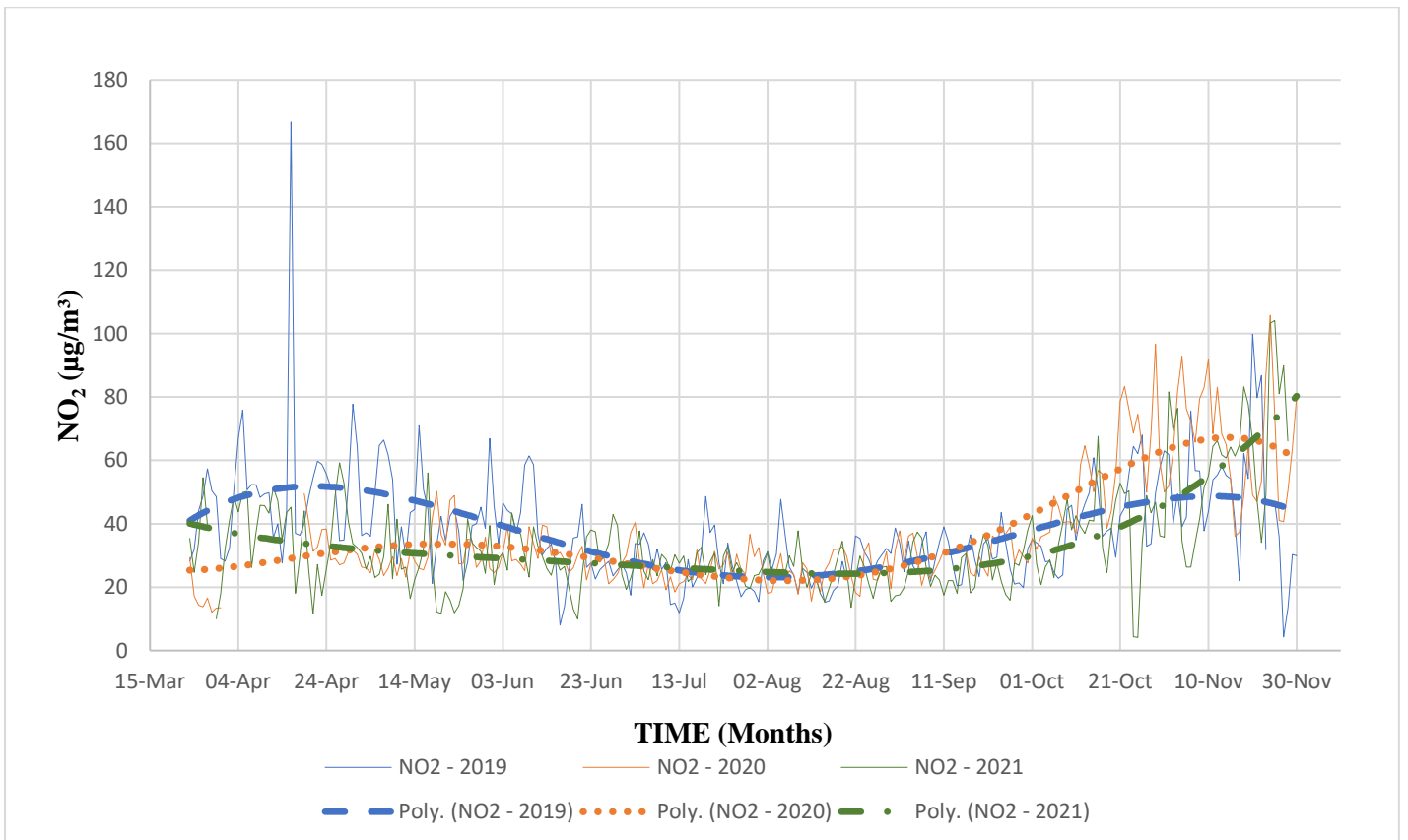


Figure 4.15: NO₂ variation around Narela landfill

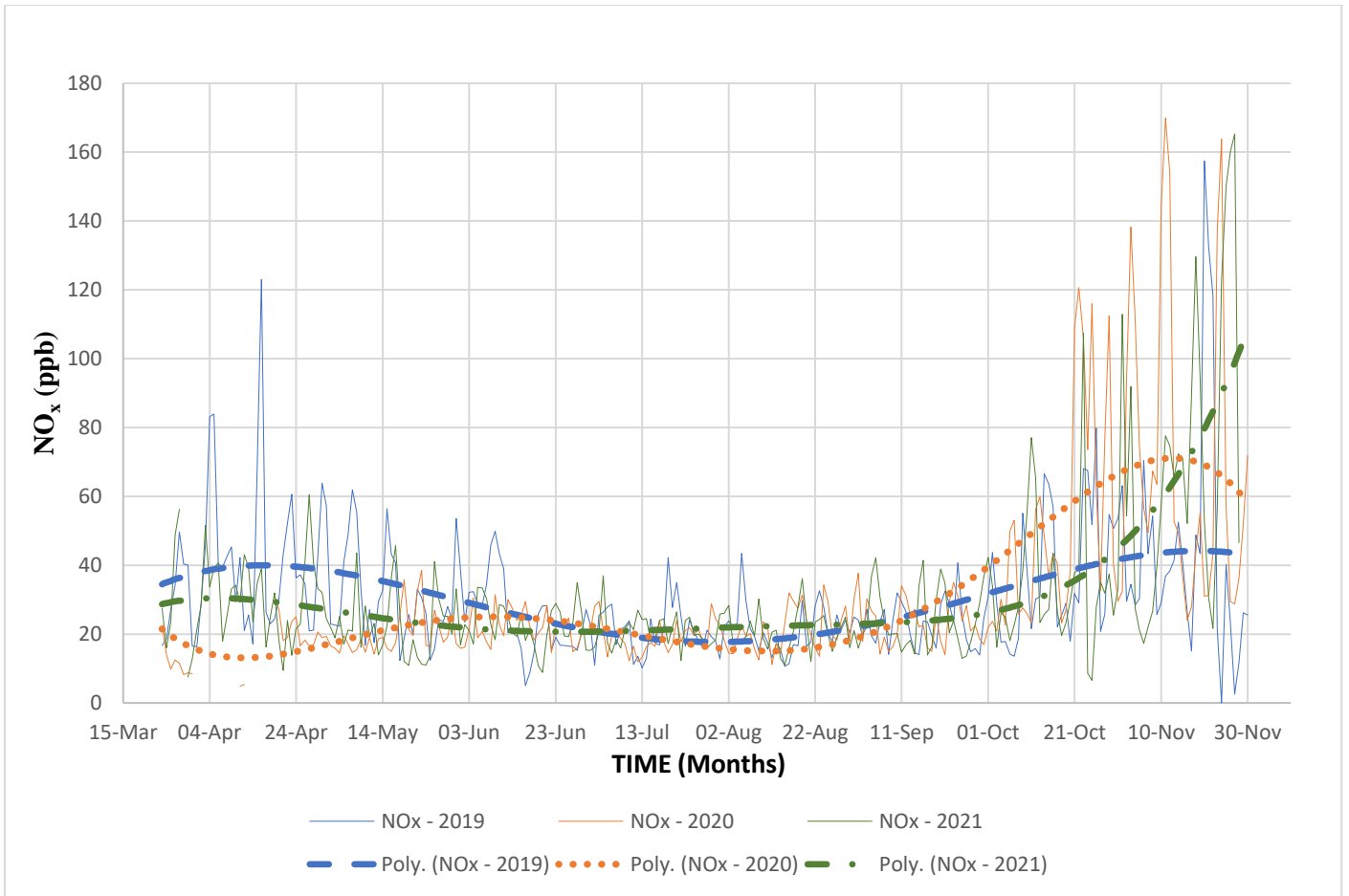


Figure 4.16: NO_x Variation around Narela landfill

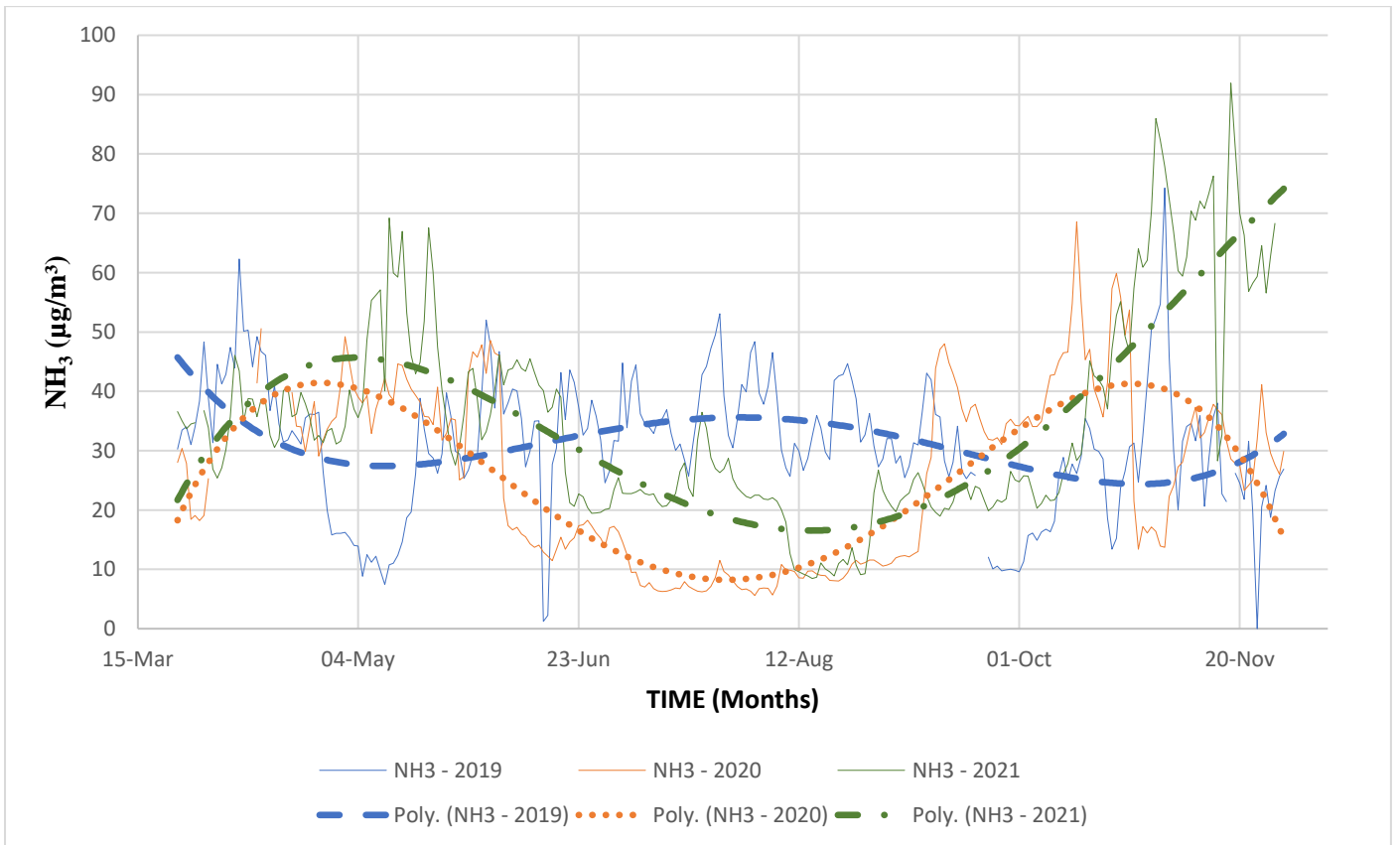


Figure 4.17: NH₃ Variation around Narela landfill

During Summer and monsoon of 2019 and 2021 SO₂ emissions were at peak with value of 41.64 µg/m³ and 49.39 µg/m³ respectively on 30th May 2019 and 01st April 2021. During lockdown (2020) emissions were at bay with maximum value of 38.11 µg/m³ on 22nd May 2020.

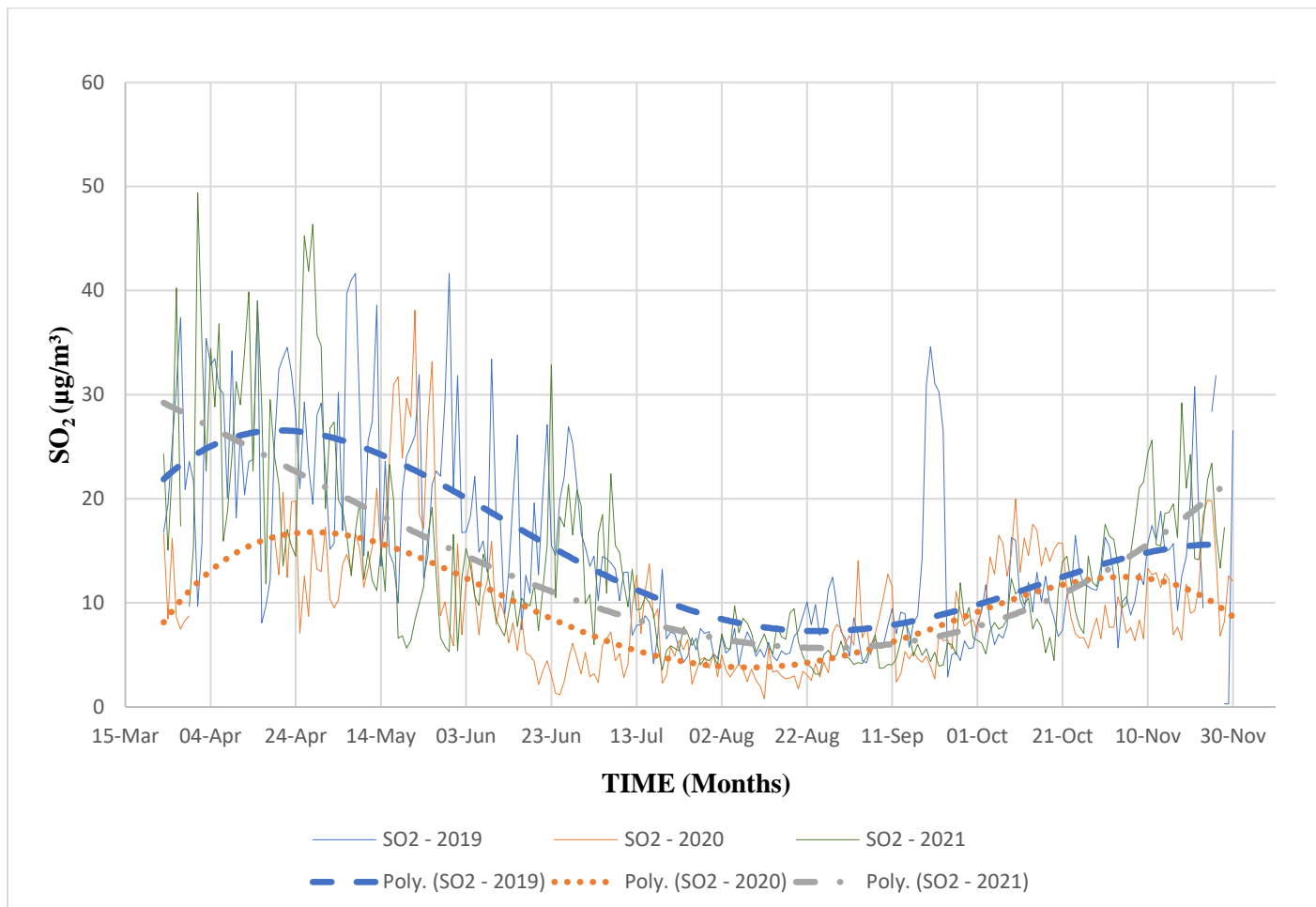


Figure 4.18: SO₂ Variation around Narela landfill

CO emissions were high all season of 2019 with maximum value 3.3 mg/m³ on 03rd November 2019. During lockdown CO were high during monsoon and winter with maximum value of 2.87 mg/m³ on 10th November 2020. CO emission peaked on monsoon and post monsoon during 2021 with maximum value of 3.36 mg/m³ on 26th August 2021. The CO didn't exceed the prescribing standard (0-4 mg/m³) given by CPCB and CCR.

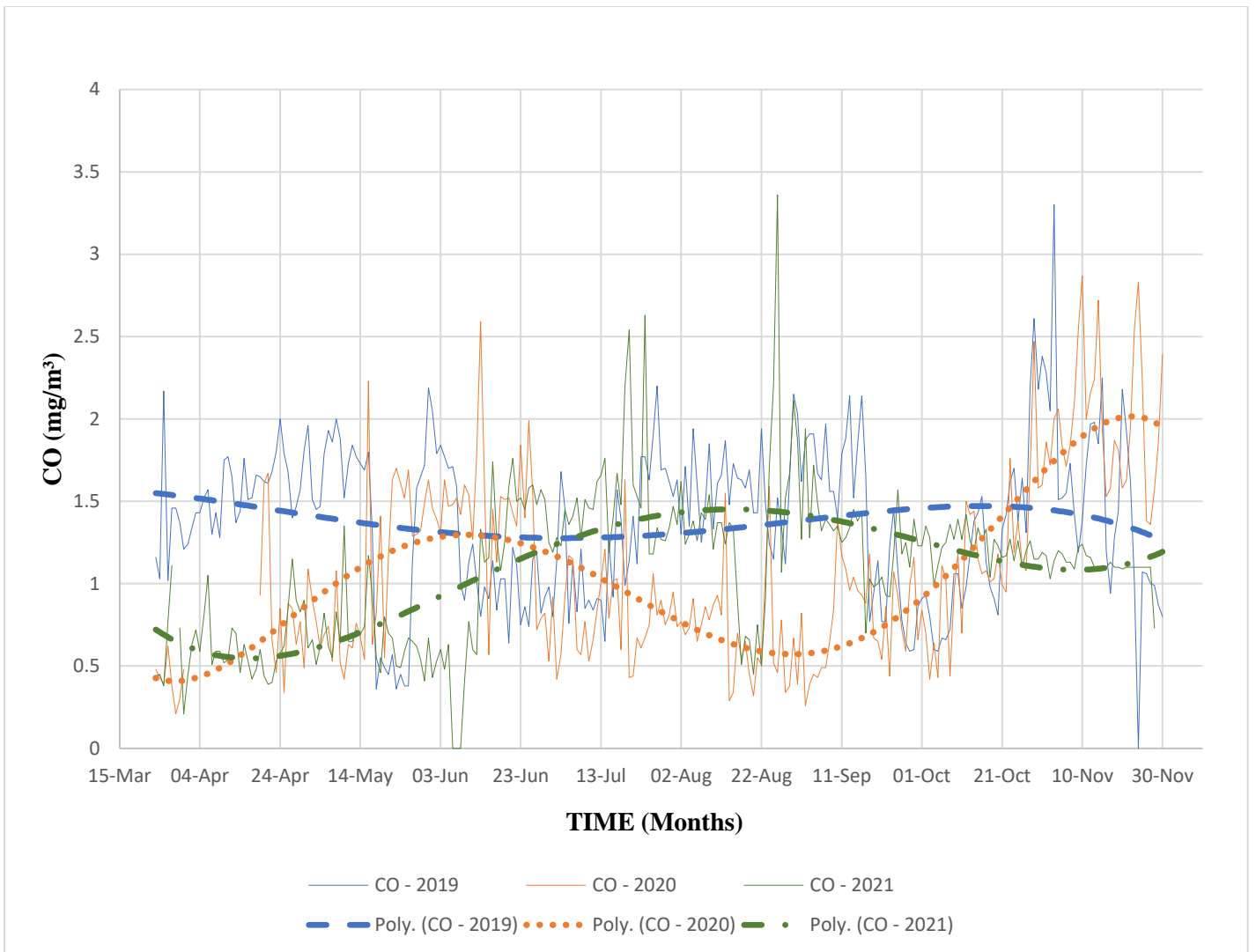


Figure 4.19: CO Variation around Narela landfill

Ozone variation in 2019 has increased in all season except in the post monsoon season, maximum value of ozone in 2019 was $99.87 \mu\text{g}/\text{m}^3$ on 22nd June. During the lockdown period ozone increased in the summer season but decreased during monsoon and post monsoon season but its value further increased in winter season with maximum value of $106.66 \mu\text{g}/\text{m}^3$ on 08th May 2020 which was within the prescribed standard ($0-180 \mu\text{g}/\text{m}^3$) given by CPCB. Ozone was all time high post lockdown i.e., in 2021.

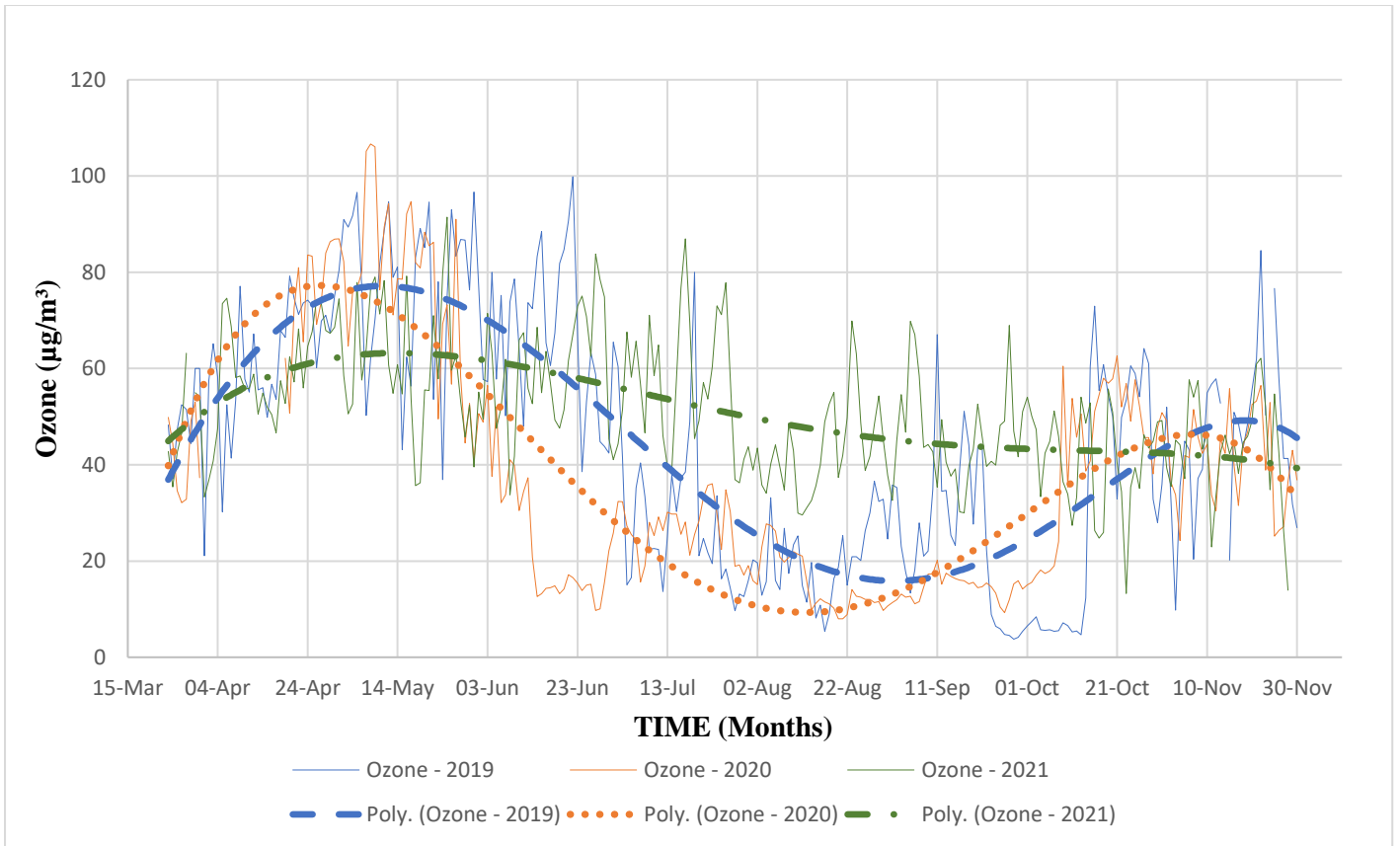


Figure 4.20: Ozone Variation around Narela landfill

Benzene was high all season in 2019 compare to 2020 and 2021 with maximum value of $8.72 \mu\text{g}/\text{m}^3$. But peak occurred in 2020 with the value of $9.77 \mu\text{g}/\text{m}^3$ in month of November and with the value of $9.55 \mu\text{g}/\text{m}^3$ in the month of June. In 2021 post lockdown Benzene peak occurred in the month of November with the value of $9.55 \mu\text{g}/\text{m}^3$.

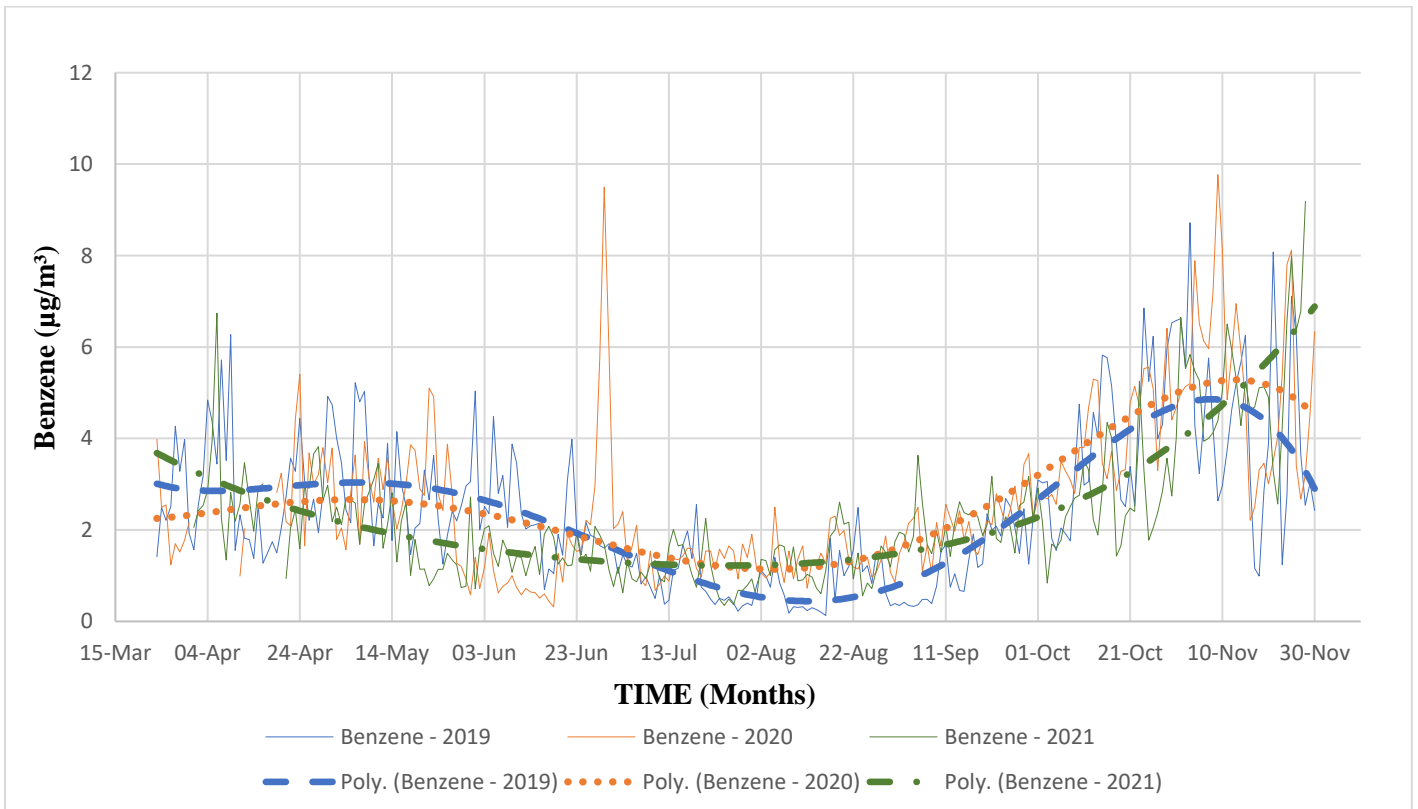


Figure 4.21: Benzene variation around Narela landfill

On average Toluene emission was maximum in 2021 compared to 2019 and 2020 but peak occurred in 2020. The summer of 2019 Toluene emission was highest compared to summer of 2020, but during monsoon, post monsoon and winter season Toluene emission was maximum in 2020 compared to 2021 with maximum value of 403.77 $\mu\text{g}/\text{m}^3$ and 361.2 $\mu\text{g}/\text{m}^3$ respectively.

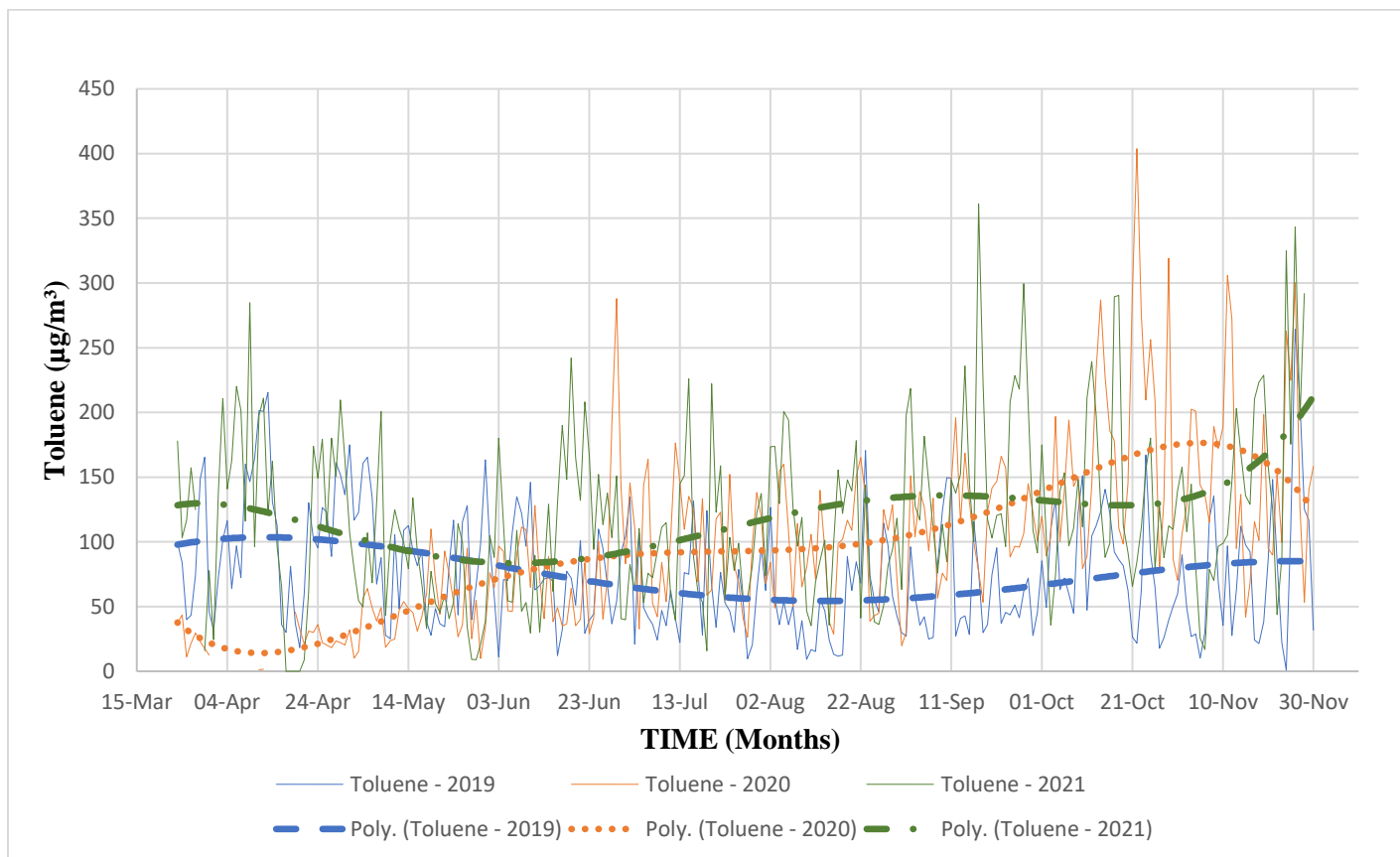


Figure 4.22: Toluene Variation around Narela landfill

4.1.3 Okhla landfill

PM_{2.5} variation was high in summer; monsoon and winter of 2019 reached the maximum value of 551.19 $\mu\text{g}/\text{m}^3$ on 03rd November 2019. During lockdown in summer and monsoon PM_{2.5} emissions were low post September value starts increasing and reached the peak in 09th November 2020 of value 547.66 $\mu\text{g}/\text{m}^3$. PM₁₀ emissions were high in summer and winter season with the peak value of 652.03 $\mu\text{g}/\text{m}^3$ on 03rd November 2019 and 740.19 $\mu\text{g}/\text{m}^3$ on 09th November 2020. During lockdown in summer the emissions were low compared to 2019 and 2021, but it started increasing post September and reached the all-time maximum value of 740.19 $\mu\text{g}/\text{m}^3$.

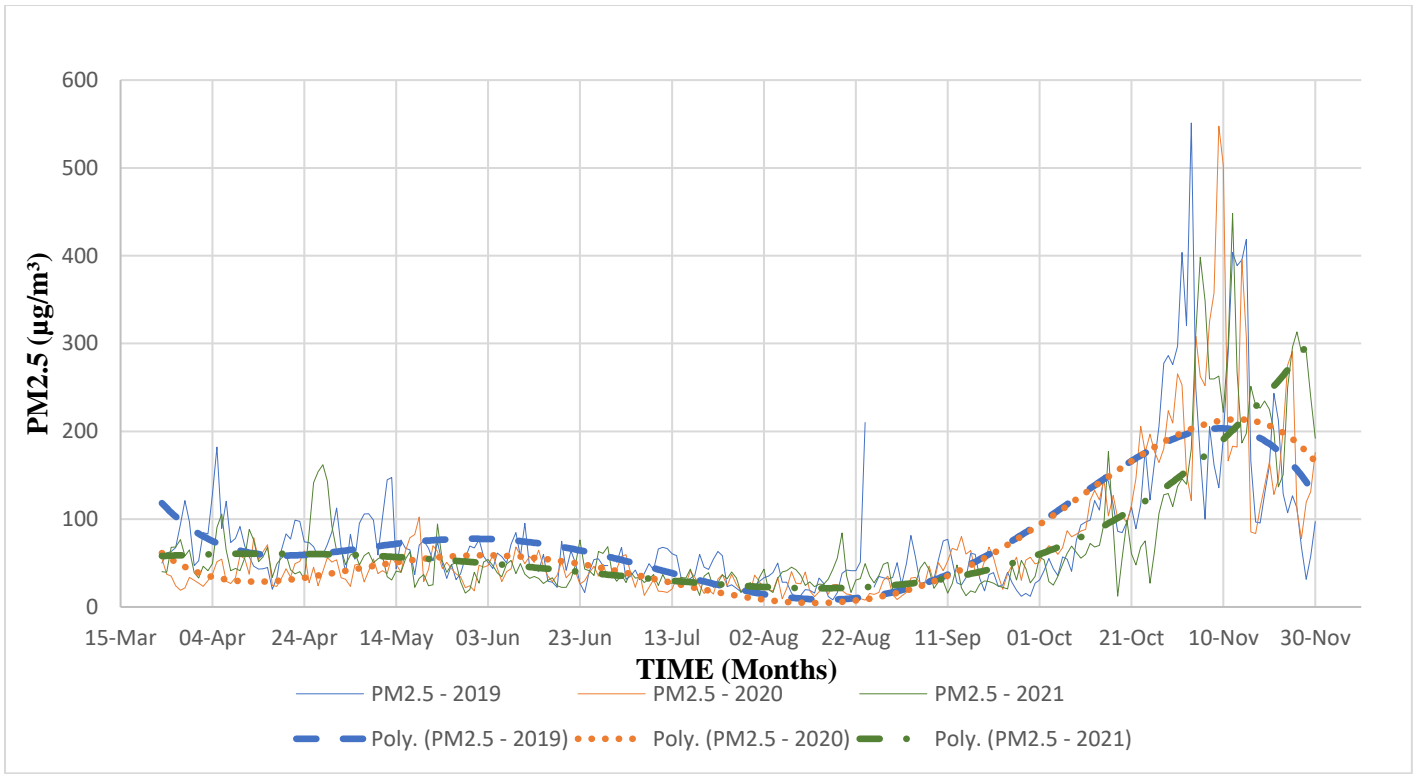


Figure 4.23: PM2.5 Variation around Okhla landfill

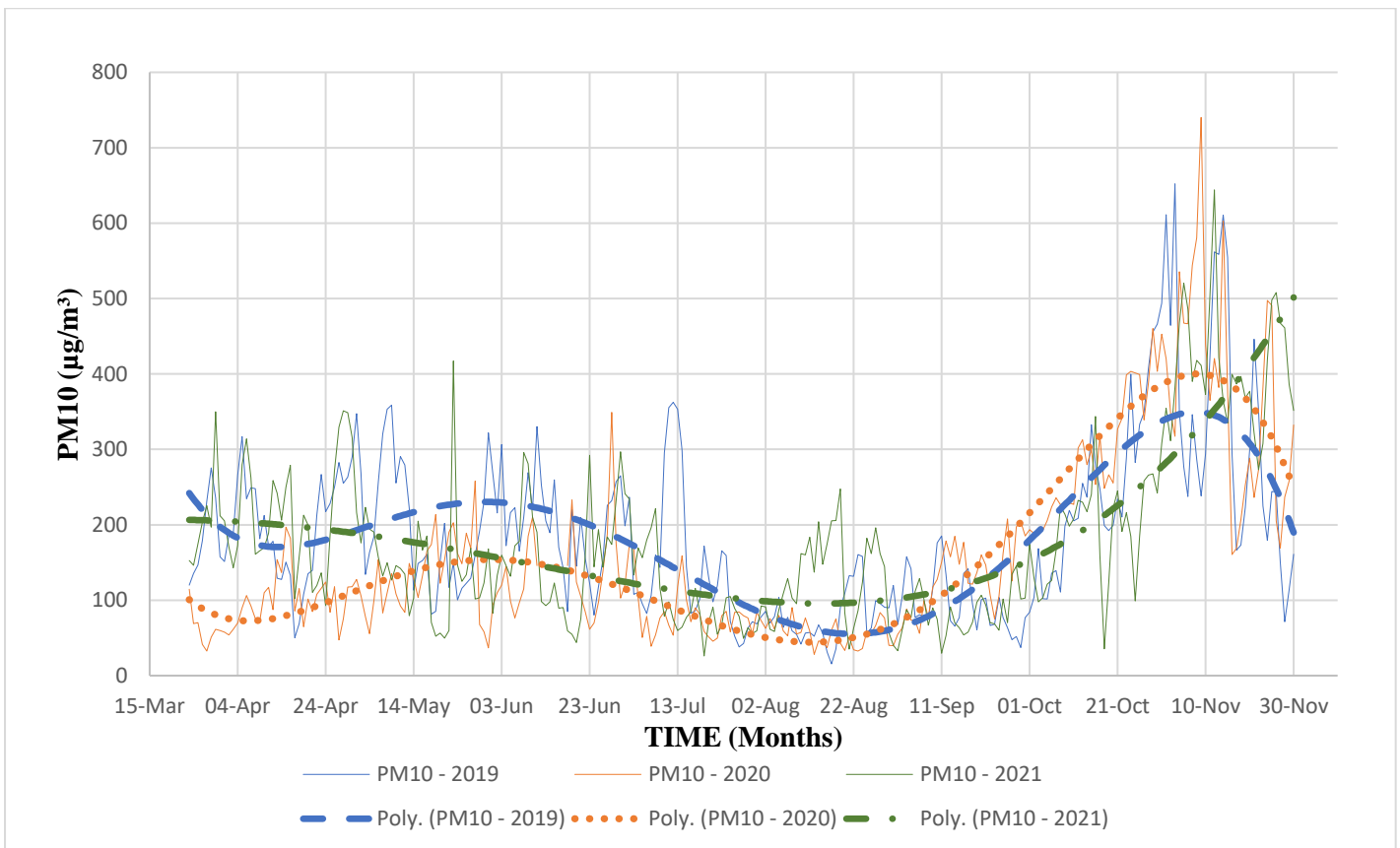


Figure 4.24: PM10 Variation around Okhla landfill

NO emissions were high in summer, monsoon, post monsoon and winter with maximum value of $225.35 \mu\text{g}/\text{m}^3$ but the peak occurred in summer. During 2020, NO emissions were low in summer and monsoon with minimum value of $.67 \mu\text{g}/\text{m}^3$ post mid-September emissions begin to rise and reached the maximum value of $213.64 \mu\text{g}/\text{m}^3$ on 12th November 2020. Post lockdown in 2021, NO emissions in summer were lower compared to 2019 but maximum compared to 2020

and reached the maximum in winter with value of $236.31 \mu\text{g}/\text{m}^3$. NO_2 emission in summer and monsoon of 2020 was lowest but post September NO_2 begin to increase and reached value of $112.06 \mu\text{g}/\text{m}^3$. In summer of 2021 emissions were high and peak occurred in winter with the value of $219.03 \mu\text{g}/\text{m}^3$ on 11th November 2021. NO_x emission in 2019 of summer was maximum compared to 2020 and 2021, but peak occurred in winter on 21st November 2019 with value of $218.37 \mu\text{g}/\text{m}^3$. During lockdown NO_x emission were lowest in summer and maximum in winter with the value of 280.26 ppb on 26th November 2021. NH_3 variation in 2020 was maximum in month of June and lowest in summer and winter with maximum value of $114.3 \mu\text{g}/\text{m}^3$, in 2021 peak was in the month of July with the value of $84.4 \mu\text{g}/\text{m}^3$.

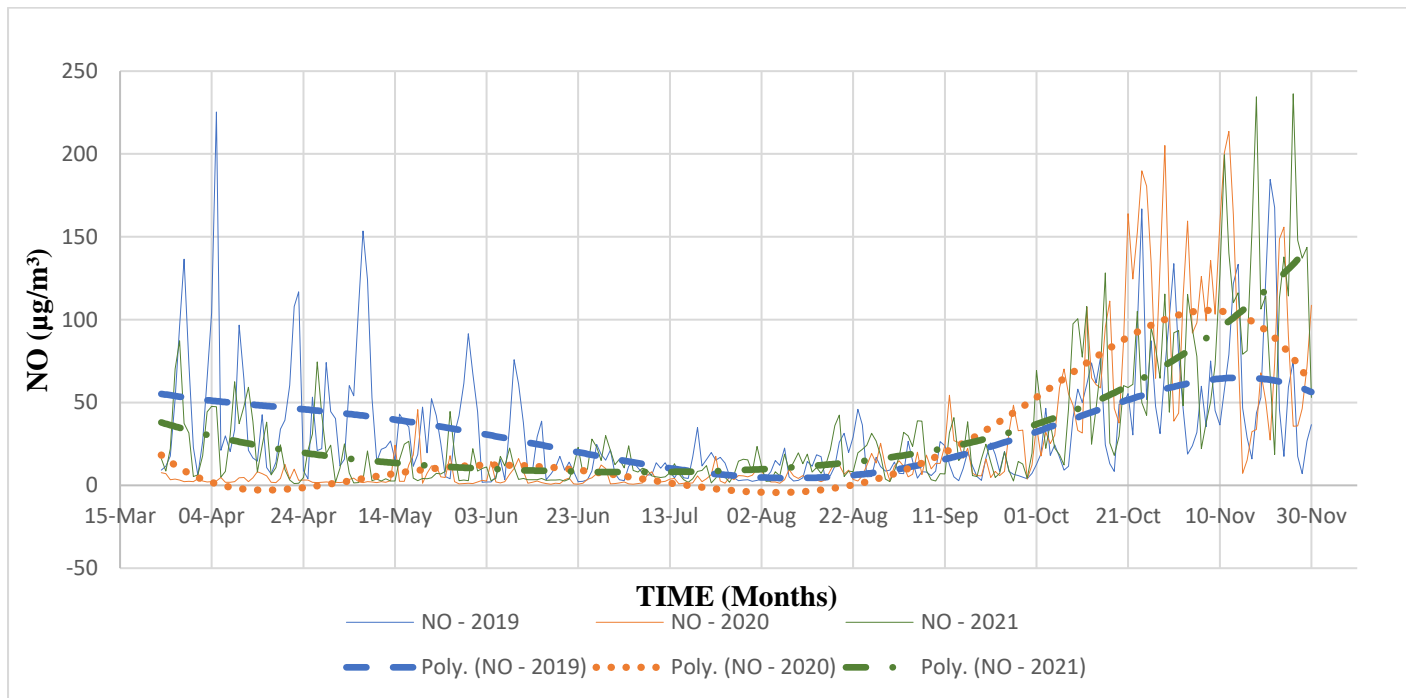


Figure 4.25: NO Variation around Okhla landfill

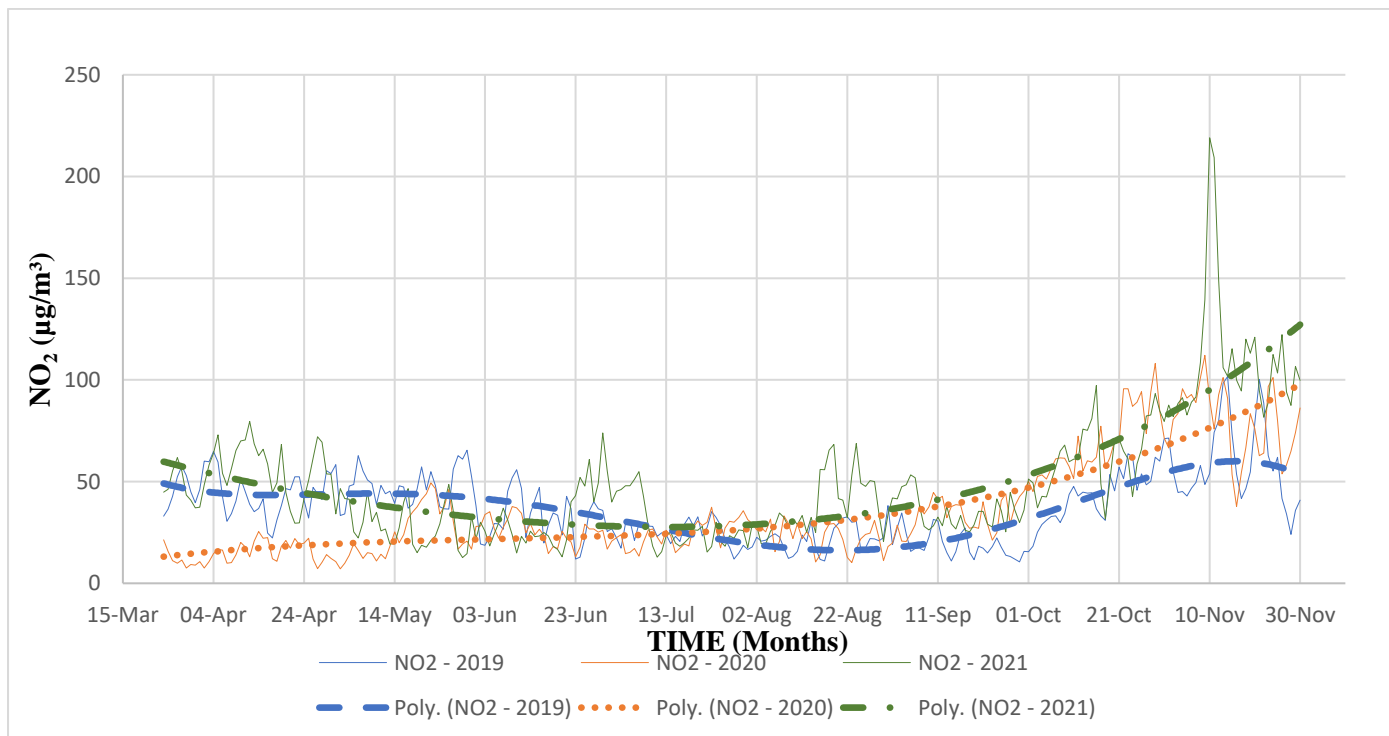


Figure 4.26: NO_2 Variation around Okhla landfill

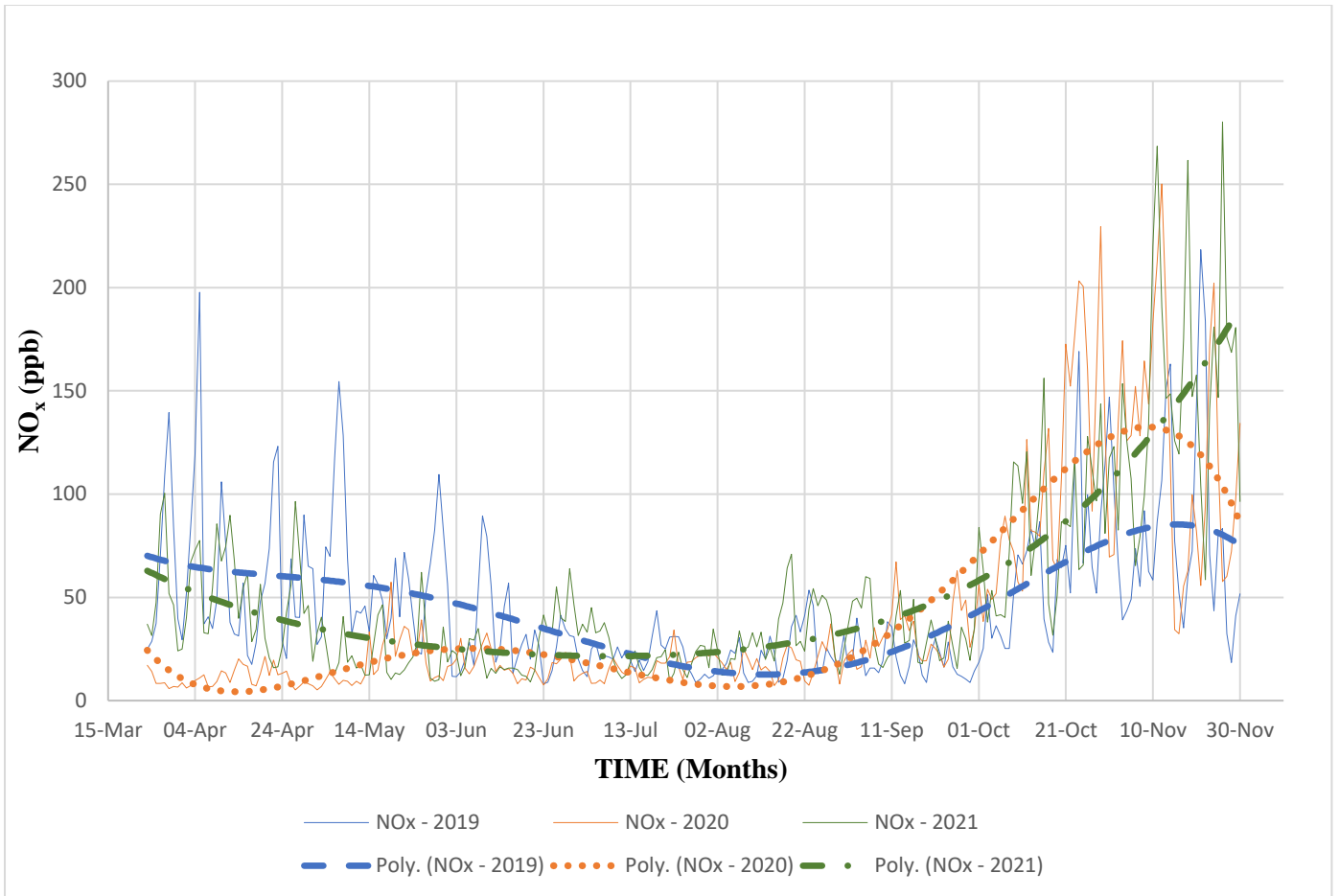


Figure 4.27: NO_x Variation around Okhla landfill

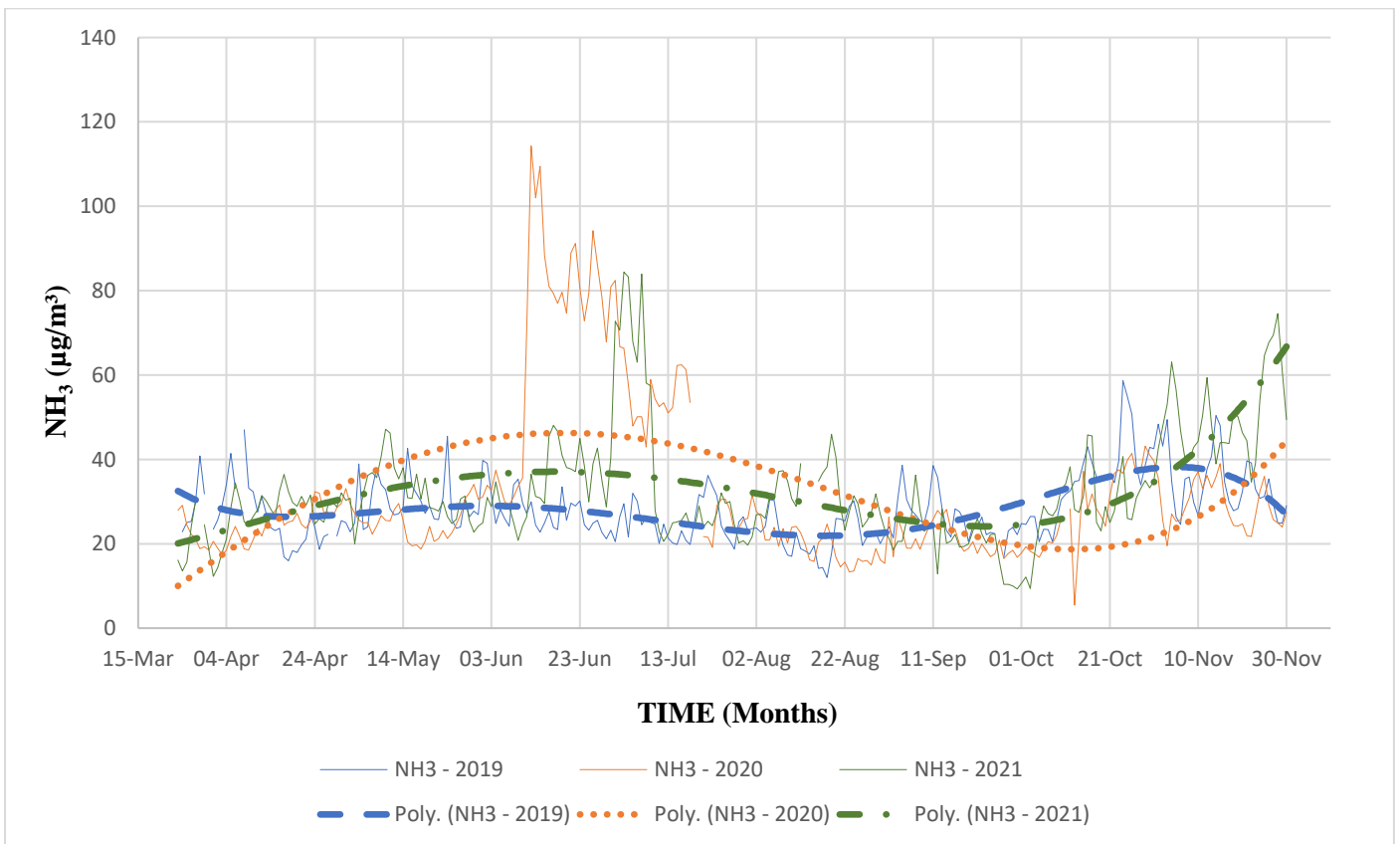


Figure 4.28: NH₃ Variation around Okhla landfill

SO₂ emission in 2021 summer and monsoon was maximum with peak value of 35.95 µg/m³ on 26th April 2021 post September emission became lowest in winter compared to 2019 and 2020. During lockdown and unlock phase SO₂ emission were lower in summer and maximum in winter with the peak value of 30.01 µg/m³ on 12th November 2020.

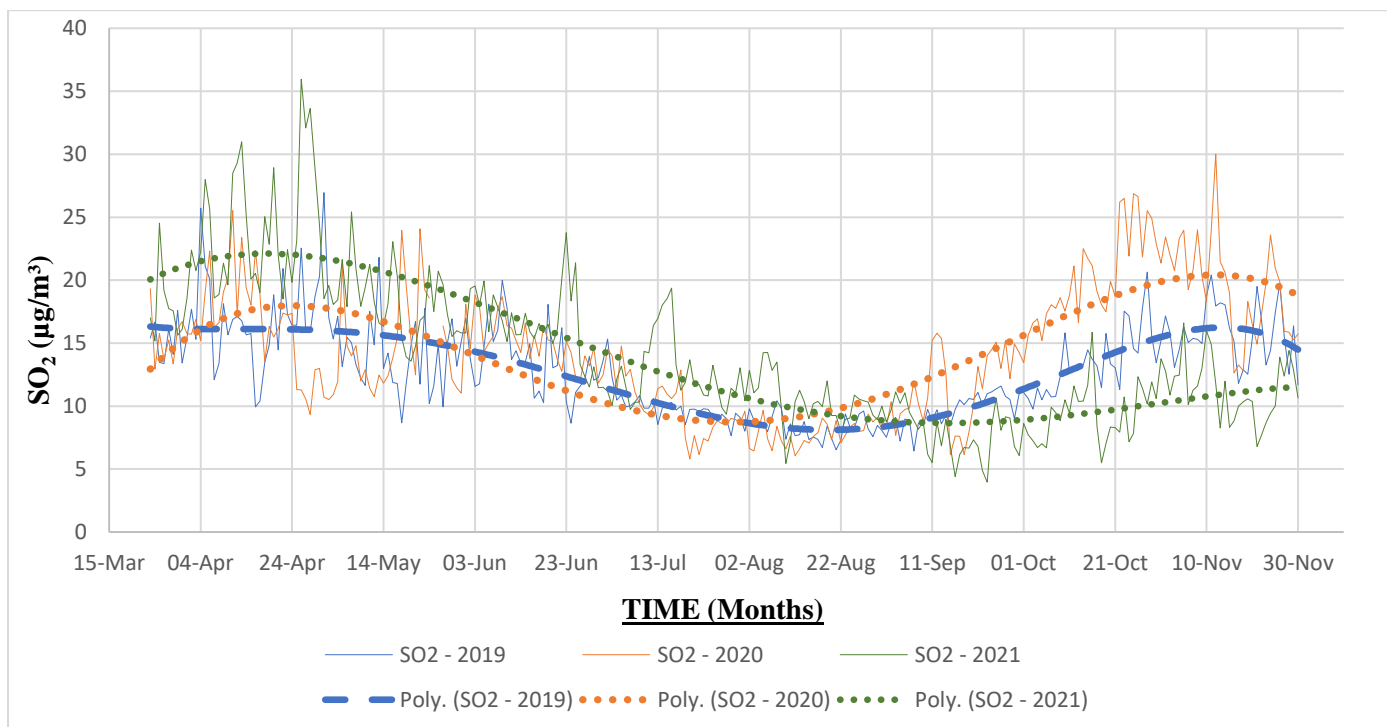


Figure 4.29: SO₂ variation around Okhla landfill

On an average CO emission in all season of 2019 was maximum with peak value of 4.35 mg/m³ on 21st November 2019. Emission in summer of 2020 was minimum but post August value begin to soar up and reached the peak value of 4.38 mg/m³ on 12th November 2020.

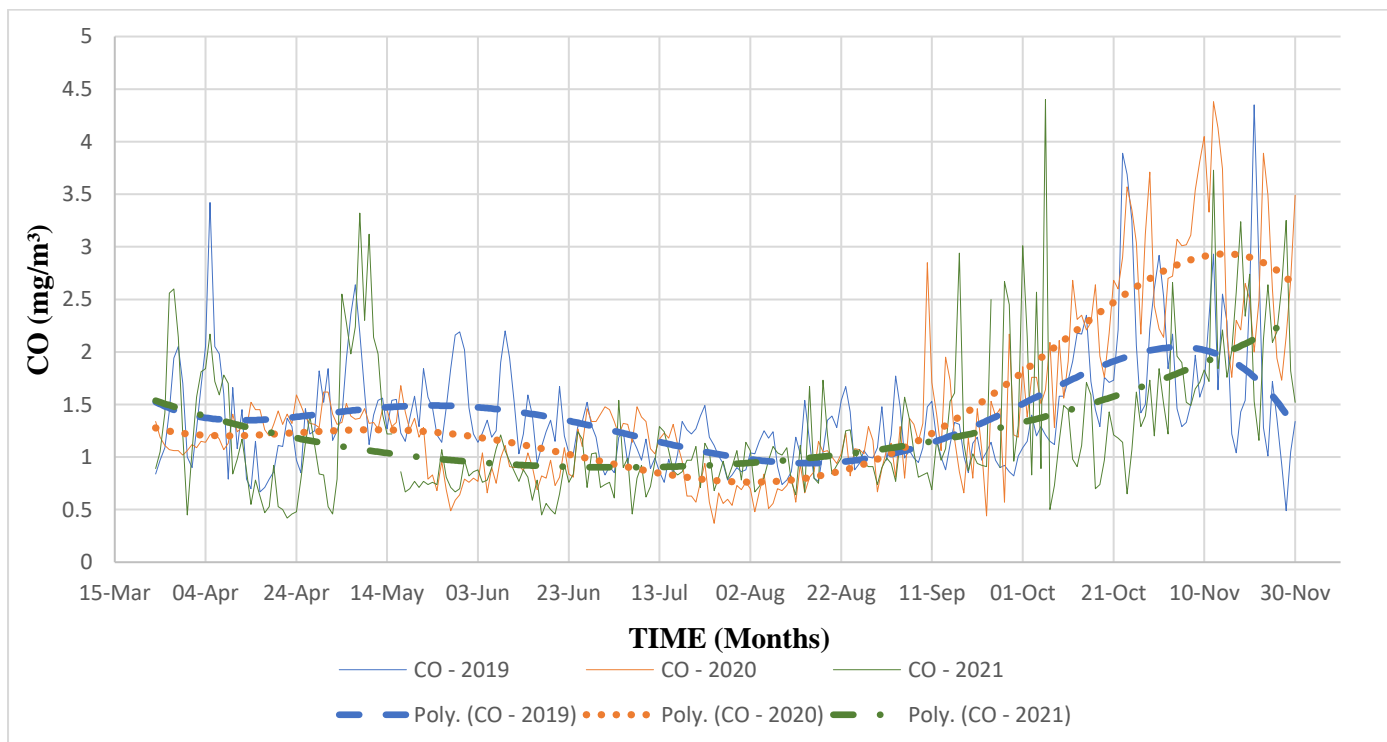


Figure 4.30: CO Variation around Okhla landfill

Ozone emission in 2021 was highest compared to 2019 and 2020 in summer and winter with maximum value of 74.41 $\mu\text{g}/\text{m}^3$ on 07th May 2021. On an average ozone emission were highest in 2020 compared to 2021 in monsoon and post monsoon season.

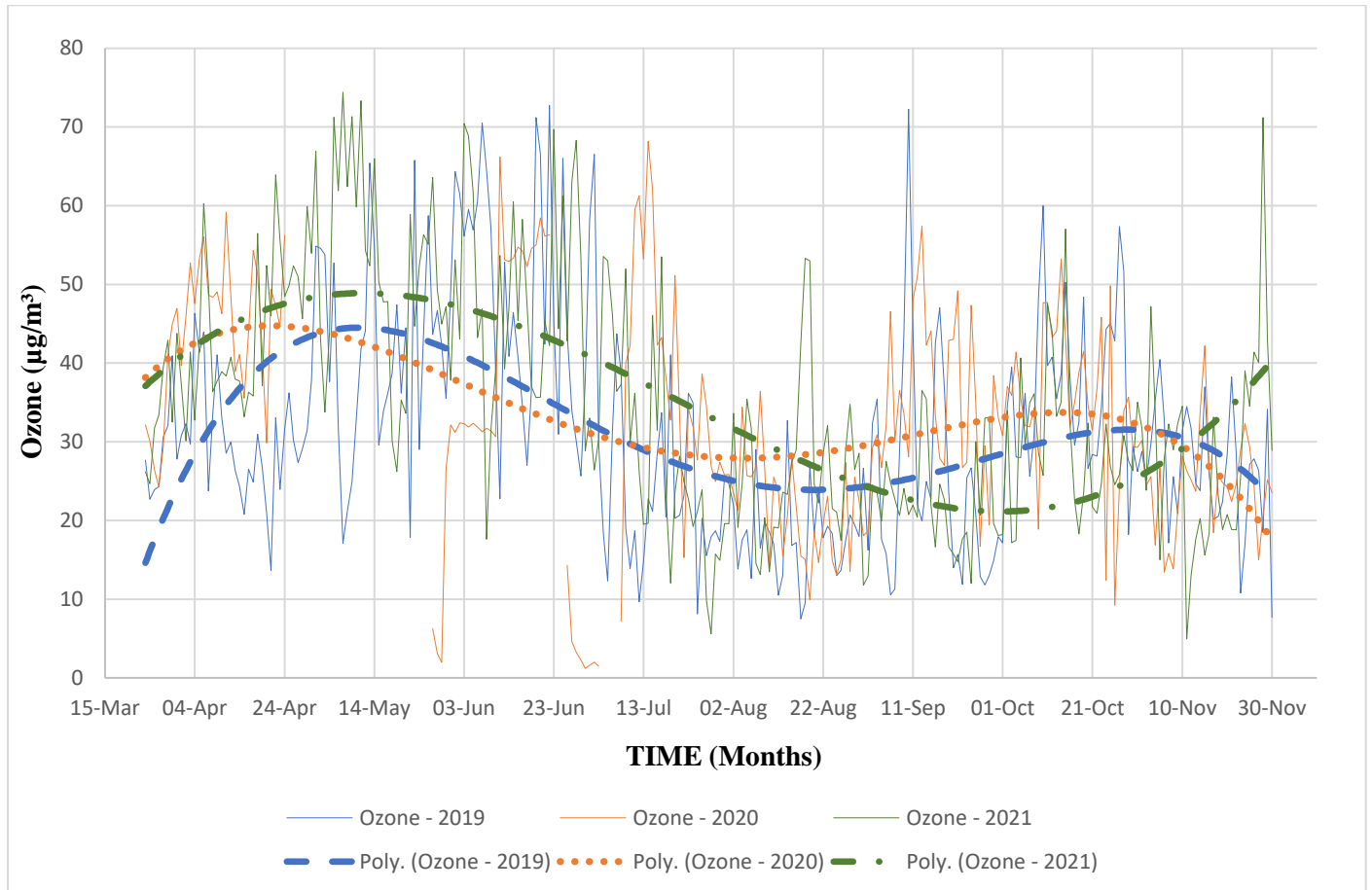


Figure 4.31: Ozone Variation around Okhla landfill

Benzene emanation in 2019 was highest in all season compared to 2020 and 2021 with the apex value of 12.92 $\mu\text{g}/\text{m}^3$ on 14th November 2019. In the course of lockdown benzene emanation were lowest .54 $\mu\text{g}/\text{m}^3$ and with peak value of 7.42 $\mu\text{g}/\text{m}^3$ on 29th October 2020. Post 2020 benzene emission were high compared to 2020 but lowest compared to 2019, with peak value of 11.5 $\mu\text{g}/\text{m}^3$ and base value of .8 $\mu\text{g}/\text{m}^3$.

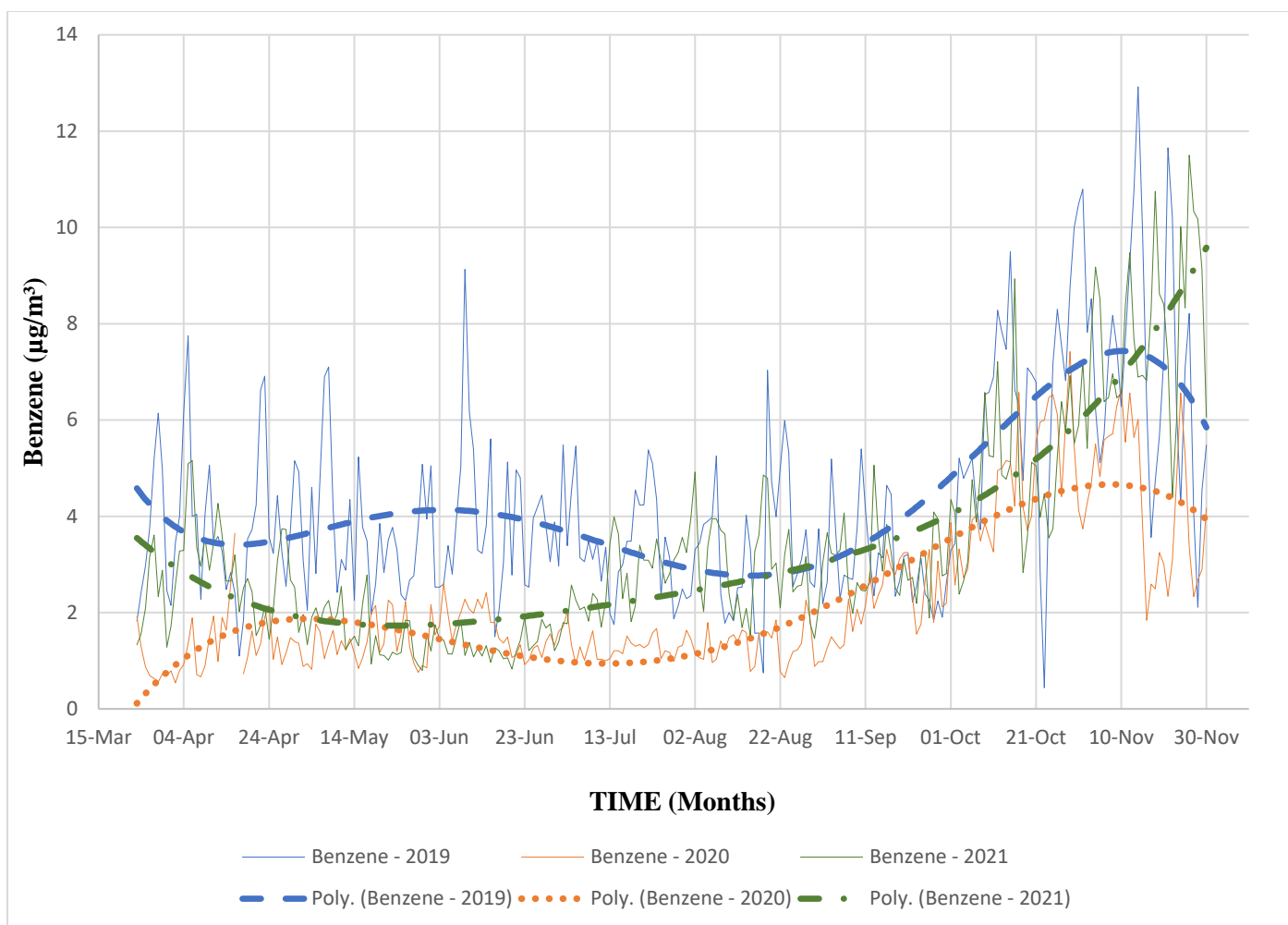


Figure 4.32: Benzene variation around Okhla landfill

Toluene emanation in summer of 2021 was lowest post summer season value begin to soar up in monsoon and winter season reached the peak value 196.97 $\mu\text{g}/\text{m}^3$ on 27th November 2021. In the course of lockdown period toluene emission begin to increase from summer season and continue to rise in monsoon, post monsoon and winter season and reached the peak value of 118.39 $\mu\text{g}/\text{m}^3$ on 29th October 2020. For 2021 period toluene emission were high in march but then its value begins to decrease post monsoon it again begins to soar up in post monsoon and winter season and reached the peak value of 196.97 $\mu\text{g}/\text{m}^3$ on 27th November 2021.

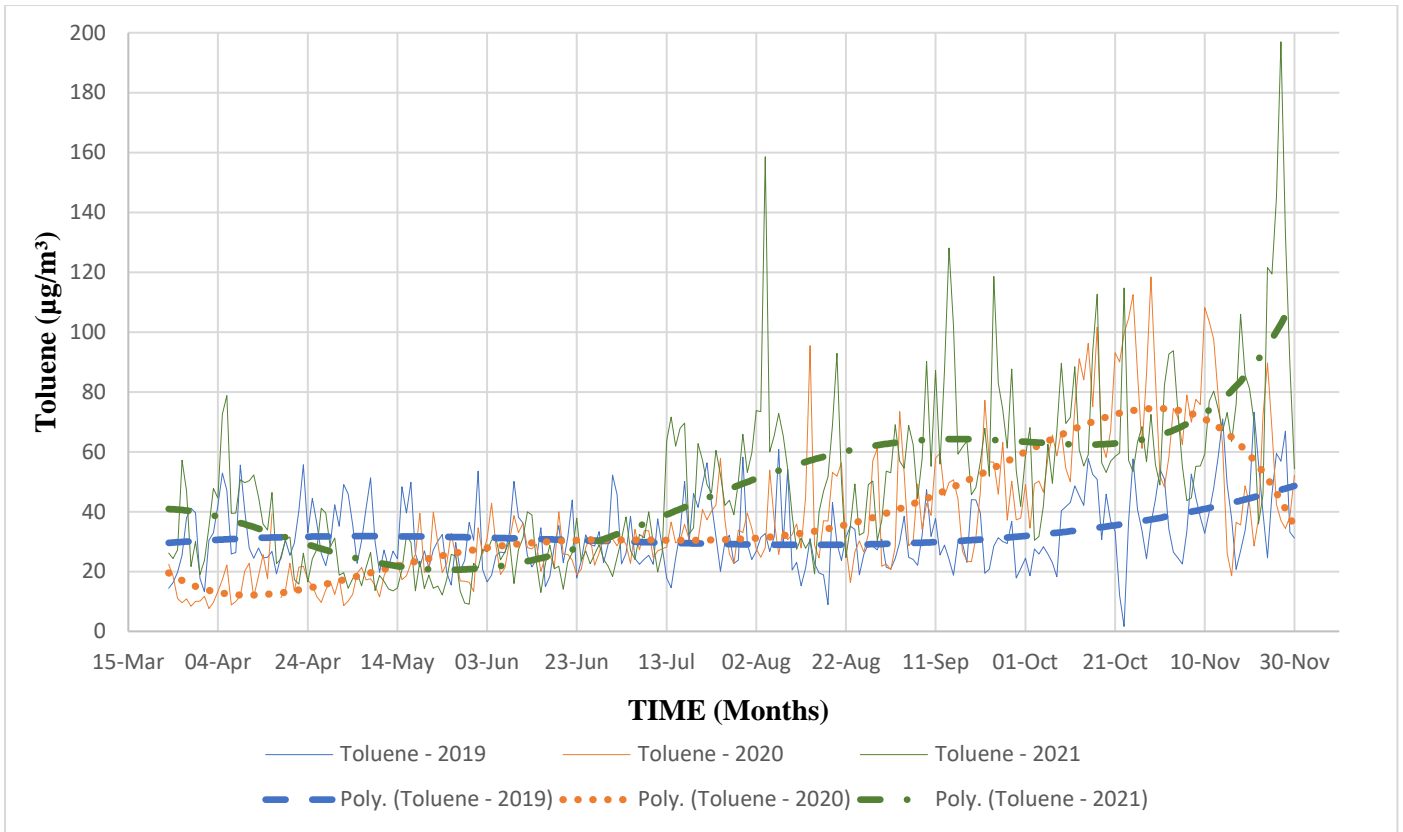


Figure 4.33: Toluene Variation around Okhla landfill

4.2 REGRESSION ANALYSIS

4.2.1 Ghazipur 2019

In Fig. 4.34 blue dots indicate the true response and the yellow dots indicate the predicted response and the vertical lines between the true response and the predicted response is the error. The yellow dots in the line are nothing but showing the regression line or how the regression should be. In a regression model, R-Squared is a mathematical measure of fit that reflects how much variation in a dependent variable is explained by the independent variable(s). This model depicts that the variation in PM2.5 will have .82 times variation in PM10, which means that movement of PM10 particles (dependent) can be explained by the movement of PM2.5 particles (independent). Fig. 4.35 shows the plot between the true response and predicted response, which means that the perfect regression model has a predicted response equal to the true response and all the points should lie on a diagonal line, but that is not the case here it means that there is some error but we can say that this model is a good model because points are scattered near the diagonal line because of having high r-squared value. There is a positive correlation coefficient between the PM2.5 and PM10 particles which is .91, which means when PM2.5 increases the value of PM10 also increases. The model summary is given below with the governing linear equation having intercept of 64.27.

RMSE (Validation): 50.338

R-Squared (Validation): .82

MSE (Validation): 2533.9

MAE (Validation): 36.966

$$y = 1.253x + 64.27$$

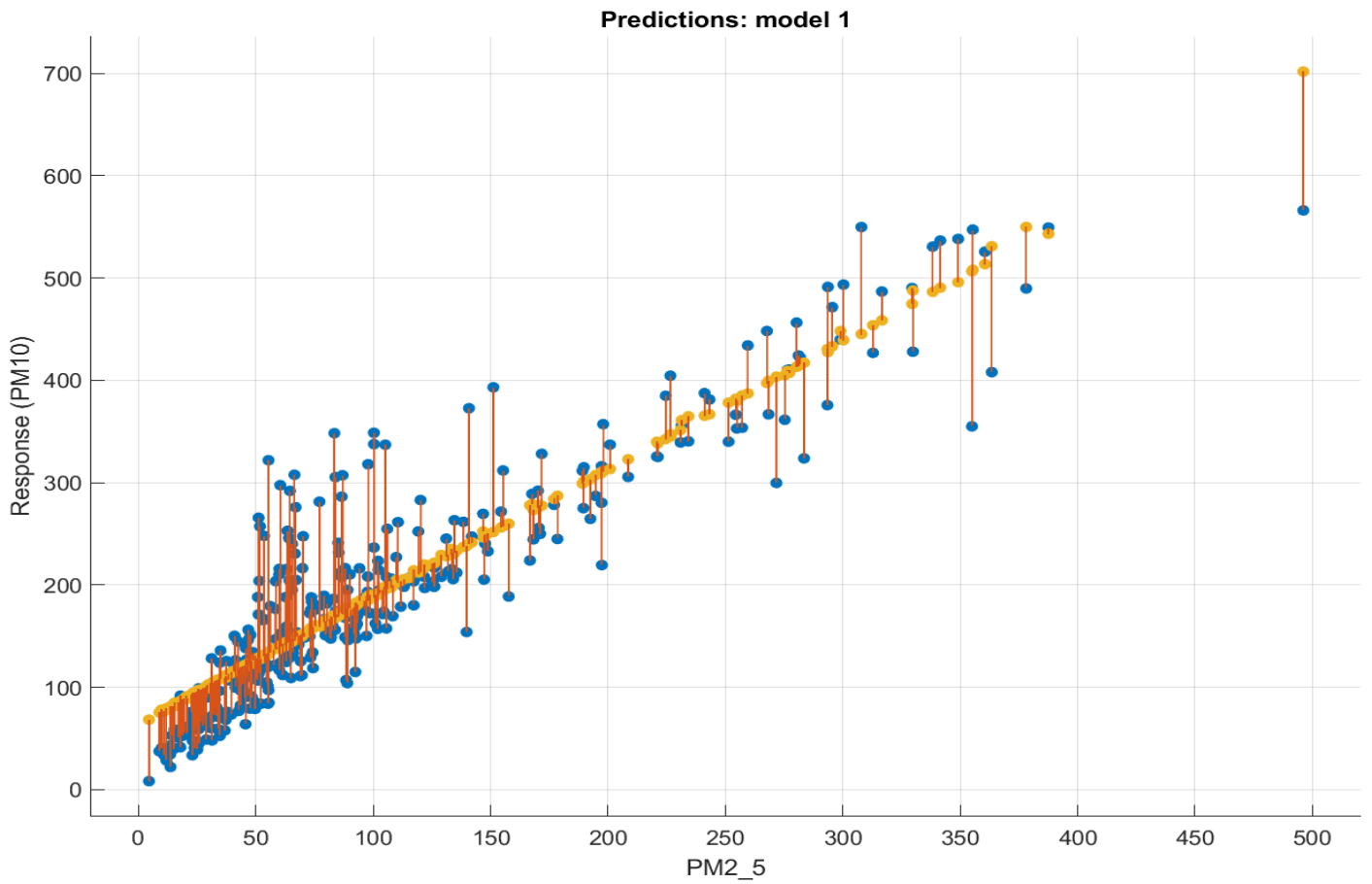


Figure 4.34: Regression model between PM2.5 and PM10

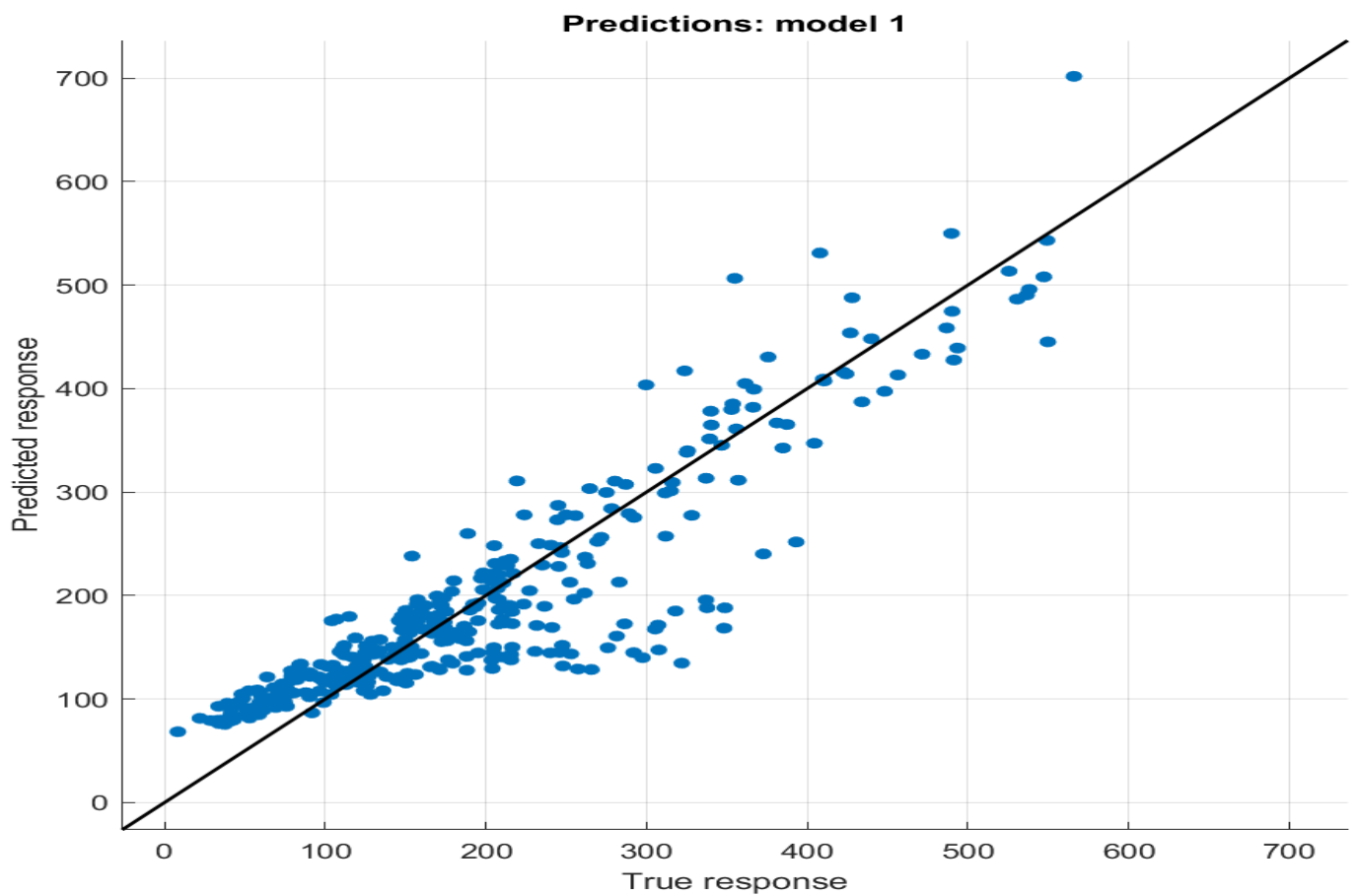


Figure 4.35: Predicted vs True response

Fig. 4.36 shows the linear regression between the NO and NO_x, from graph shows that the error between the true and predicted value is not much than that of PM2.5 and PM10. Which means that the variation in Nitrogen Oxide (NO) will have .95 times variation in the NO_x value, which means that the NO_x is highly influenced by NO, this model has the high r-squared value. It also means that the movement of NO_x particles (dependent) can be explained by the movement of NO particles (independent). There is a positive correlation between the NO and NO_x of .98. Fig. 4.37 shows the graph between true response and predicted response, here most of the points lie on a regression line which shows that the model is good because predictions are scattered near the line. The governing equation and the model summary are given below:

RMSE (Validation): 8.9465

R-Squared (Validation): .95

MSE (Validation): 80.04

MAE (Validation): 6.311

$$y = 1.134x + 16.30$$

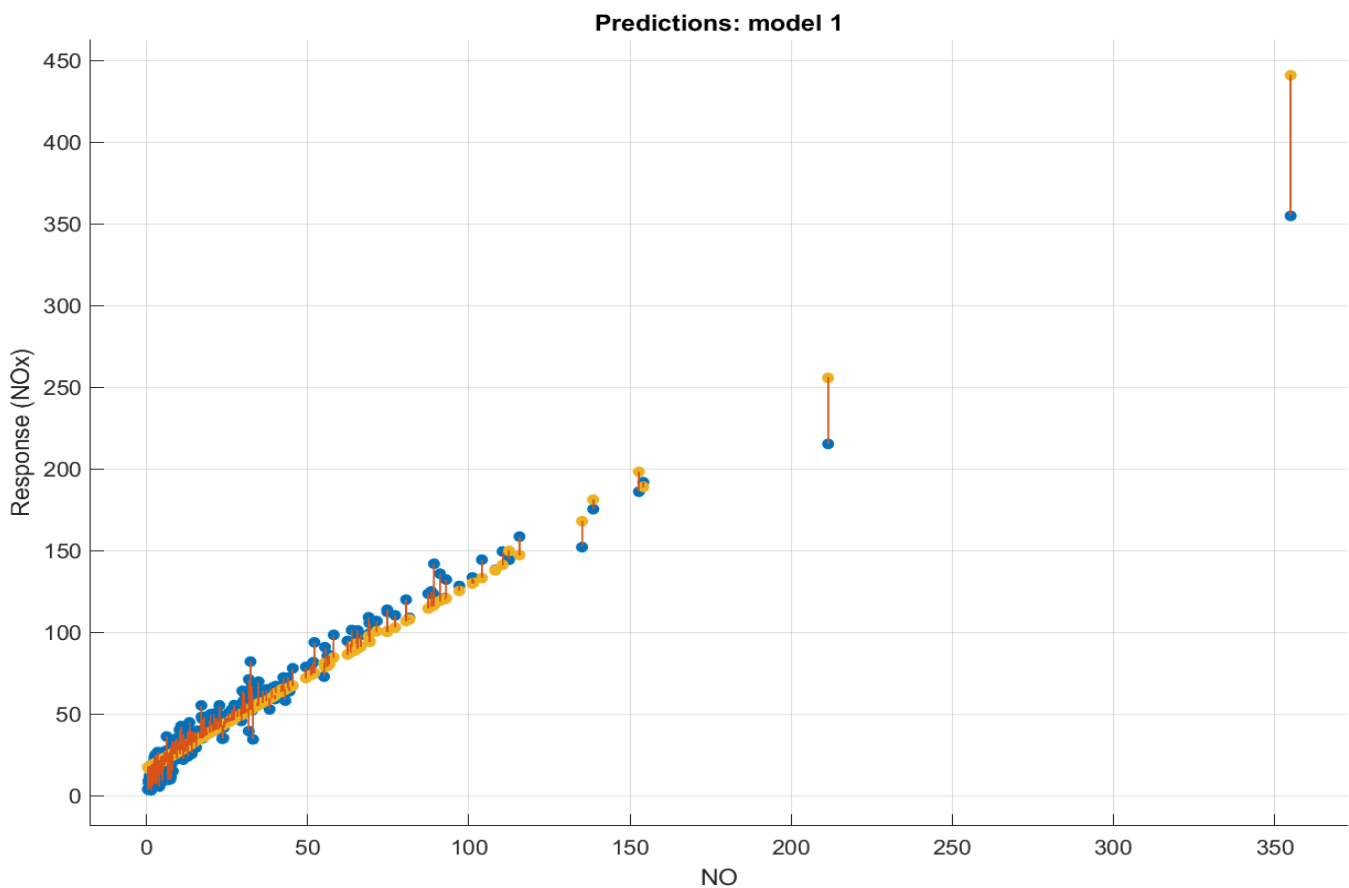


Figure 4.36: Regression model between NO and NO_x

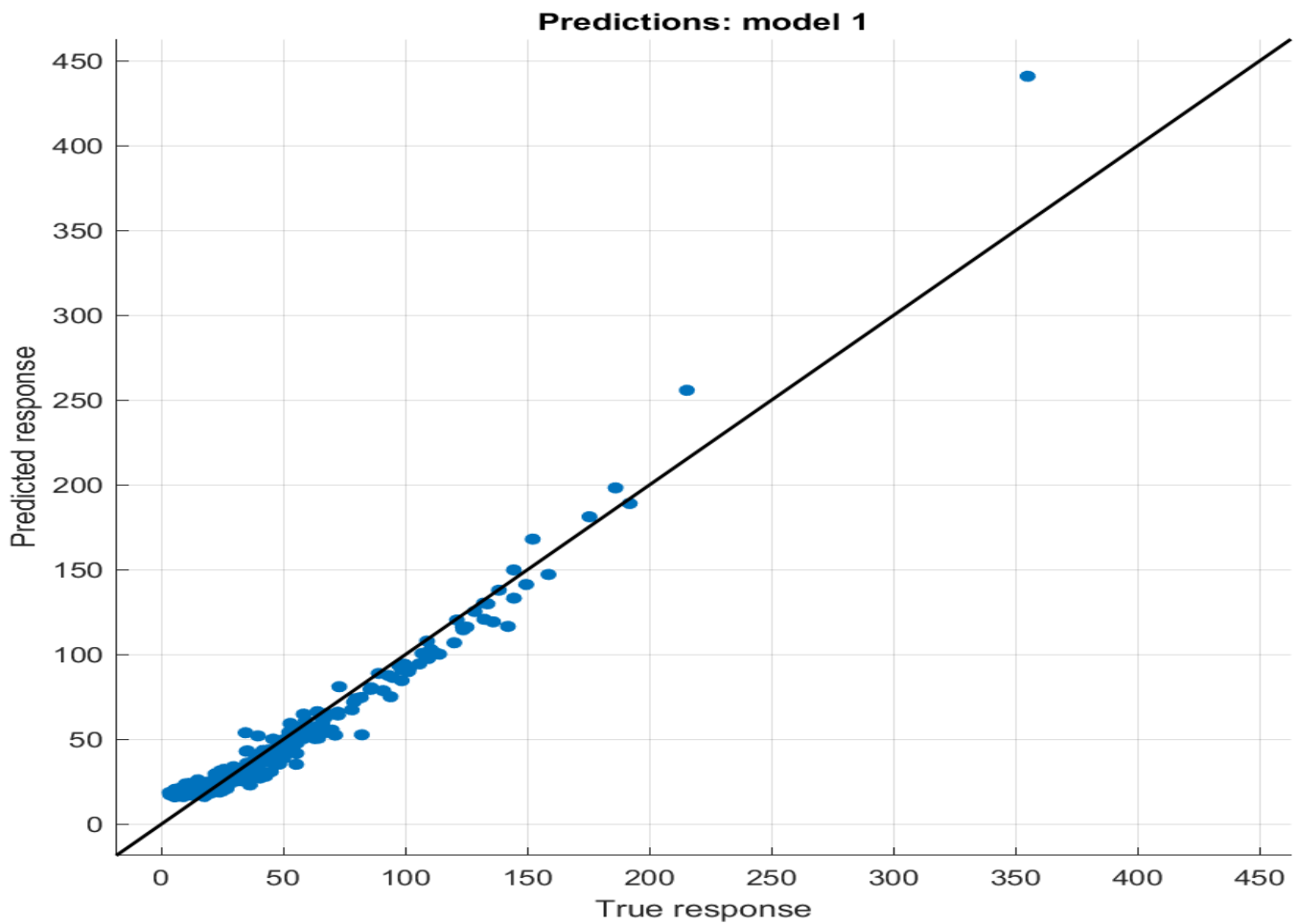


Figure 4.37: Predicted vs True response

4.2.2 Ghazipur 2020

Fig. 4.38 shows the regression between PM2.5 and PM10 particles for year 2020, when compared to 2019 this graph shows less error than the 2019 one which means that variation in PM2.5 will have .92 times variation in PM10 particles, means that PM10 is more highly influenced by PM2.5 particles in the year 2020. The correlation between PM2.5 and PM10 is .96, means that the PM2.5 and PM10 are not only highly correlated but also affect in the variation of each other. The governing equation and the model summary are given below:

RMSE (Validation): 35.025

R-Squared (Validation): .92

MSE (Validation): 1228.6

MAE (Validation): 25.436

$$y = 1.277x + 42.37$$

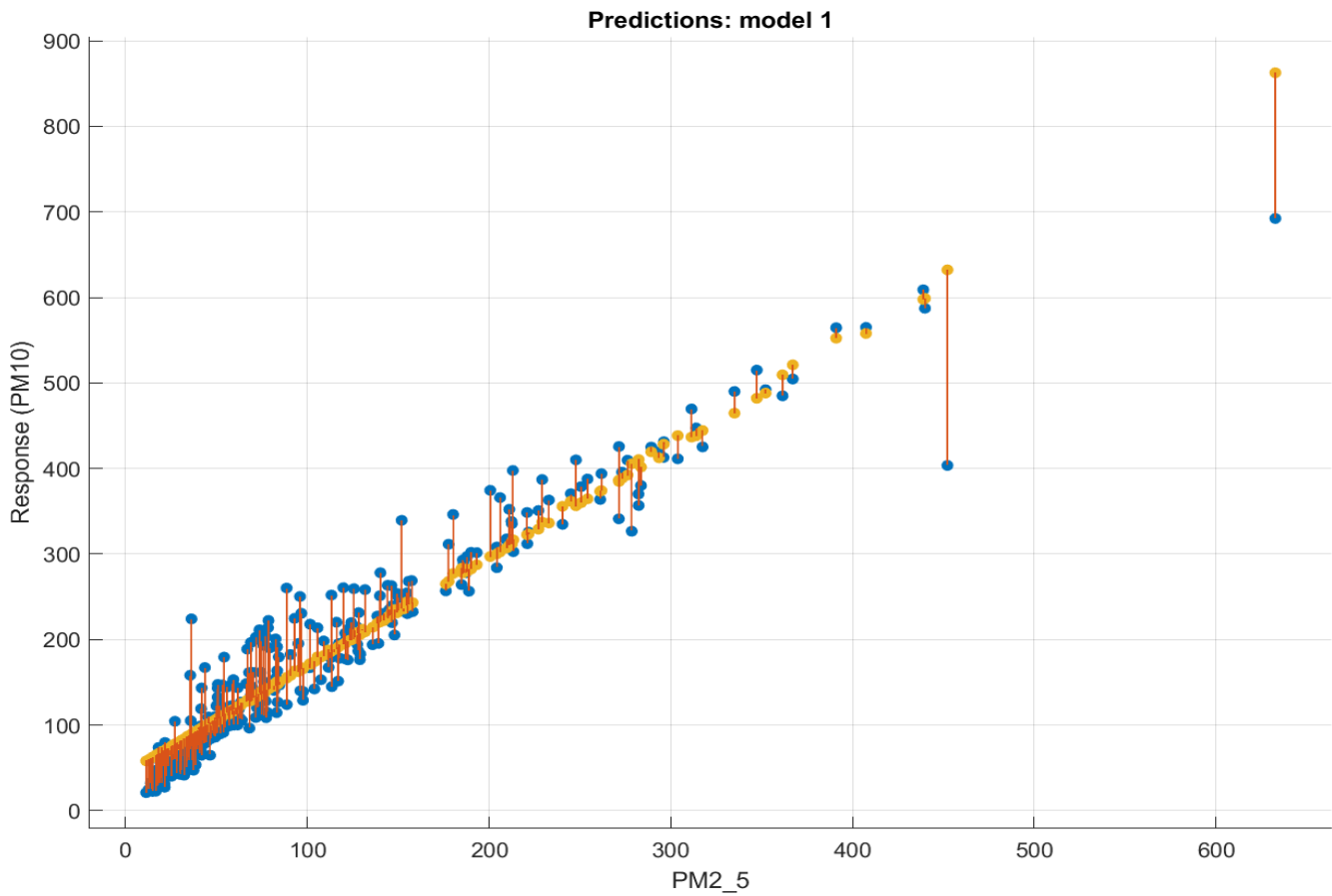


Figure 4.38: Regression model between PM2.5 and PM10

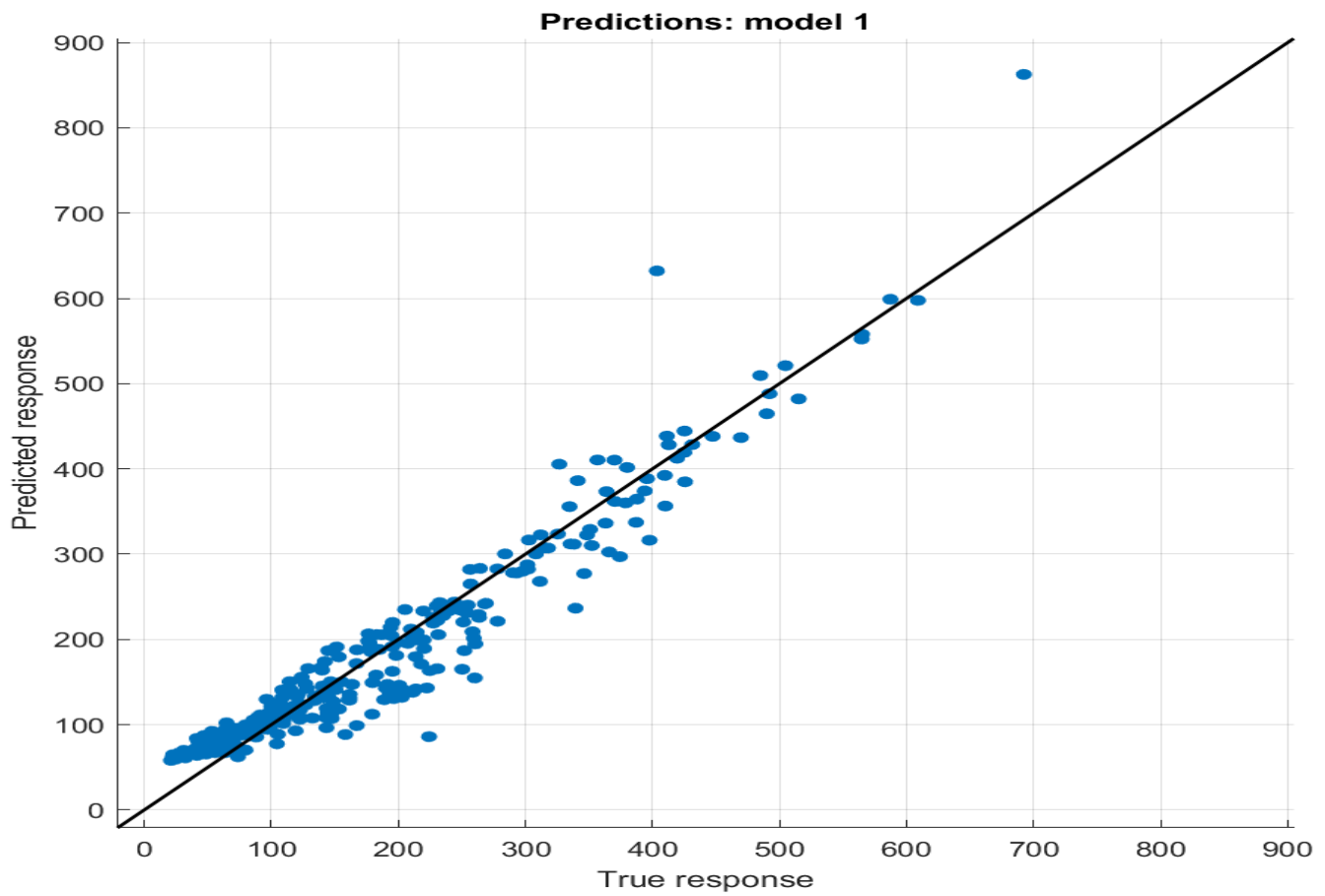


Figure 4.39: Predicted vs True response

Fig. 4.40 shows the regression model between NO and NO_x and the error between the true and the predicted response is similar to that of the 2019. Having r-squared value of .94, which shows that the variation in the Nitrogen Oxide (NO) will have .94 times the variation in the Oxide of Nitrogen (NO_x). Like in 2019 the NO_x is highly influenced by the NO. There is a positive correlation between them in 2020 was .97, which means that the NO and NO_x are highly influenced by each other. Emission of one particle will eventually impact the variation of another particle. Fig. 4.41 shows the graph between the true and predicted response when the value of particles was less than 100 μg/m³ they were close to regression line meaning they did influence each other variation, when the emission crosses the 100 μg/m³ we can see there is not much variation or influence between them. The governing equation and the model summary are given below:

RMSE (Validation): 11.978

R-Squared (Validation): .94

MSE (Validation): 143.48

MAE (Validation): 8.4675

$$y = 1.137x + 15.54$$

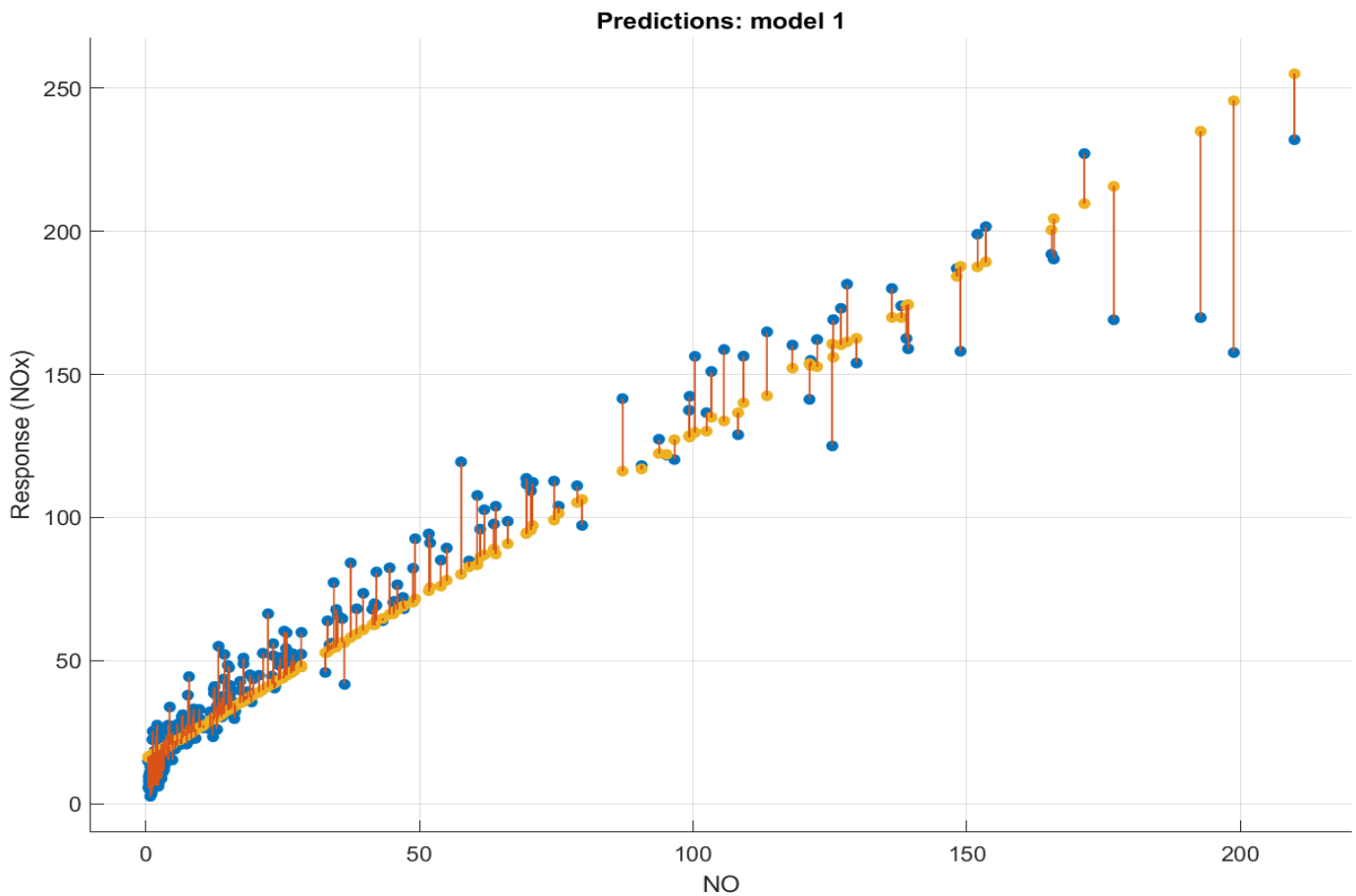


Figure 4.40: Regression model between NO and NO_x

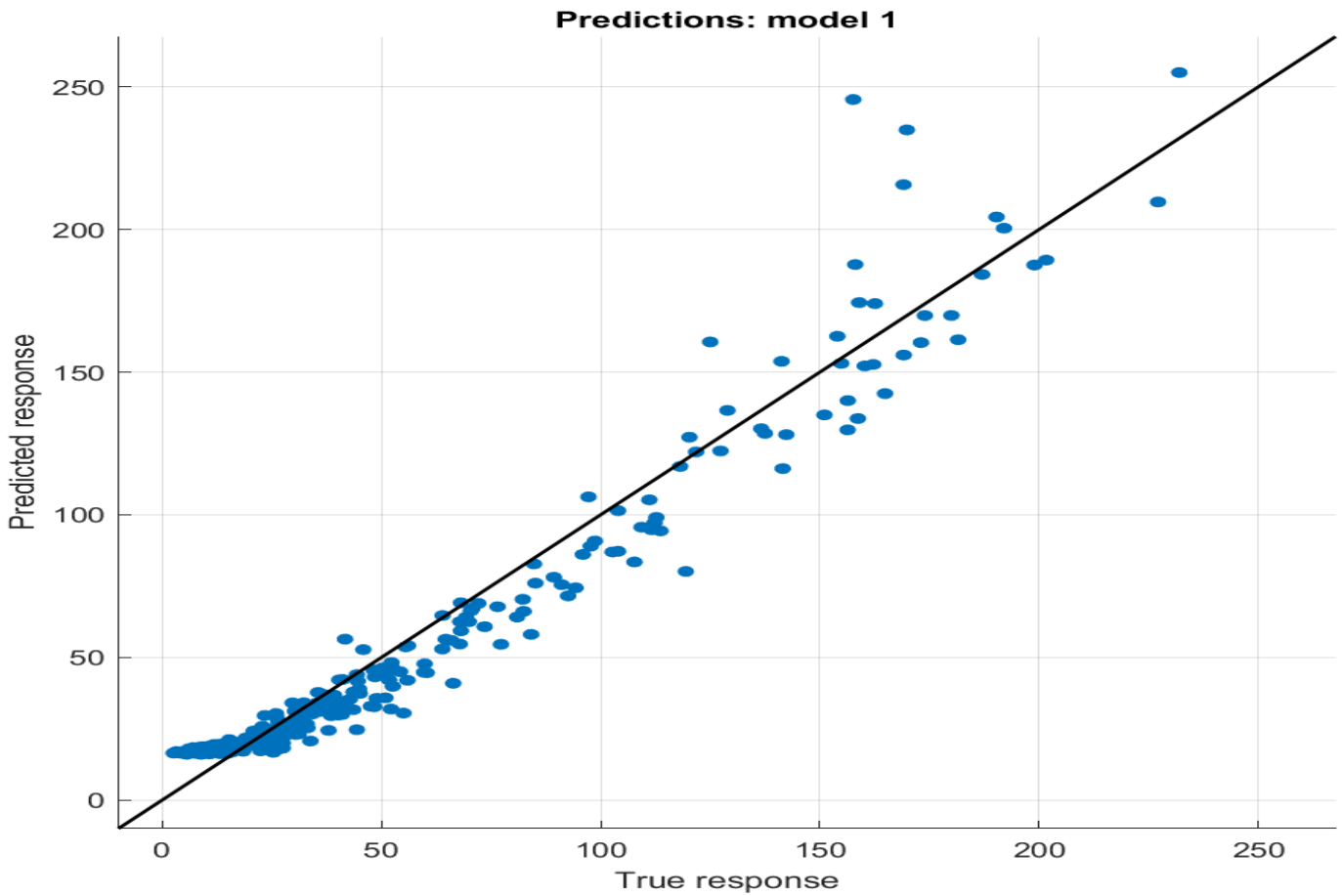


Figure 4.41: Predicted vs True response

In Fig. 4.42 shows that the model between NO_2 and NO_x when the value is below $25 \mu\text{g}/\text{m}^3$ we can see there is not much error between the values as the value of emission goes on increasing large error can be seen. This model gives the negative slope meaning that the Oxide of Nitrogen (NO_x) decreases as the Nitrogen dioxide (NO_2) increases. The r-squared value is .81, meaning that the variation in the NO_2 will have the .81 times the variation in the NO_x . There is a positive correlation between NO_2 and NO_x of value .9. The governing equation and the model summary are given below:

RMSE (Validation): 21.95

R-Squared (Validation): .81

MSE (Validation): 481.79

MAE (Validation): 14.408

$$y = 3.035x - 19.11$$

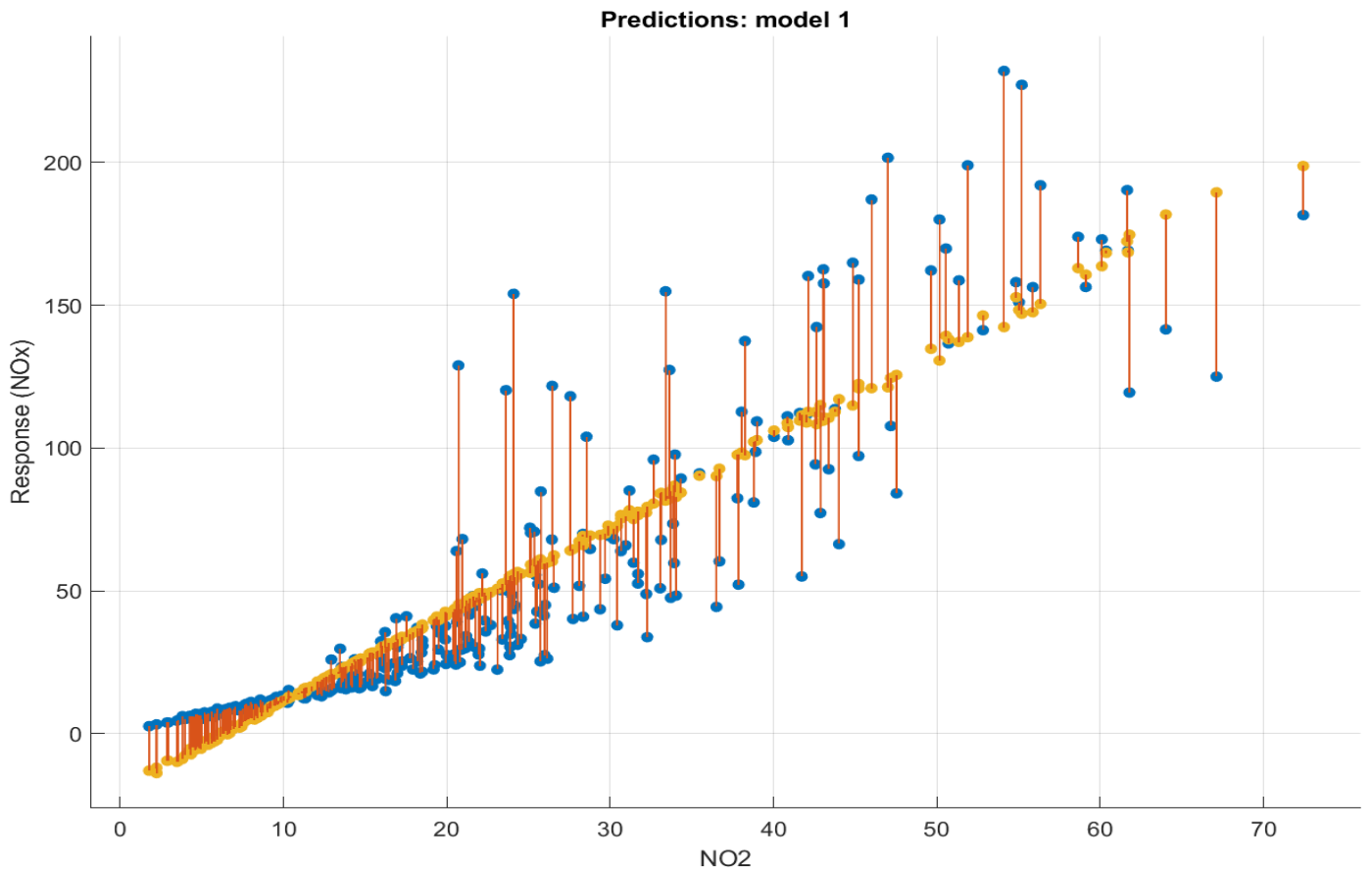


Figure 4.42: Regression model between NO₂ and NO_x

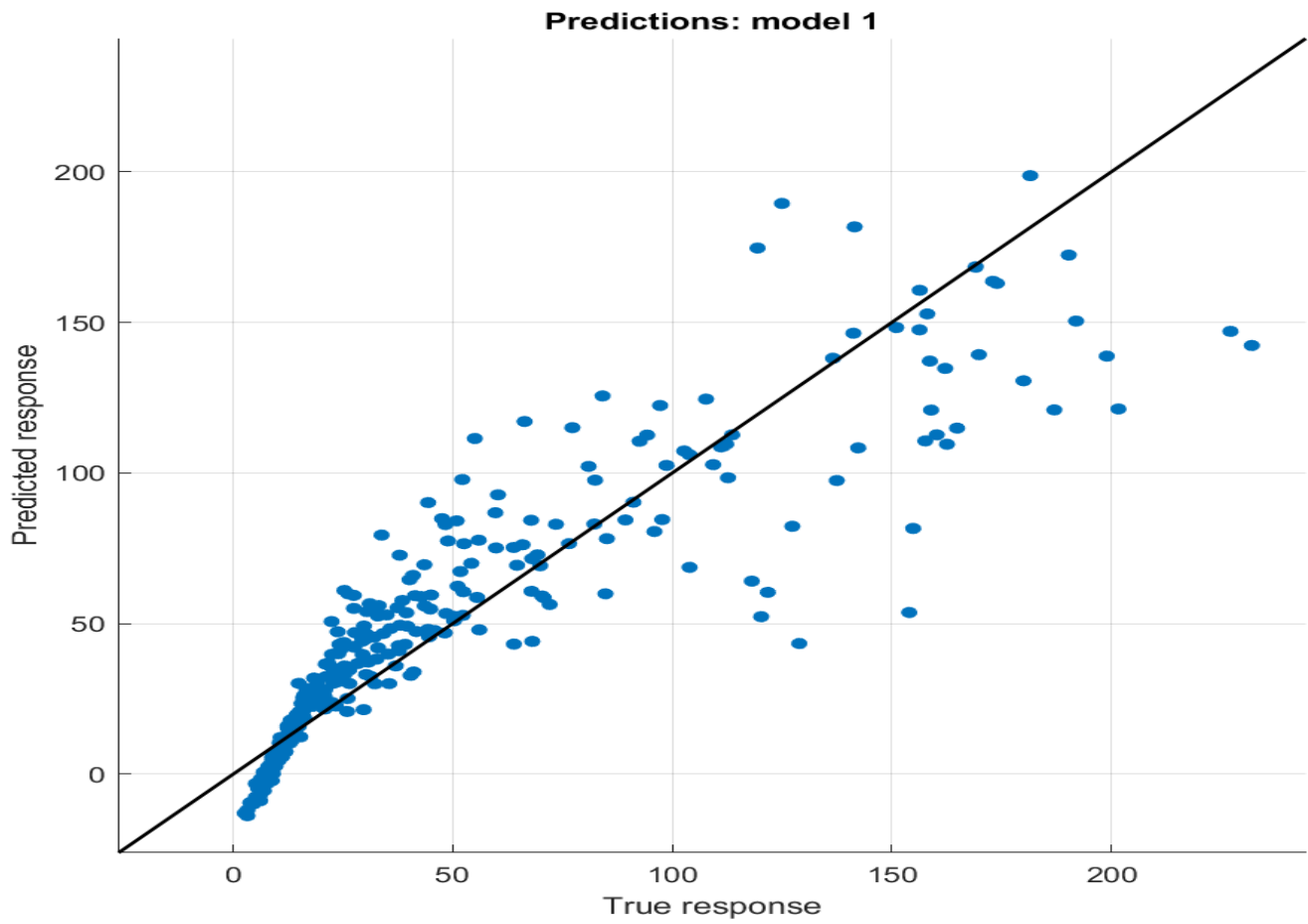


Figure 4.43: Predicted vs True response

4.2.3 Narela 2019

Fig. 4.44 shows the variation of PM2.5 and PM10 for Narela monitoring station, yellow dots shows the predicted response and the blue is the true response and the vertical line are the errors. The r-squared value between them is .76, which means the variation of PM2.5 will affect the PM10 particles by .76 times, meaning the variation between particles around Ghazipur landfill was maximum than that of in Narela landfill. Particulate Matter will affect the residents living around the Ghazipur landfill more than that of living around Narela landfill. In Fig. 4.45 we can observe that when the value was under 200 $\mu\text{g}/\text{m}^3$ the particles were close to regression line but as the value increases value disperses abruptly. There is a positive correlation between particles of value .88. The governing equation and the model summary are given below:

RMSE (Validation): 61.856

R-Squared (Validation): .76

MSE (Validation): 3826.2

MAE (Validation): 45.729

$$y = 1.282x + 91.12$$

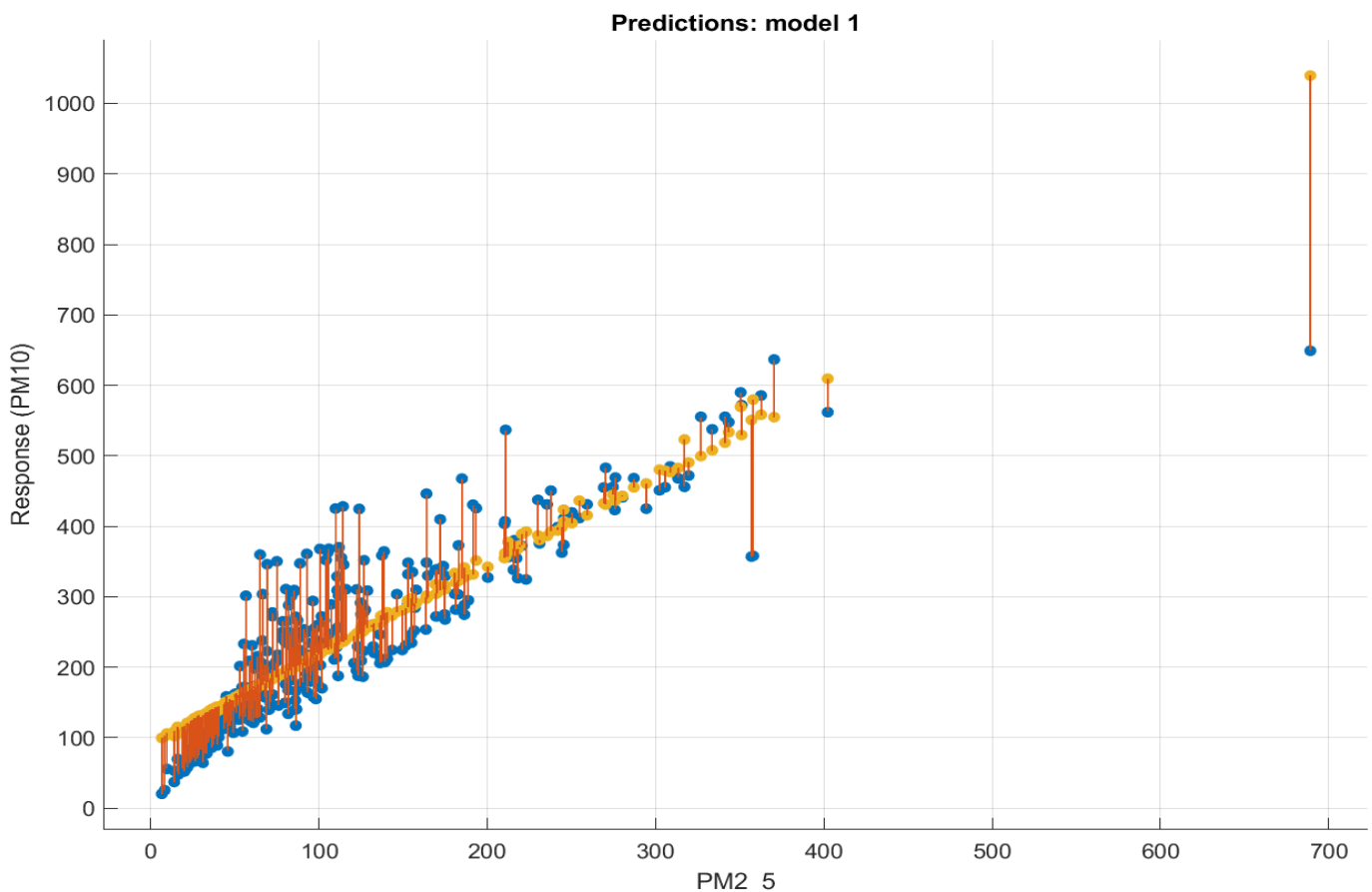


Figure 4.44: Regression model between PM2.5 and PM10

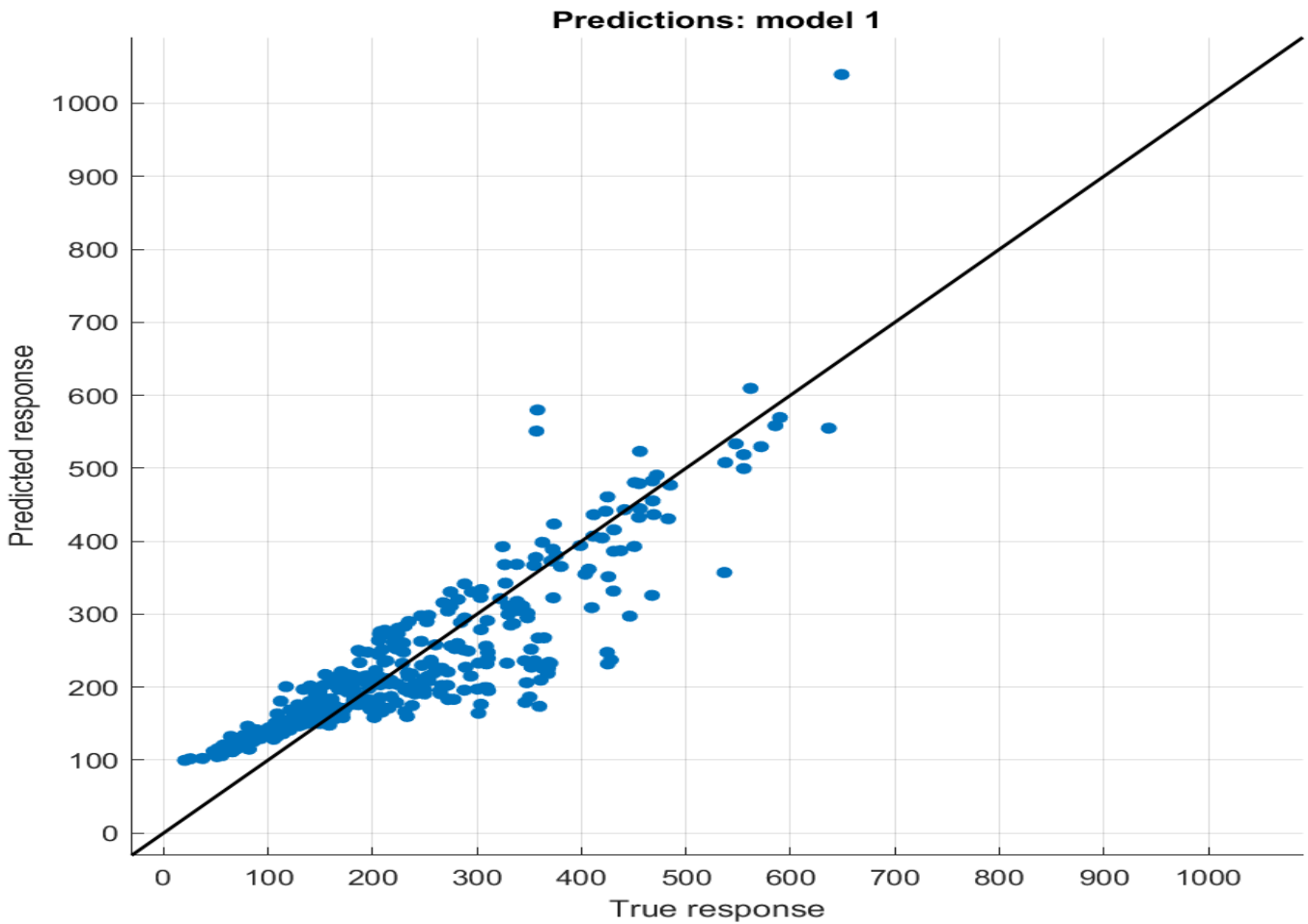


Figure 4.45: Predicted vs True response

Fig. 4.46 shows the regression model between NO and NO_x, errors in this model were less compared to Ghazipur 2020 with high r-squared value of .94, depicting that the variation in NO will have .94 times variation in NO_x. In Fig. 4.47 most of the points were close to regression line depicting that the model is a good fit with the least error. There is a positive correlation between the particles is .95 indicating that the NO and NO_x are highly correlated. The governing equation and the model summary are given below:

RMSE (Validation): 8.465

R-Squared (Validation): .94

MSE (Validation): 71.657

MAE (Validation): 5.78

$$y = 0.9988x + 17.98$$

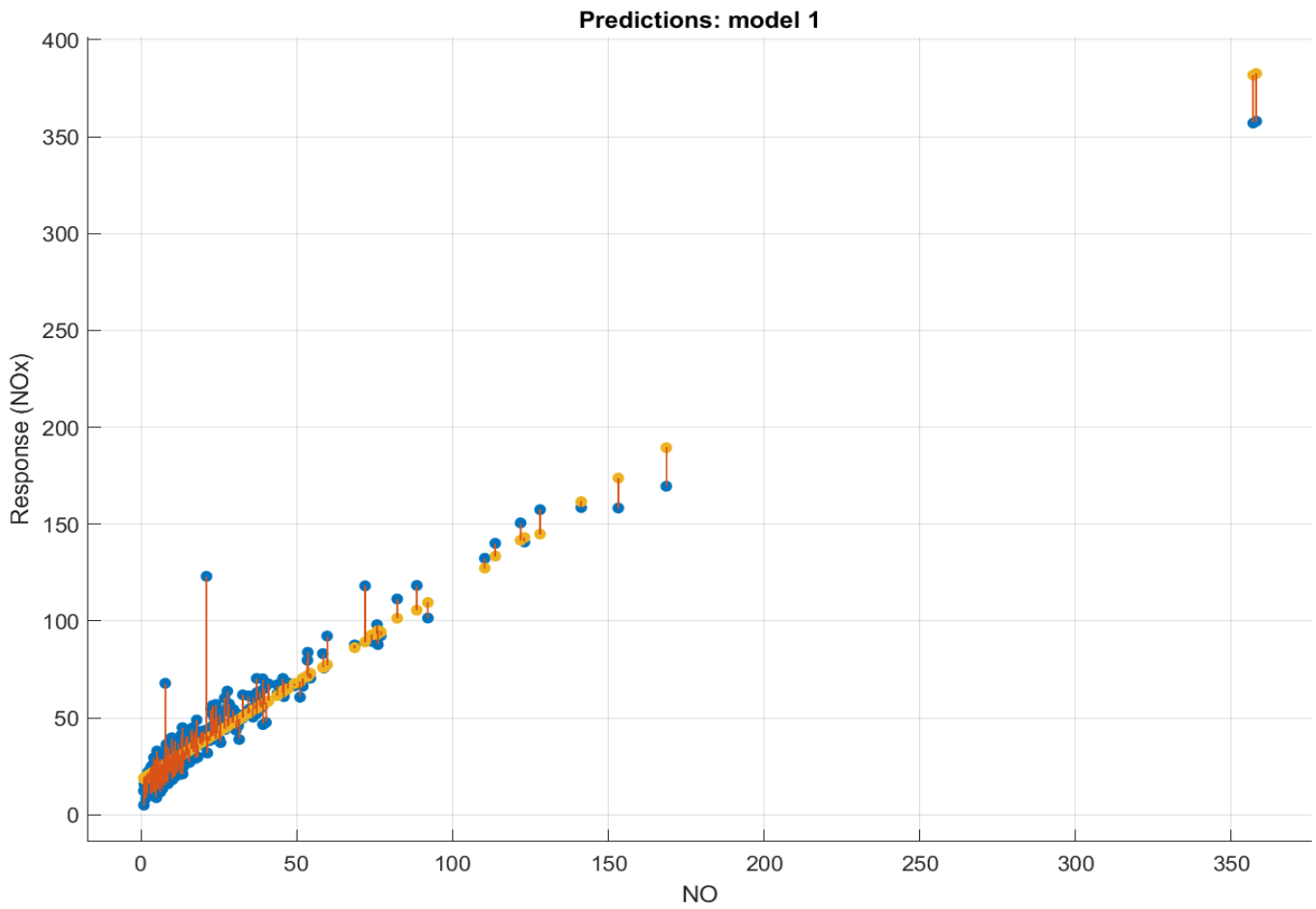


Figure 4.46: Regression model between NO and NO_x

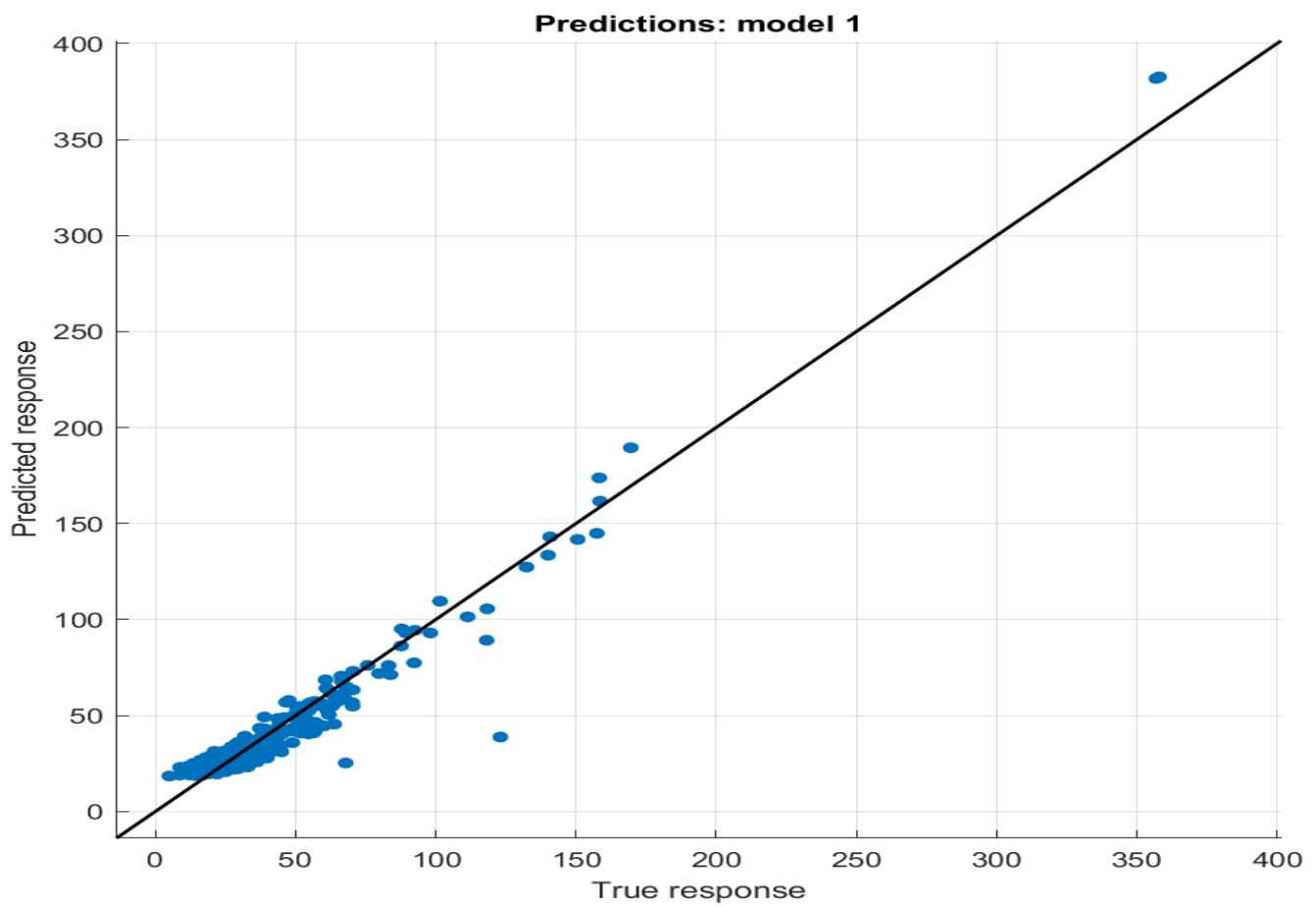


Figure 4.47: Predicted vs True response

Fig. 4.48 shows the regression model between Nitrogen dioxide (NO₂) and oxides of Nitrogen (NO_x) as the particle's emission increases its deviation from the predicted points increases meaning error increases. The r-squared value of the model is .81 meaning that the variation in NO₂ will have .81 times the variation in NO_x. Fig. 4.49 shows the graph between true response and predicted response in the graph most of the points lie within the regression line indicating that the model is a good fit model. The correlation between the particles is .82, indicating that the particles are highly correlated, variation in one particle affects the variation in other. The governing equation and the model summary are given below:

RMSE (Validation): 15.445

R-Squared (Validation): .81

MSE (Validation): 238.54

MAE (Validation): 9.0737

$$y = 1.088x - 7.621$$

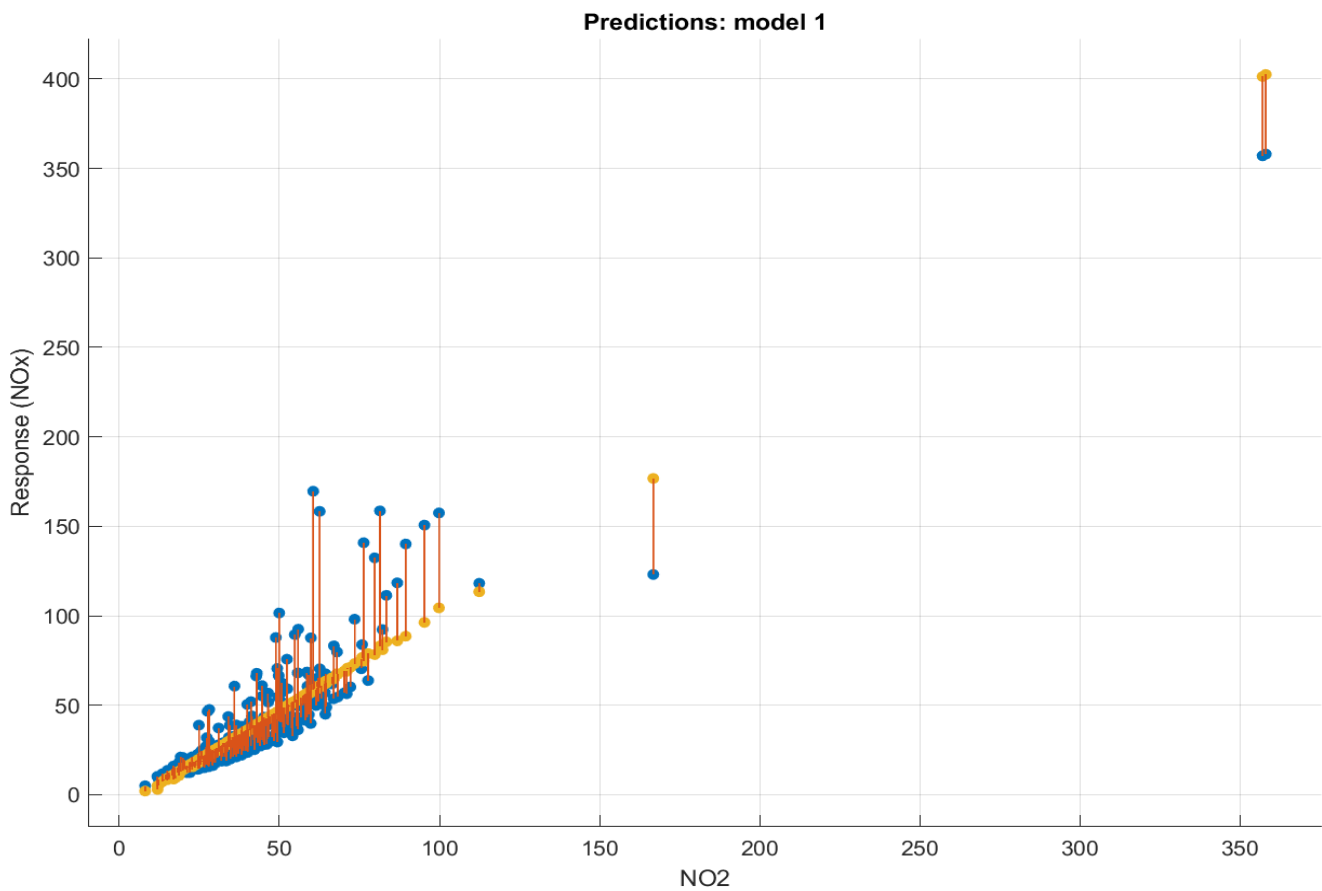


Figure 4.48: Regression model between NO₂ and NO_x

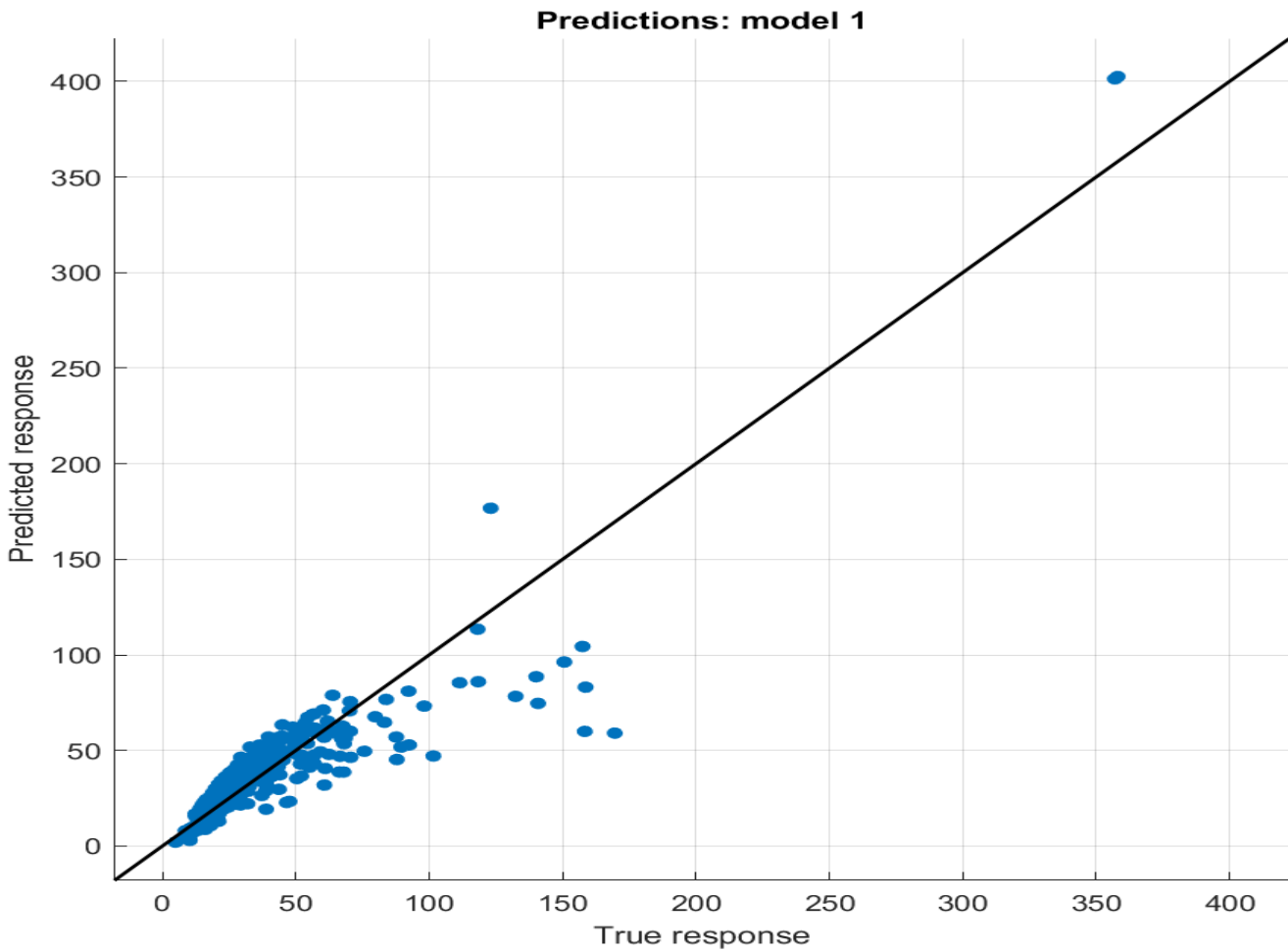


Figure 4.49: Predicted vs True response

4.2.4 Narela 2020

Fig. 4.50 shows the regression between PM2.5 and PM10 as the value increases the error between the true and the predicted value increases. The r-squared value between PM2.5 and PM10 is .89 somewhat less than that of Ghazipur in 2020, meaning that the variation in PM2.5 will have the .89 times variation in PM10. There is a positive correlation between PM2.5 and PM10 of value .94 indicating that the particles are highly correlated. Fig. 4.51 shows the graph between the True and predicted response, most of the points are close to regression line indicating the good fit model. The governing equation and the model summary are given below:

RMSE (Validation): 44.981

R-Squared (Validation): .89

MSE (Validation): 2023.3

MAE (Validation): 33.9

$$y = 1.401x + 69.58$$

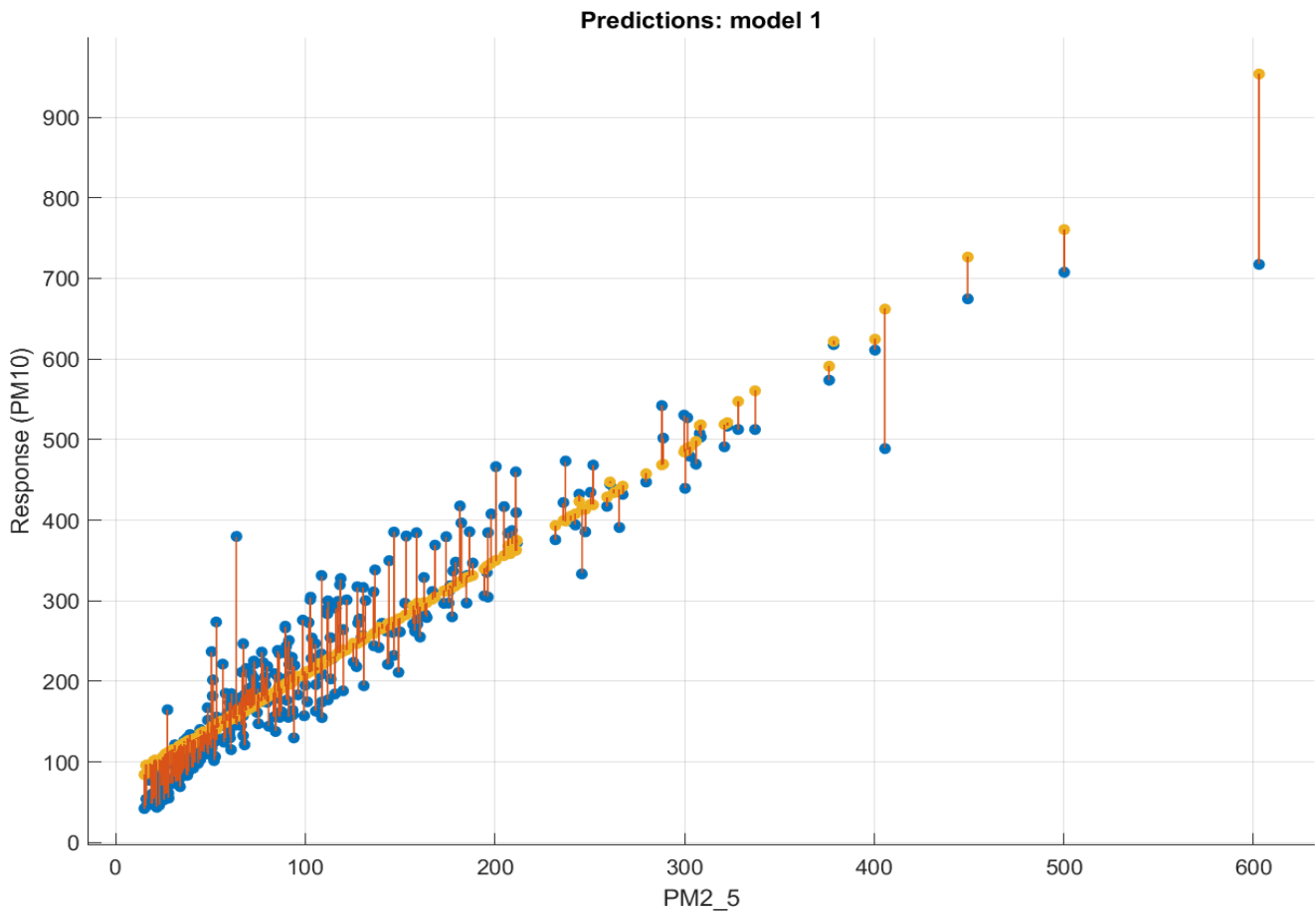


Figure 4.50: Regression model between PM2.5 and PM10

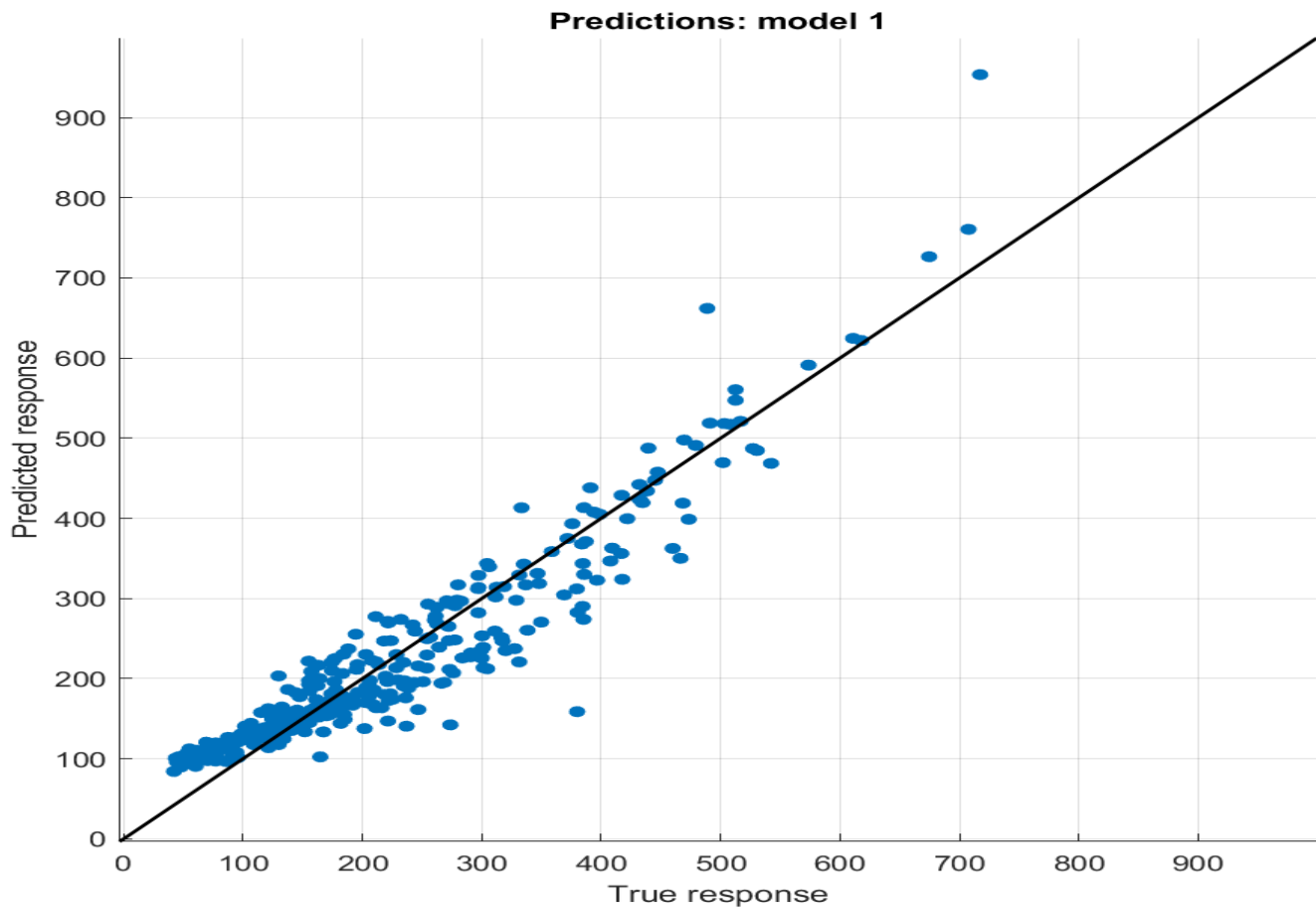


Figure 4.51: Predicted vs True response

Fig. 4.52 shows the regression model between NO and NO_x, the error between the true and the predicted value is not high as compared to the Narela 2019 and Ghazipur 2020. The model has a high r-squared value of .95, depicting that the variation in NO will have the .95 times variation in NO_x. The movement of NO_x particles (dependent) can be explained by the movement of the NO particles (independent). In Fig. 4.53 compared to Narela 2019 and Ghazipur 2020 most of the points are close to regression line indicating that the model is a good fit. There is a positive correlation of .97 indicating that the variation in NO will directly affect the NO_x particles. The governing equation and the model summary are given below:

RMSE (Validation): 6.9385

R-Squared (Validation): .95

MSE (Validation): 48.143

MAE (Validation): 5.0239

$$y = 1.079x + 16.61$$

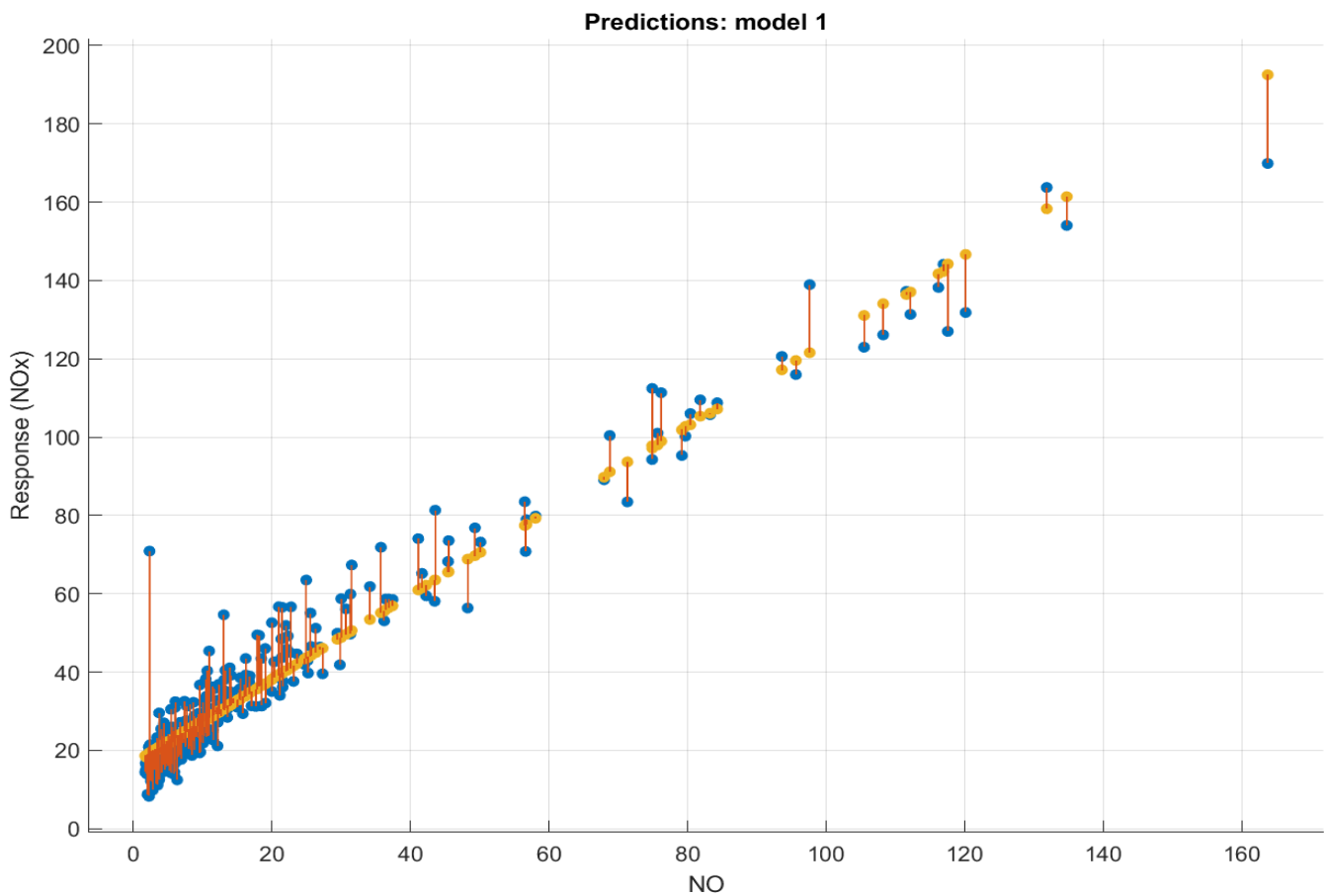


Figure 4.52: Regression between NO and NO_x

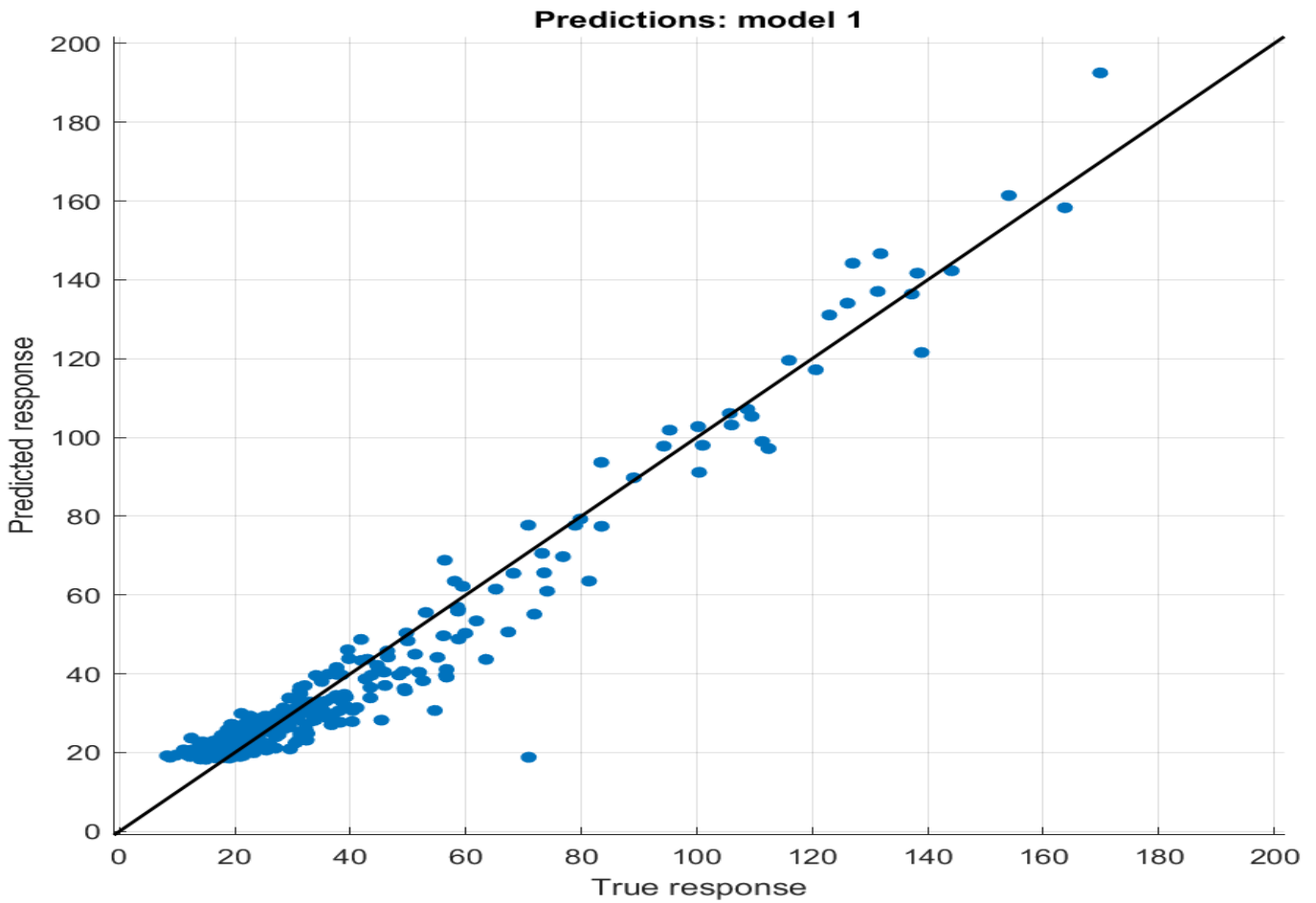


Figure 4.53: Predicted vs True response

Fig. 4.54 shows the regression between Nitrogen dioxide (NO_2) and Oxides of Nitrogen (NO_x), when the value was within 40 there wasn't much variation or the error in the model, as the value increases variation or error also increases. The r-squared value of this model is .73, indicating that the variation in NO_2 will have .73 times variation in the NO_x . There is a positive correlation of value .86 indicating that the variation in NO_2 will directly affect the NO_x . In Fig. 4.55 when the value is within 40 units, most of the points lie within the regression line, beyond 40 units error goes on increasing. The governing equation and model summary are given below:

RMSE (Validation): 15.371

R-Squared (Validation): .73

MSE (Validation): 236.38

MAE (Validation): 9.2875

$$y = 1.367x - 18.42$$

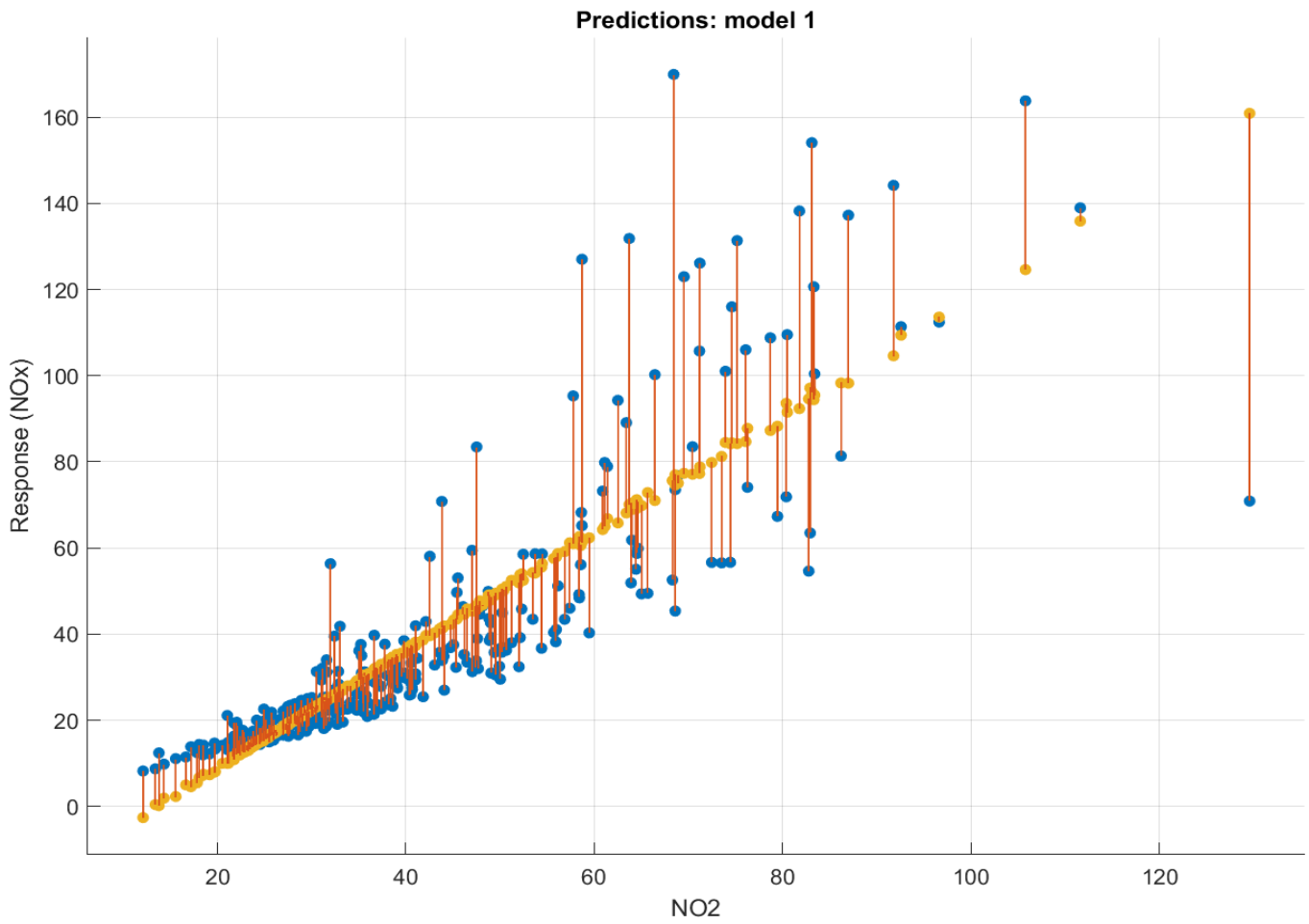


Figure 4.54: Regression model between NO₂ and NO_x

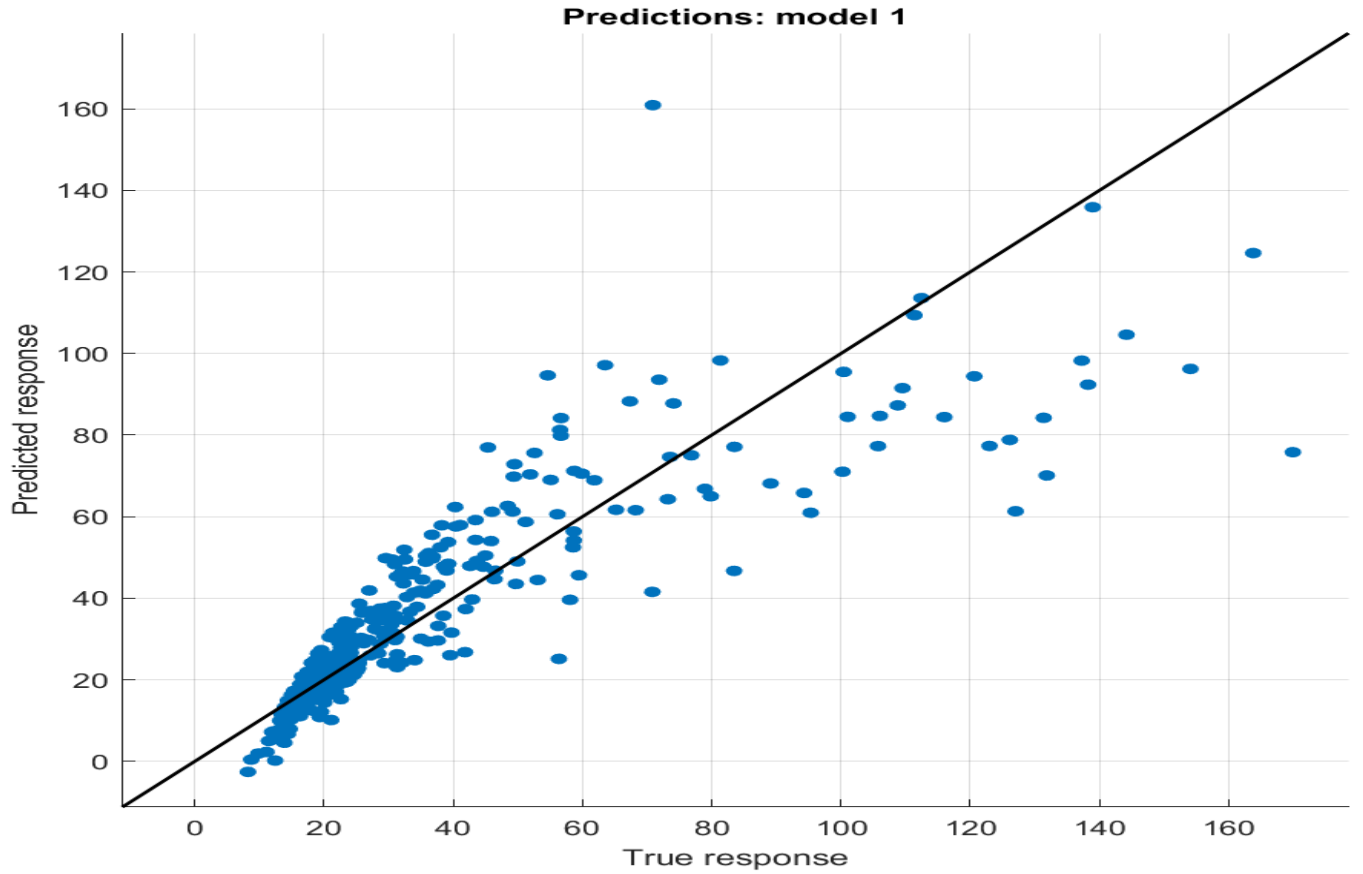


Figure 4.55: Predicted vs True response

4.2.5 Okhla 2019

Fig. 4.56 shows regression between PM2.5 and PM10, the error in this model is more than that of in Narela 2019 and Ghazipur 2019. The r-squared value of this model is .85, indicating that the variation in PM2.5 will have .85 times the variation in the PM10. There is a positive correlation between PM2.5 and PM10 of value .92, indicating there is a strong correlation between the particles. Fig. 4.57 shows the graph between predicted and true response, here we can see that most of the point lies near the regression line, indicating that model is fairly good. The governing equation and the model summary are given below:

RMSE (Validation): 52.05

R-Squared (Validation): .85

MSE (Validation): 2709.2

MAE (Validation): 38.694

$$y = 1.217x + 82.56$$

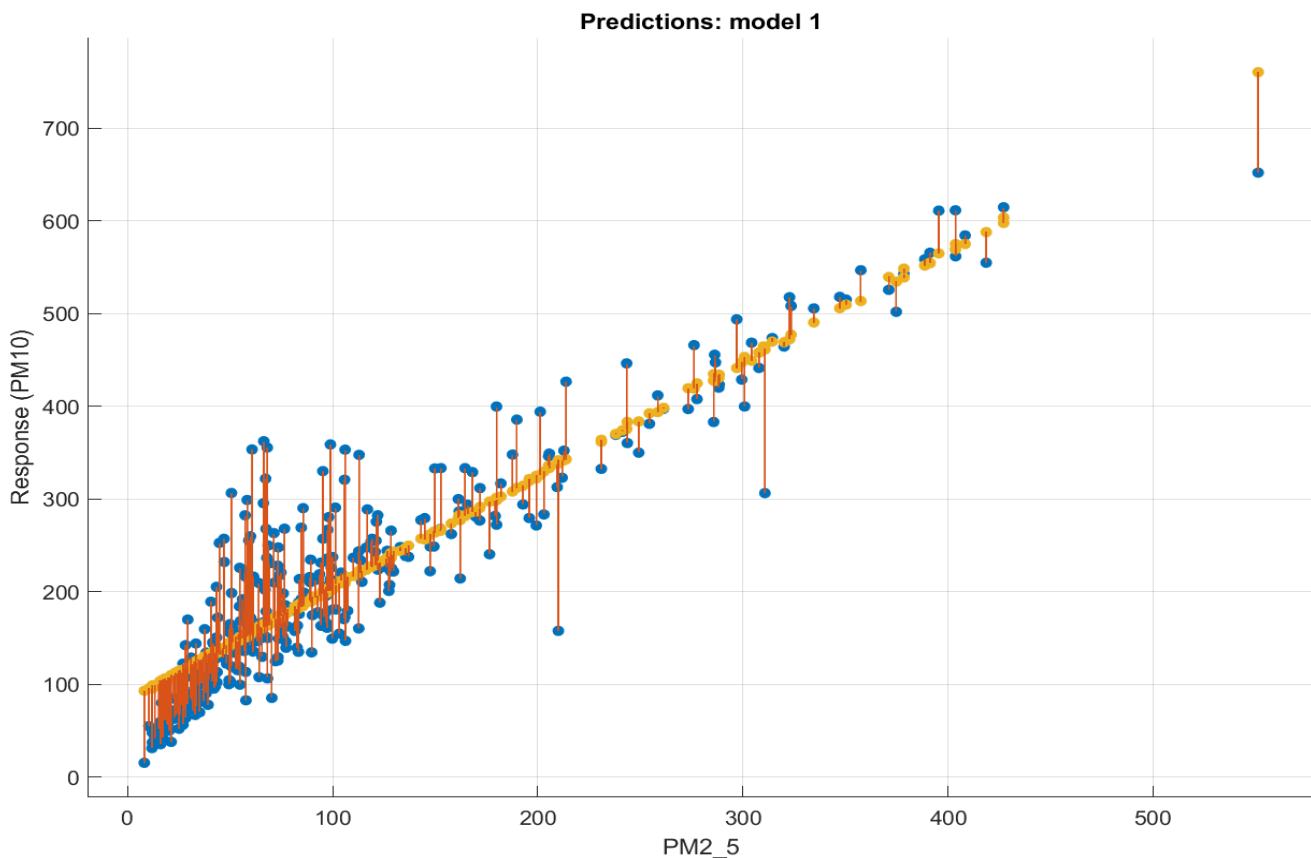


Figure 4.56: Regression model between PM2.5 and PM10

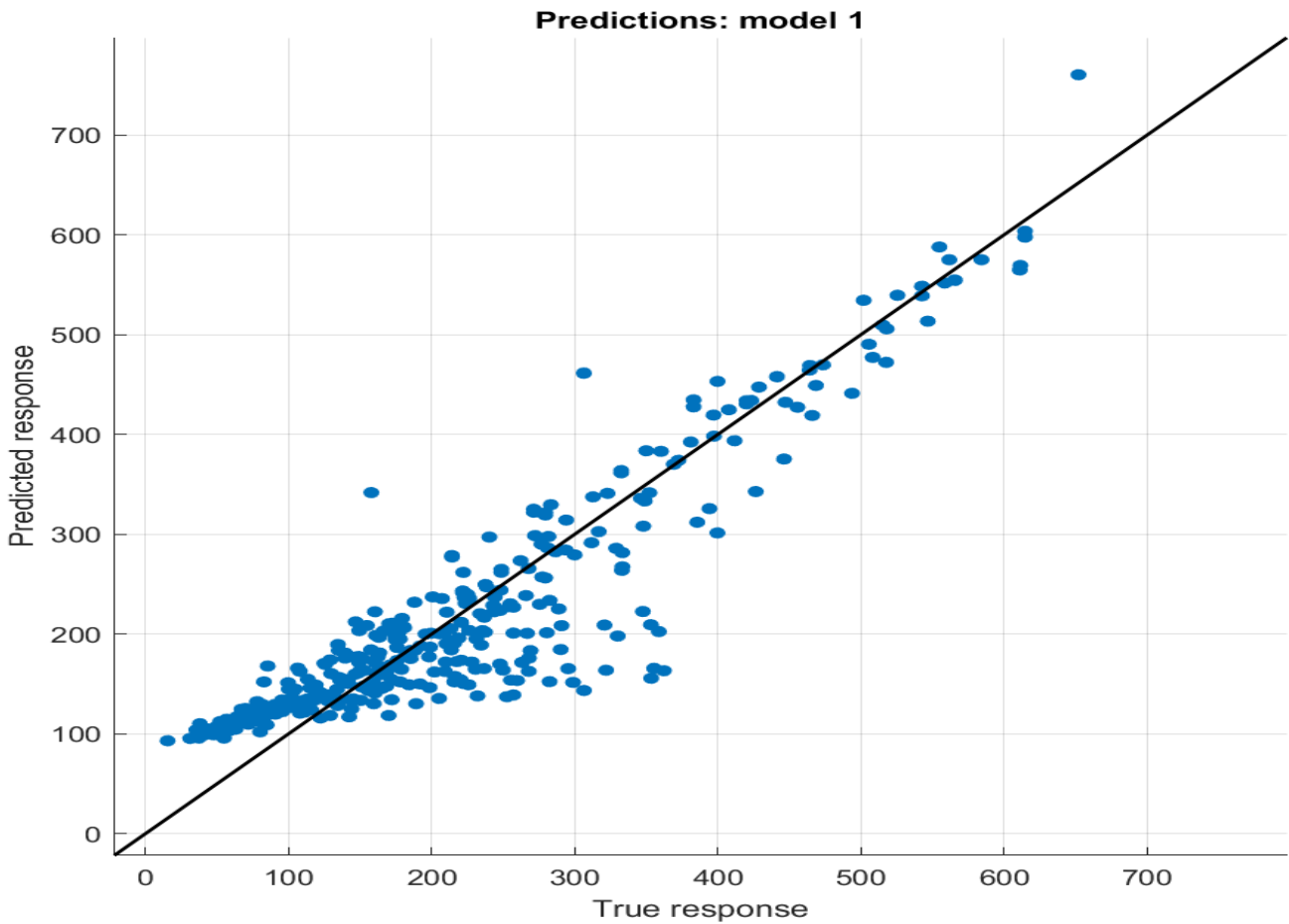


Figure 4.57: Predicted vs True response

Fig. 4.58 shows the regression model between the NO and NO_x, error in this model is very less as compared to that of Ghazipur and Narela. The r-squared value of this model is .98, indicating that the variation in NO will have .98 times the variation in NO_x. There is a positive correlation of value .99, indicating that the when NO increases NO_x also increases. Fig. 4.59 indicates that most of the points were close to regression line indicates that model is a good fit. The governing equation and model summary are given below:

RMSE (Validation): 6.2465

R-Squared (Validation): .98

MSE (Validation): 39.019

MAE (Validation): 4.6839

$$y = 0.9726x + 14.59$$

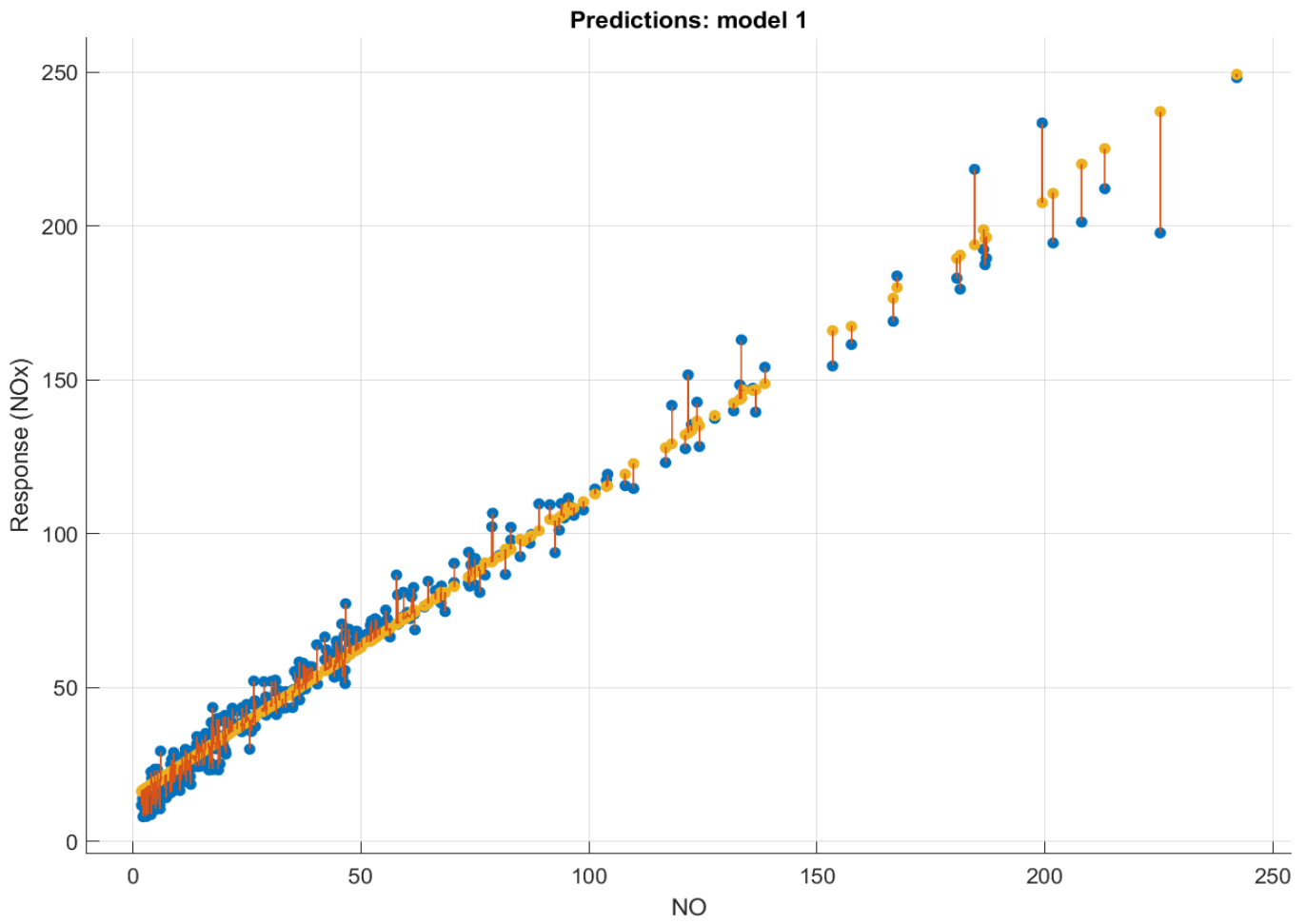


Figure 4.58: Regression model between NO and NO_x

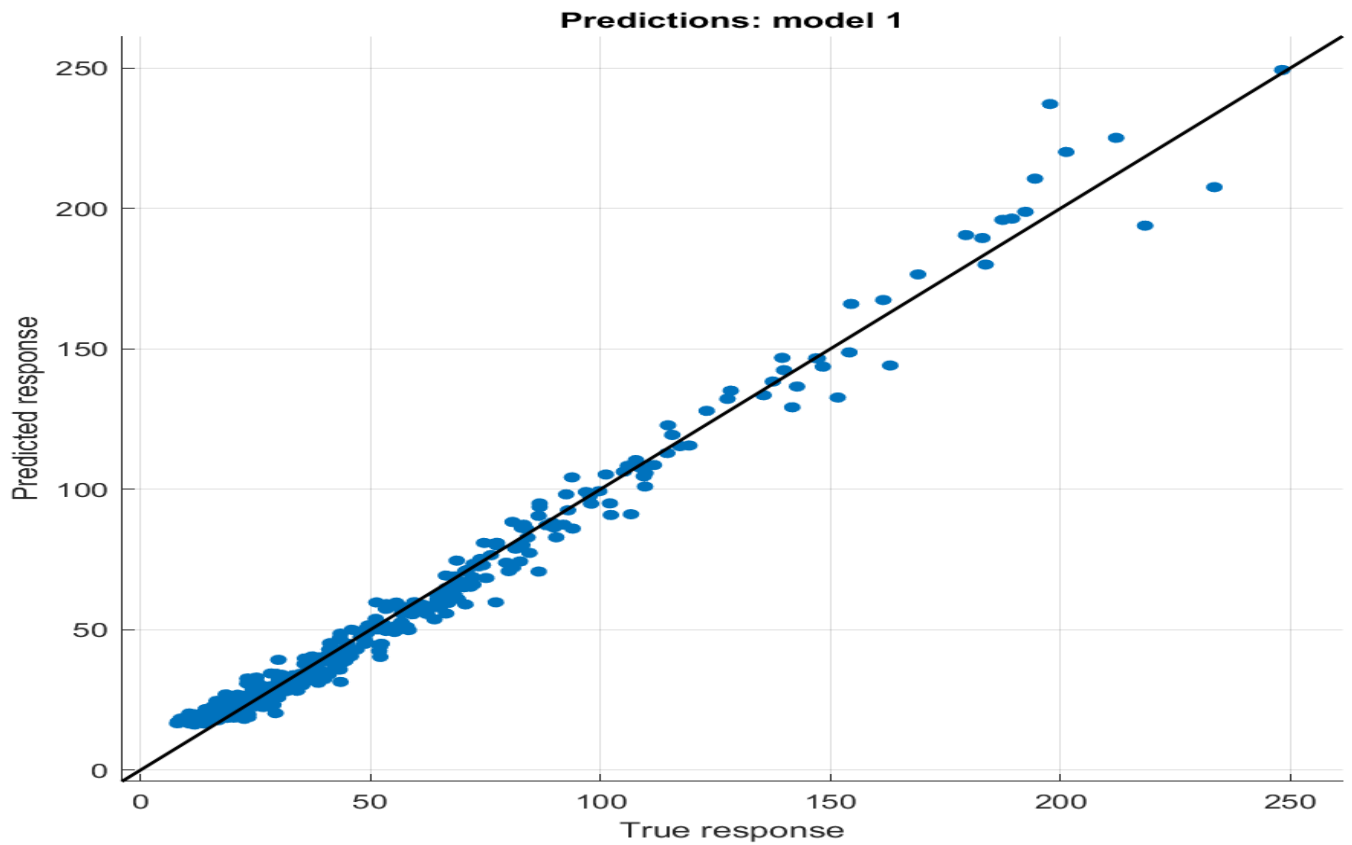


Figure 4.59: Predicted vs True response

Fig. 4.60 shows the regression model between NO₂ and NO_x, as the value is within 40 units there isn't much variation in the true and the predicted value or we can say there is less error, on the other hand as the emission value increases variation or the error increases abruptly, that's why the model has low r-squared value of .71. There is a positive correlation of .84, indicating particle are related to each other and affect their emission. Fig. 4.61 shows that the when the value is within 50 units there isn't much deviation of points from the regression line but as the value increases its deviation from the regression line increases meaning error increases. The governing equation and the model summary are given below:

RMSE (Validation): 24.106

R-Squared (Validation): 0.71

MSE (Validation): 581.11

MAE (Validation): 17.334

$$y = 2.267x - 33.95$$

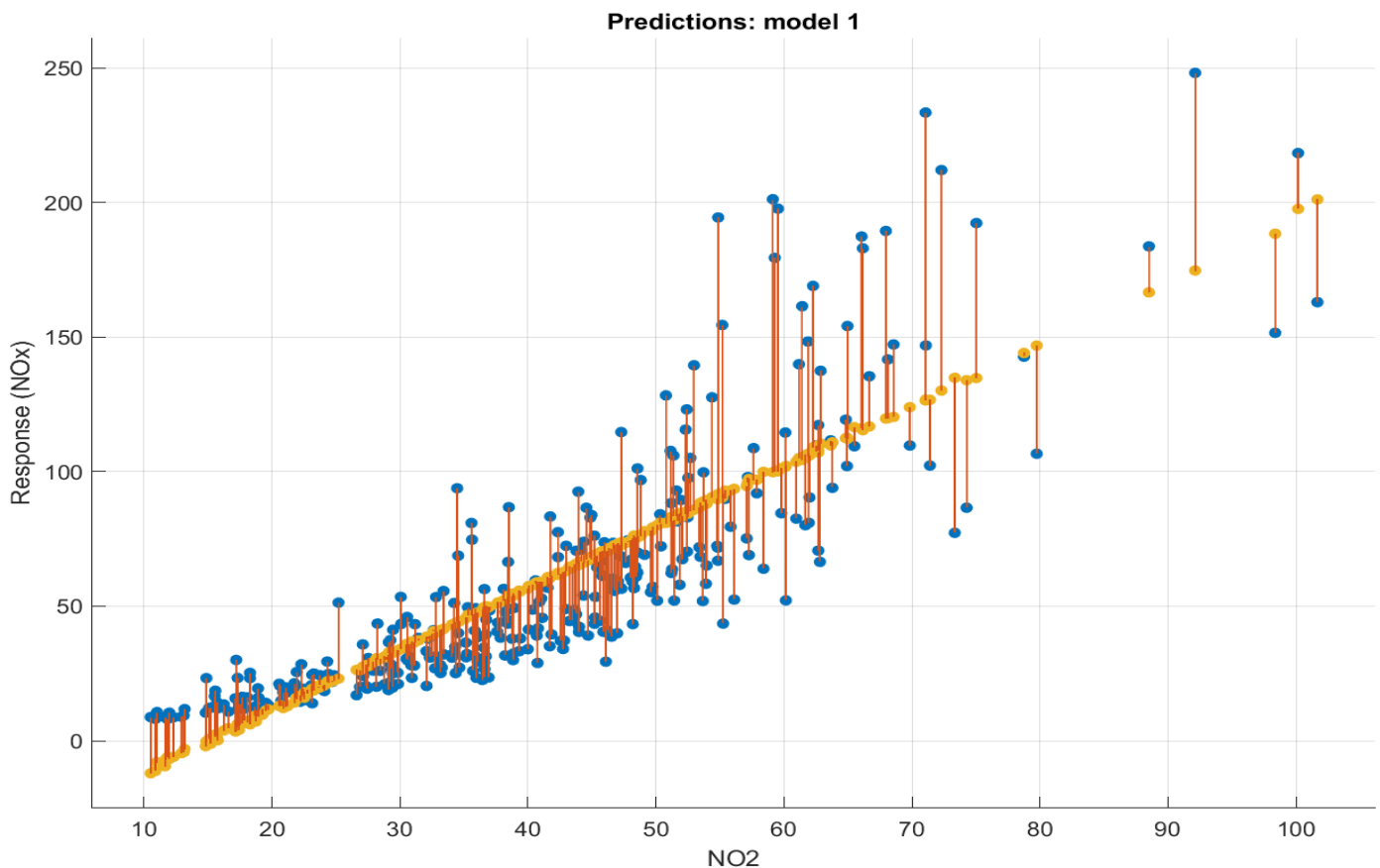


Figure 4.60: Regression model between NO₂ and NO_x

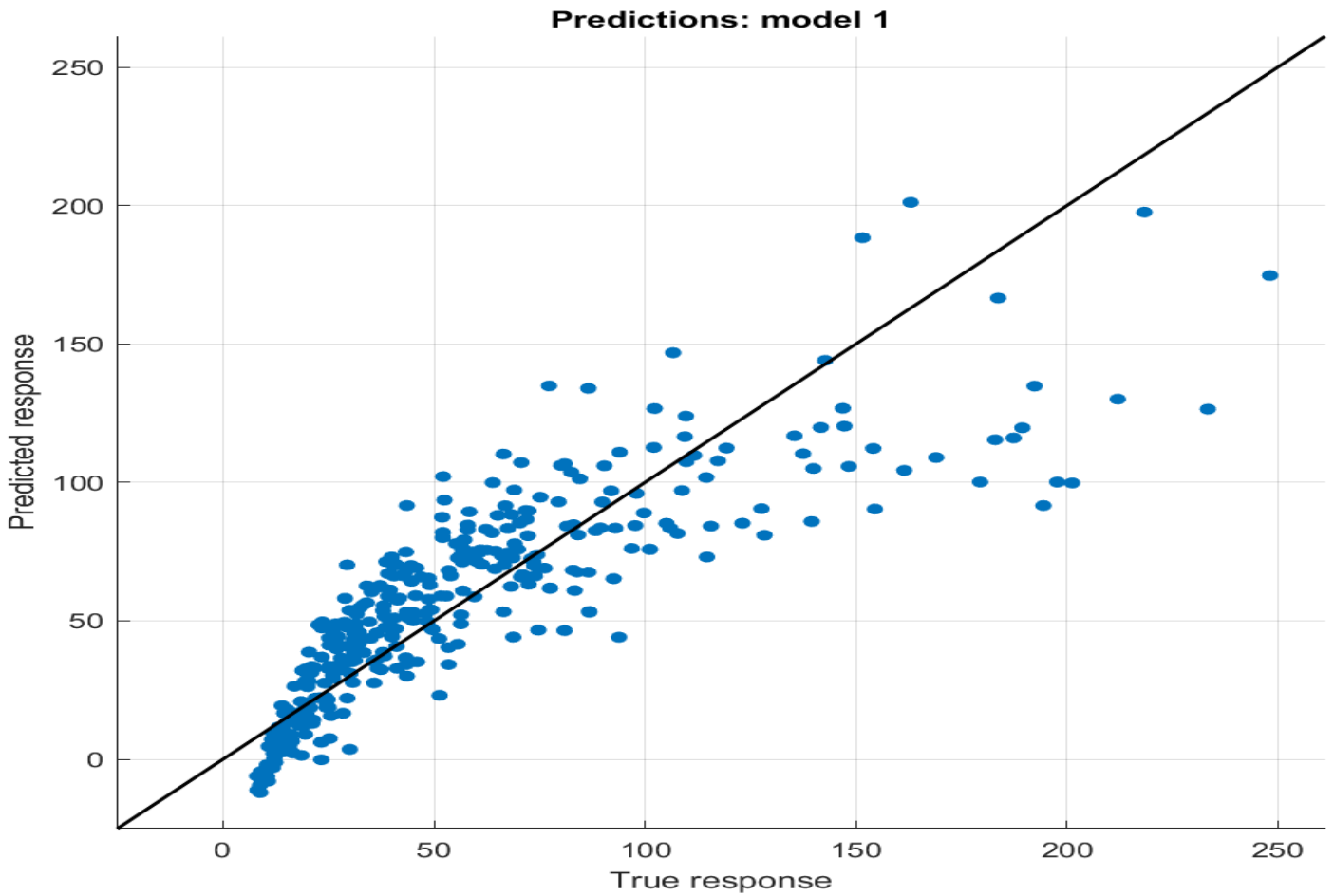


Figure 4.61: Predicted vs True response

4.2.6 Okhla 2020

Fig. 4.62 shows regression model between PM2.5 and PM10, blue dots indicate true value and yellow dots indicate predicted value and the vertical line between them is the error in the model. The r-squared value of the model is .88, indicating that the variation in PM2.5 will have .88 times the variation in the PM10. It also means that the movement of PM10 particles (dependent) can be explained by the movement of PM2.5 particles (independent). The correlation coefficient between the particles is .94, indicating that the PM2.5 have high influence on PM10 particles. In Fig. 4.63 the graph between the true and predicted response when the value was within 200 units points were closer to the regression line as the value increases particles disperse abruptly from the regression line. The governing equation and the model summary are given below:

RMSE (Validation): 46.859

R-Squared (Validation): .88

MSE (Validation): 2195.7

MAE (Validation): 34.964

$$y = 1.368x + 60.52$$

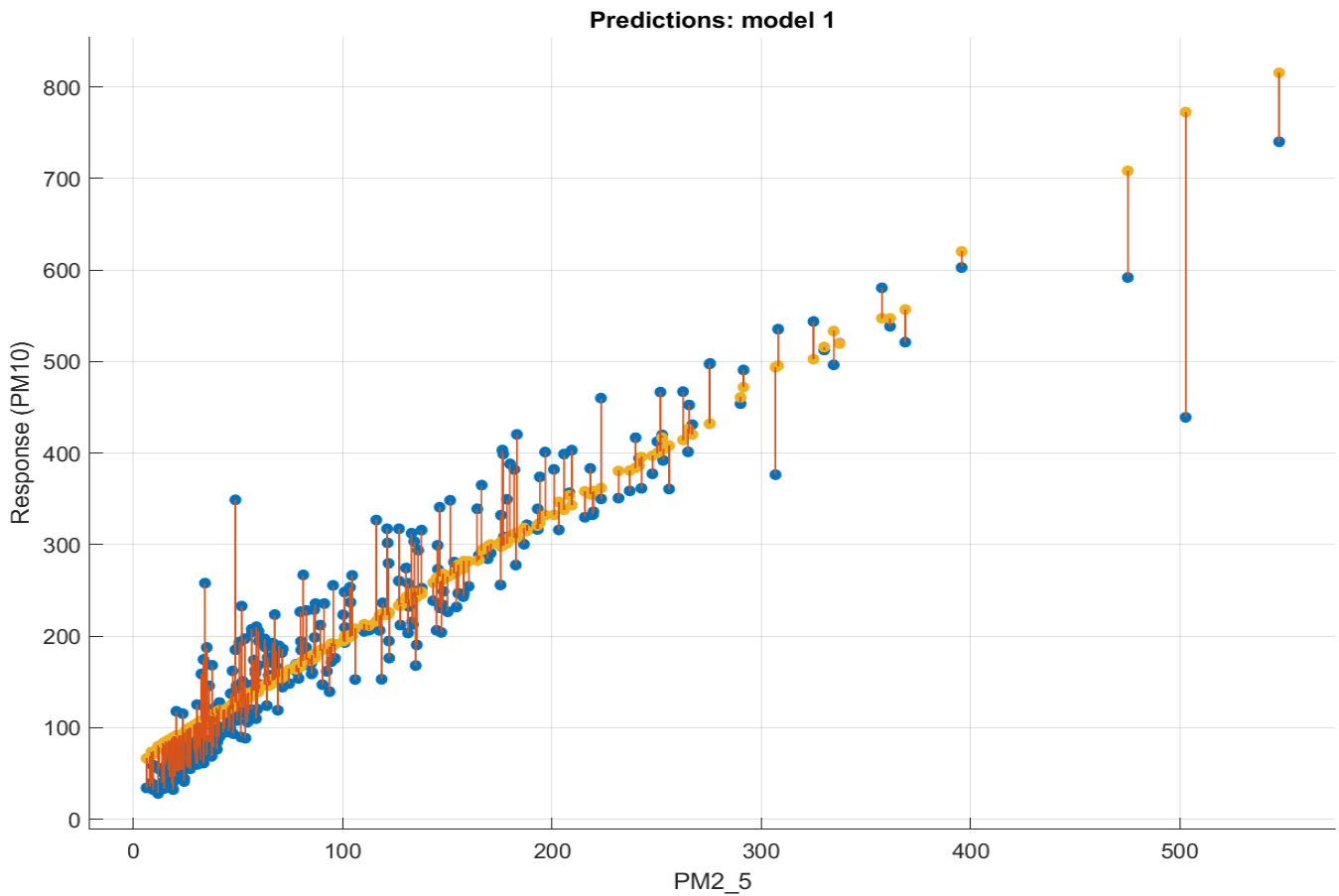


Figure 4.62: Regression model between PM2.5 and PM10

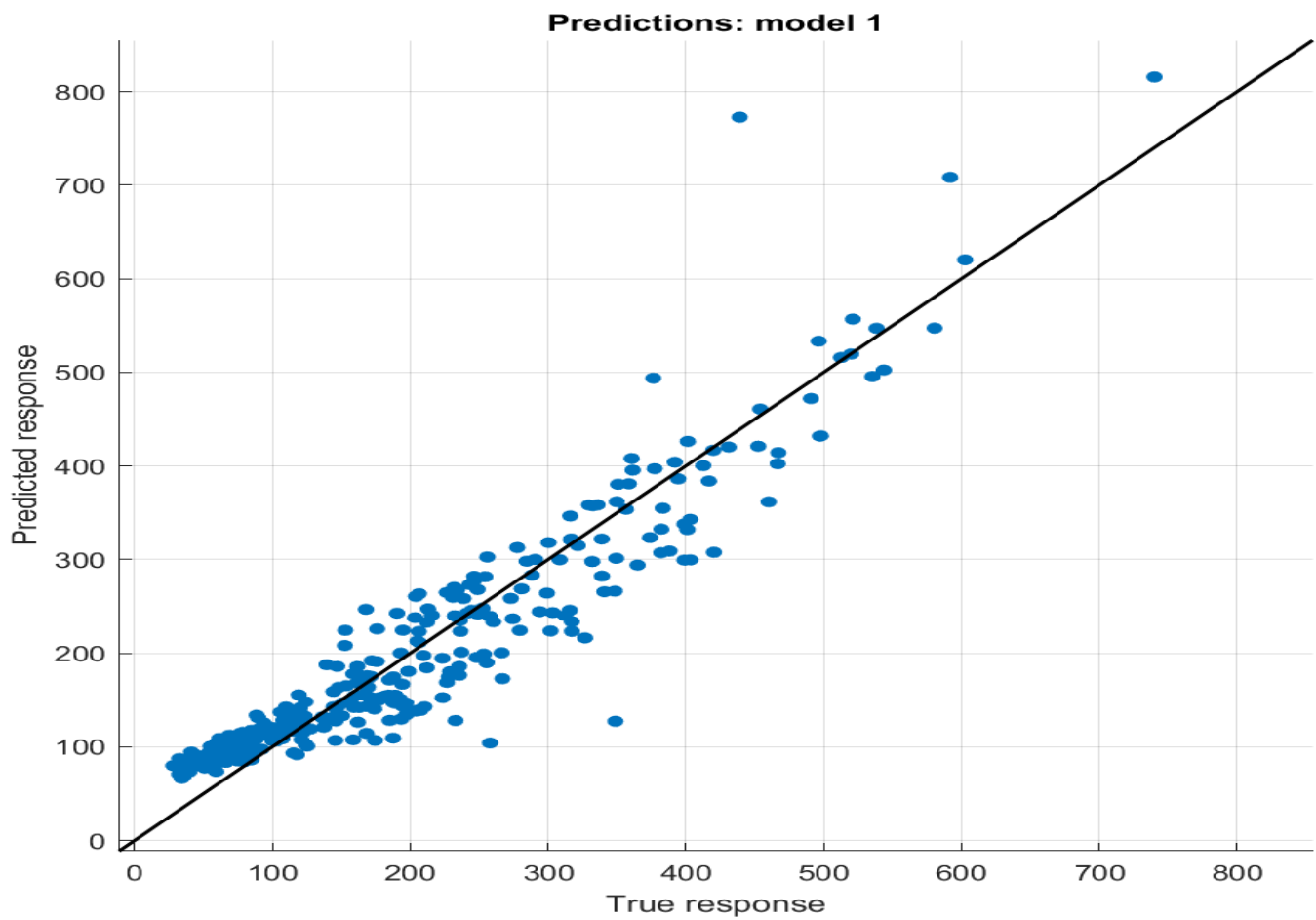


Figure 4.63: Predicted vs True response

Fig. 4.64 shows the regression model between NO and NO_x, compared to Narela 2020 and Ghazipur 2020, Okhla 2020 has the least error meaning deviation of true points from predicted points. The r-squared value is 0.98 which is high compare to Narela and Ghazipur in 2020, meaning that variation in NO will affect the variation in NO_x by .98 times. There is a positive correlation coefficient between NO and NO_x of about 0.99, indicating that the variation or change in one particle will directly affect the variation and change in another particle. Fig. 4.65 shows the graph between true and predicted response, we can observe that the points are close to regression line indicating that the model is a good fit with least error. The governing equation and the model summary are given below:

RMSE (Validation): 7.1296

R-Squared (Validation): 0.98

MSE (Validation): 50.831

MAE (Validation): 5.3697

$$y = 1.05x + 14.04$$

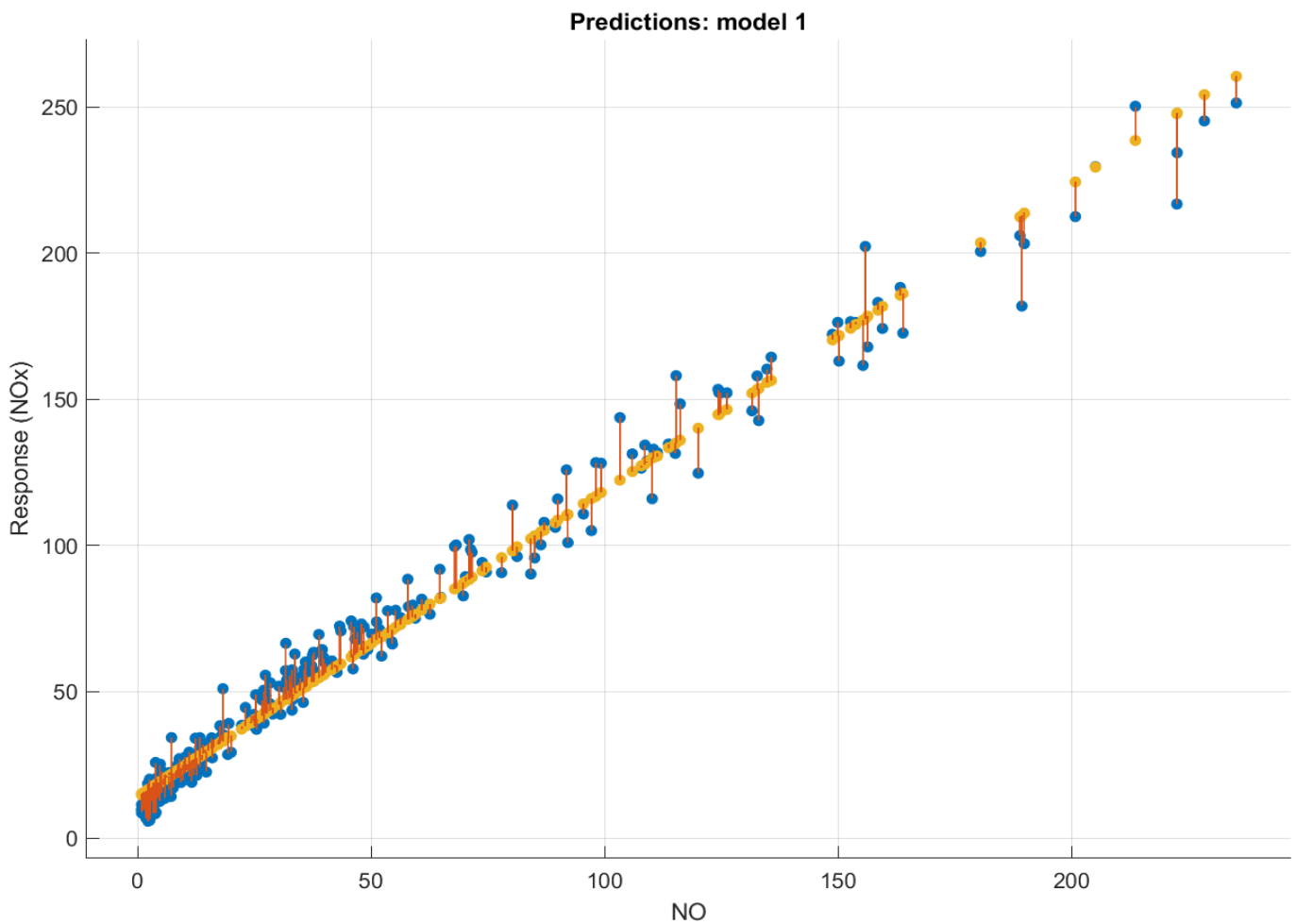


Figure 4.64: Regression model between NO and NO_x

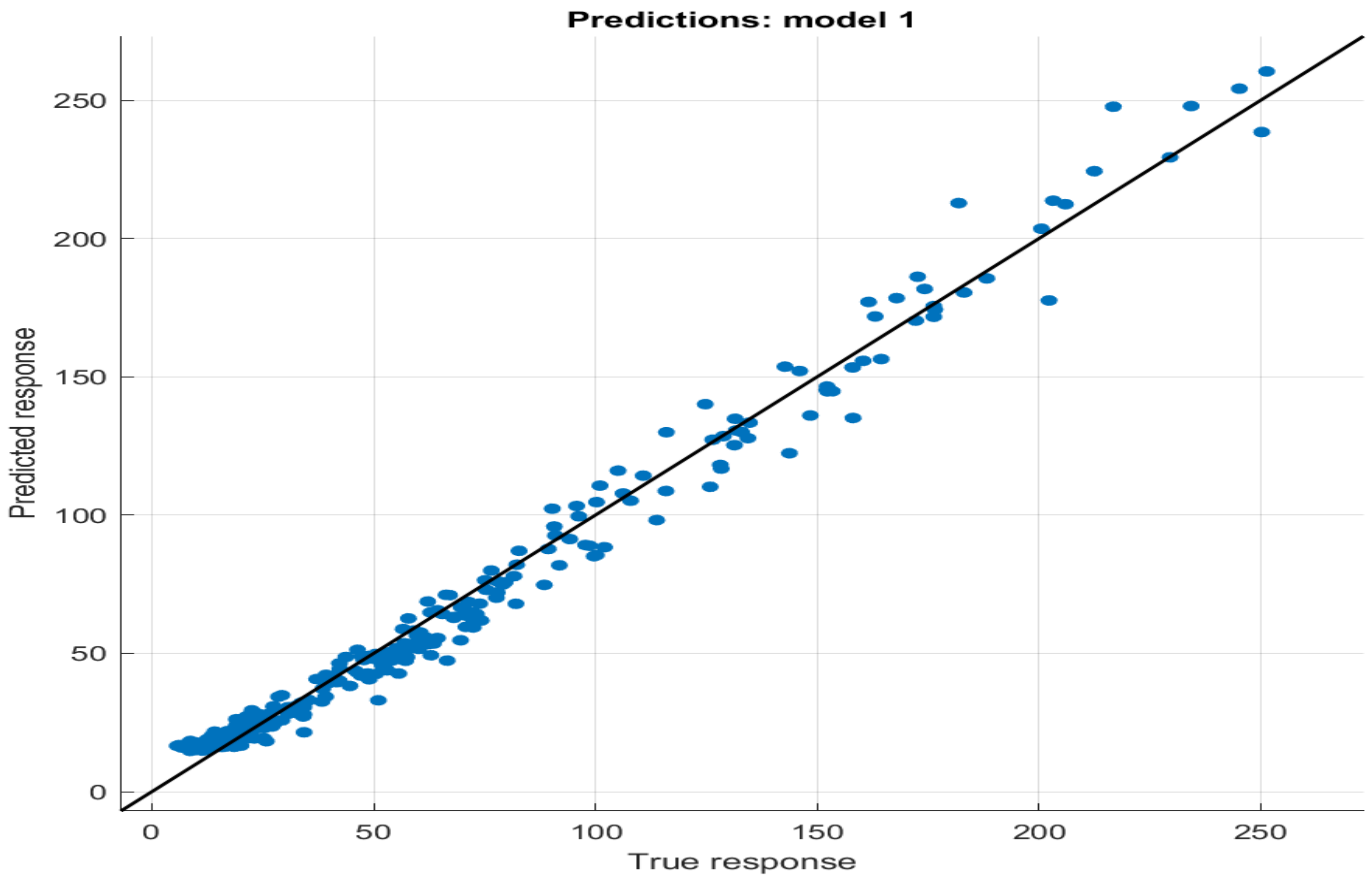


Figure 4.65: Predicted vs True response

Fig. 4.66 shows the regression model between Nitrogen dioxide (NO_2) and Oxide of Nitrogen (NO_x), as the value is within 40 units deviation of true value from predicted value is less or we can say error is less as value increases error also increases. The r-squared value for this model is 0.78, indicating that the variation in NO_2 will affect the NO_x by 0.78 times. There is a positive correlation between NO_2 and NO_x of value 0.89, indicating that the variables are highly correlated. Fig. 4.67 shows the graph between true and predicted response, when the value was within 50 units we can see the particles were close to regression line indicating model is a good fit, but as the value increases we can see large deviation of points from the regression line. The governing equation and the model summary are given below:

RMSE (Validation): 25.533

R-Squared (Validation): 0.78

MSE (Validation): 651.92

MAE (Validation): 16.448

$$y = 1.99x - 29.3$$

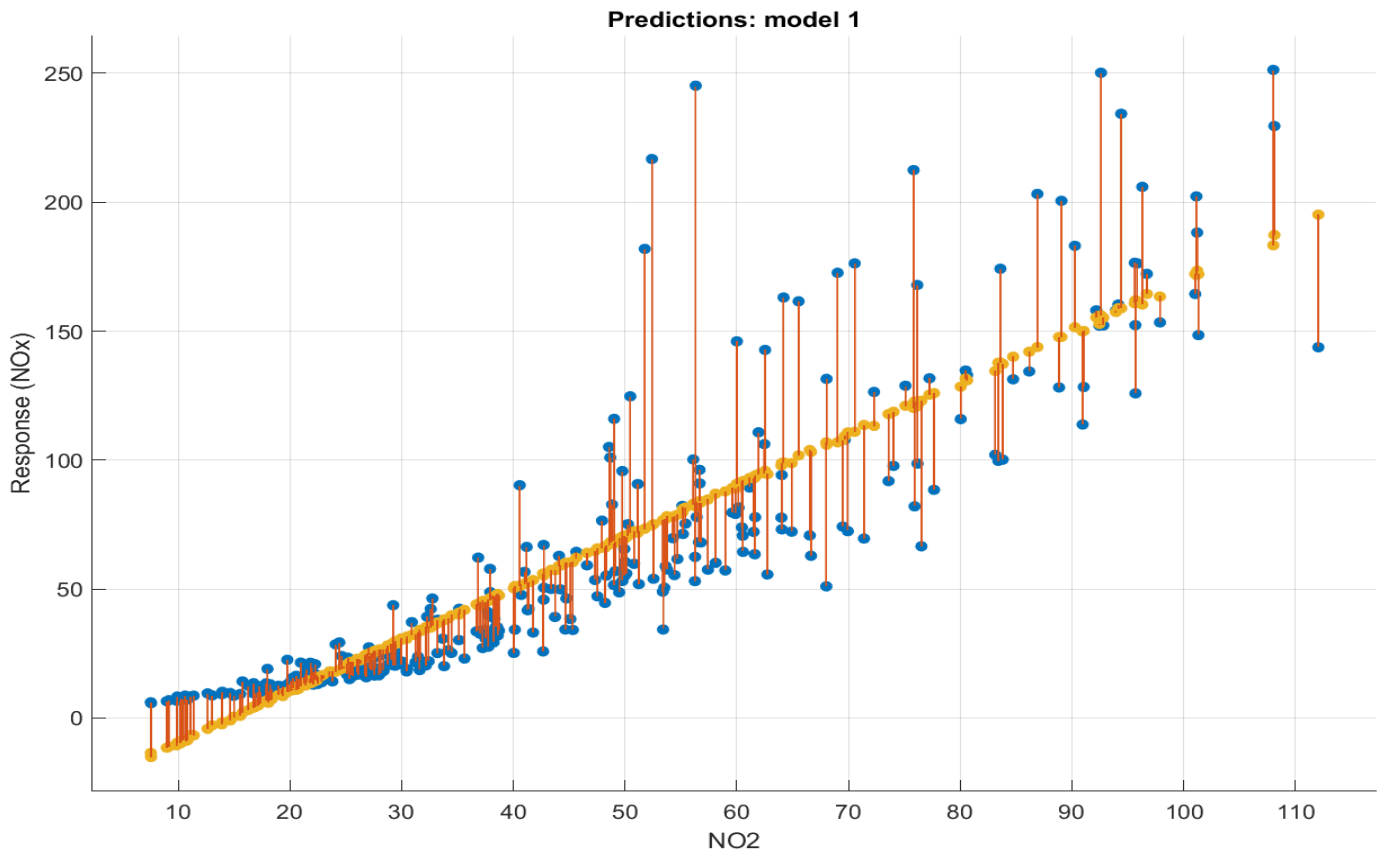


Figure 4.66: Regression model between NO₂ and NO_x

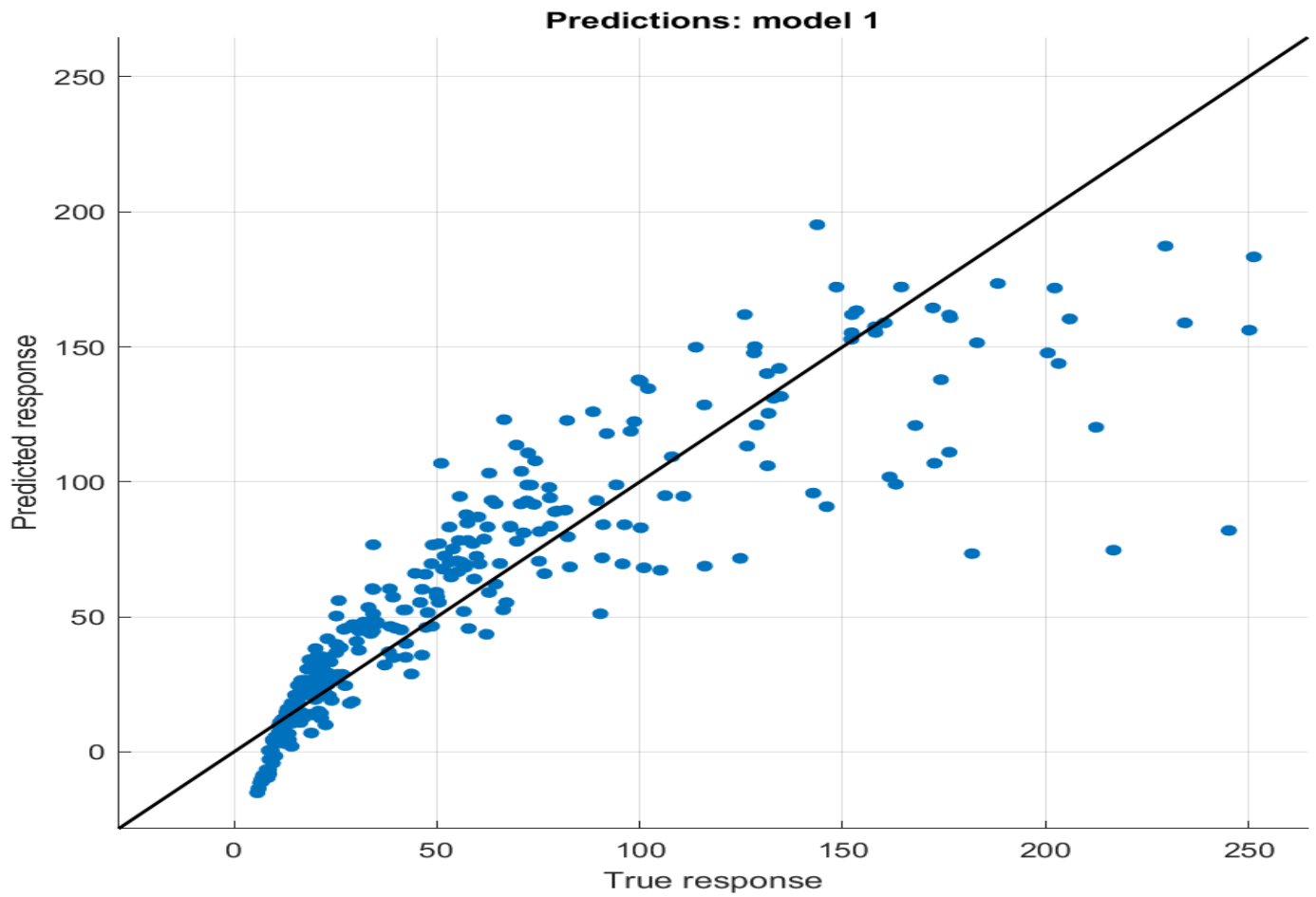


Figure 4.67: Predicted vs True response

Table 4.1: Summary of Regression model of PM2.5 vs PM10

PARAMETERS	Ghazipur 2019	Ghazipur 2020	Narela 2019	Narela 2020	Okhla 2019	Okhla 2020
RMSE (Validation):	50.338	35.025	61.856	44.981	52.05	46.859
R-Squared (Validation):	.82	.92	.76	.89	.85	.88
MSE (Validation):	2533.9	1228.6	3826.2	2023.3	2709.2	2195.7
MAE (Validation):	39.966	25.436	45.729	33.9	38.694	38.964
Governing Equation:	$y = 1.253x + 64.27$	$y = 1.277x + 42.37$	$y = 1.282x + 91.12$	$y = 1.401x + 69.58$	$y = 1.217x + 82.56$	$y = 1.368x + 60.52$

Table 4.2: Summary of Regression model of NO₂ vs NO_x

PARAMETERS	Ghazipur 2019	Ghazipur 2020	Narela 2019	Narela 2020	Okhla 2019	Okhla 2020
RMSE (Validation):	NIL	21.95	15.445	15.371	24.106	25.533
R-Squared (Validation):	NIL	.81	.81	.73	.71	.78
MSE (Validation):	NIL	481.79	238.54	236.38	581.11	651.92
MAE (Validation):	NIL	14.408	9.0737	9.2875	17.334	16.448
Governing Equation:	NIL	$y = 3.035x - 19.11$	$y = 1.088x - 7.621$	$y = 1.367x - 18.42$	$y = 2.267x - 33.95$	$y = 1.99x - 29.3$

Table 4.3: Summary of Regression model of NO vs NO_x

PARAMETERS	Ghazipur 2019	Ghazipur 2020	Narela 2019	Narela 2020	Okhla 2019	Okhla 2020
RMSE (Validation):	8.9465	11.978	8.465	6.9385	6.2465	7.1296
R-Squared (Validation):	.95	.94	.94	.95	.98	.98
MSE (Validation):	80.04	143.48	71.657	48.143	39.019	50.831
MAE (Validation):	6.311	8.4675	5.78	5.0239	4.6839	5.3697
Governing Equation:	$y = 1.134x + 16.30$	$y = 1.137x + 15.54$	$y = 0.9988x + 17.98$	$y = 1.079x + 16.61$	$y = 0.9726x + 14.59$	$y = 1.05x + 14.04$

Above table summarize the regression model by mathematical result and linear equation using MATLAB. The model between PM_{2.5} vs PM₁₀, NO vs NO_x, and NO₂ vs NO_x have been shown using two graph one is the regression model and the other is graph between predicted and true response, the former shows the how much the error is there between true and predicted values and the latter shows how fit the graph really is or how the values are deviated from the regression line.

Chapter 5

CONCLUSION

Unlike other studies, in the present study air pollutant emission and its impact around landfill has been analysed with the latest three years data (2019, 2020 and 2021), variation of several air pollutants like PM_{2.5}, PM₁₀, NO, NO₂, NO_x, SO₂, CO, Ozone, Toluene and Benzene. Foremost, correlation and descriptive statistics of each year for each landfill monitoring station has been calculated and air pollutants variation with temporal variation (wind speed, wind direction, solar radiation, ambient temperature and rainfall) has been observed. Variation of each pollutant for each year has been shown and the trendline has been drawn to know how the pollutants has been from 24th March to 30th of November. During winter season emission has been the highest compared to all season, monsoon has been the lowest and summer season is in between the winter and monsoon. In 2019 Ghazipur monitoring station Benzene has shown the maximum emission compared to all other pollutants, other pollutants have shown maximum emission in 2021. For Narela monitoring station, most of the peak of pollutants occurred in winter season except for the NO₂ which occurred in summer of 2019, SO₂ occurred in summer of 2021, ozone in summer of 2020 and CO monsoon of 2021. Benzene peak occurred in monsoon and winter of 2020, and toluene has shown increasing trendline in 2020. For Okhla landfill monitoring, winter season has seen maximum emission out of all the season, and monsoon has seen the least emission. Benzene emission around Okhla landfill has been the maximum during 2019 for all season. Toluene has an increasing trend in 2021. Lockdown effect can be seen in the graph, lockdown did reduce the emission of air pollutants except for few pollutants who continue to rise even during when the world was in shut down condition.

Regression model has shown that the whenever there is a change or variation in PM_{2.5}, NO and NO₂, we can observe the change in PM₁₀ and NO_x. We can see the all model has r-squared value of more than 0.80 except for few, and the graph between predicted vs true response has also shown which indicated that the which model can be a good fit curve or good model. Some the good fit curve is NO vs NO_x for Ghazipur 2019 and 2020; Narela 2019 and 2020; exceptionally good fit curve with 0.98 r-squared value for Okhla 2019 and 2020. The curve between NO₂ vs NO_x has only given negative intercept, which indicate that one parameter decreases while other increases for certain time. The future prediction of PM₁₀ and NO_x can be made which is 'Y' value in an equation, by putting value of 'X' which is PM_{2.5}, NO and NO₂. This study provides governing bodies confidence that strict implementation of air quality management strategies would result in a considerable improvement in air quality in India.

5.1 FUTURE SCOPE

In the present study only one monitoring station has been chosen to find out the emissions that are happening around the landfill, in future more than one monitoring station can be chosen to know the accuracy of the emissions. High volume sampler can be used to collect Total Suspended Particulates (TSP) sample to know the air quality around landfill and can see how the values are closely related to each other.

REFERENCES


- Atabi, F., Ehyaei, M. A., & Ahmadi, M. H. (1994). Calculation of CH₄ and CO₂ Emission Rate in Kahrizak Landfill Site with Land GEM Mathematical Model. In *World Sustainability Forum*. <http://www.sciforum.net/conference/wsf-4>
- Bera, B., Bhattacharjee, S., Shit, P. K., Sengupta, N., & Saha, S. (2021). Significant impacts of COVID-19 lockdown on urban air pollution in Kolkata (India) and amelioration of environmental health. In *Environment, Development and Sustainability* (Vol. 23, Issue 5, pp. 6913–6940). <https://doi.org/10.1007/s10668-020-00898-5>
- Białowicz, J. S., Rogula-Kozłowska, W., & Krasuski, A. (2021). Contribution of landfill fires to air pollution – An assessment methodology. *Waste Management*, 125, 182–191. <https://doi.org/10.1016/j.wasman.2021.02.046>
- CALIFORNIA AIR RESOURCE BOARD. (2022). *Inhalable Particulate Matter and Health (PM_{2.5} and PM₁₀)*.
- Chakraborty, M., Sharma, C., Pandey, J., Singh, N., & Gupta, P. K. (2011). Methane emission estimation from landfills in Delhi: A comparative assessment of different methodologies. *Atmospheric Environment*, 45(39), 7135–7142. <https://doi.org/10.1016/j.atmosenv.2011.09.015>
- CPCB. (2022). *Central Control Room for Air Quality Management - All India*.
- Das, D., Majhi, B. K., Pal, S., & Jash, T. (2016). Estimation of Land-fill Gas Generation from Municipal Solid Waste in Indian Cities. *Energy Procedia*, 90, 50–56. <https://doi.org/10.1016/j.egypro.2016.11.169>
- Dave, P. N., Sahu, L. K., Tripathi, N., Bajaj, S., Yadav, R., & Patel, K. (2020). Emissions of non-methane volatile organic compounds from a landfill site in a major city of India: impact on local air quality. *Heliyon*, 6(7), e04537. <https://doi.org/10.1016/j.heliyon.2020.e04537>
- Dewi, S., Kusumaningtyas, A., Aldrian, E., Wati, T., & Atmoko, D. (2018). *The Recent State of Ambient Air Quality in Jakarta*. 2343–2354. <https://doi.org/10.4209/aaqr.2017.10.0391>
- Fallahizadeh, S., Rahmatinia, M., Mohammadi, Z., Vaezzadeh, M., Tajamiri, A., & Soleimani, H. (2019). Estimation of methane gas by LandGEM model from Yasuj municipal solid waste landfill, Iran. *MethodsX*, 6, 391–398. <https://doi.org/10.1016/j.mex.2019.02.013>
- Gautam, S. (2020). The Influence of COVID-19 on Air Quality in India: A Boon or Inutile. *Bulletin of Environmental Contamination and Toxicology*, 104(6), 724–726. <https://doi.org/10.1007/s00128-020-02877-y>

- Gollapalli, M., & Kota, S. H. (2018). Methane emissions from a landfill in north-east India: Performance of various landfill gas emission models. *Environmental Pollution*, 234, 174–180. <https://doi.org/10.1016/j.envpol.2017.11.064>
- Hoffman, S. (2021). Estimation of prediction error in regression air quality models. *Energies*, 14(21). <https://doi.org/10.3390/en14217387>
- Jolly, S., & Ahmad, N. (2021). The municipal solid waste disposal of Okhla landfill in Delhi: locating legal framework and institutional responses. *International Journal of Environment and Waste Management*, 28(4), 487. <https://doi.org/10.1504/ijewm.2021.10042471>
- Liu, Y., Lu, W., Guo, H., Ming, Z., Wang, C., Xu, S., Liu, Y., & Wang, H. (2016). Aromatic compound emissions from municipal solid waste landfill: Emission factors and their impact on air pollution. *Atmospheric Environment*, 139, 205–213. <https://doi.org/10.1016/j.atmosenv.2016.05.043>
- Mehmet, Ş. (2020). *Science of the Total Environment Impact of weather on COVID-19 pandemic in Turkey*. 728. <https://doi.org/10.1016/j.scitotenv.2020.138810>
- Murk, J. B. (1955). Sources of Air Pollution Literature. In *Industrial & Engineering Chemistry* (Vol. 47, Issue 5). <https://doi.org/10.1021/ie50545a028>
- Nagar, P. K., Singh, D., Sharma, M., Kumar, A., Aneja, V. P., George, M. P., Agarwal, N., & Shukla, S. P. (2017). Characterization of PM_{2.5} in Delhi: role and impact of secondary aerosol, burning of biomass, and municipal solid waste and crustal matter. *Environmental Science and Pollution Research*, 24(32), 25179–25189. <https://doi.org/10.1007/s11356-017-0171-3>
- Nathanson, J. A. (2020). *Air Pollution*. <https://www.britannica.com/science/air-pollution>
- Osra, F. A., Ozcan, H. K., Alzahrani, J. S., & Alsoufi, M. S. (2021). Municipal solid waste characterization and landfill gas generation in kakia landfill, makkah. *Sustainability (Switzerland)*, 13(3), 1–13. <https://doi.org/10.3390/su13031462>
- Pani, S. K., Lin, N. H., & RavindraBabu, S. (2020). Association of COVID-19 pandemic with meteorological parameters over Singapore. *Science of the Total Environment*, 740, 140112. <https://doi.org/10.1016/j.scitotenv.2020.140112>
- Paraskaki, I., & Lazaridis, M. (2005). Quantification of landfill emissions to air: A case study of the Ano Liosia landfill site in the greater Athens area. *Waste Management and Research*, 23(3), 199–208. <https://doi.org/10.1177/0734242X05054756>
- Sahoo, P. K., Mangla, S., Pathak, A. K., Salāmao, G. N., & Sarkar, D. (2021). Pre-to-post lockdown impact on air quality and the role of environmental factors in spreading the COVID-19 cases - a study from a worst-hit state of India. *International Journal of Biometeorology*, 65(2), 205–222.

<https://doi.org/10.1007/s00484-020-02019-3>

- Sahoo, P. K., Powell, M. A., Mittal, S., & Garg, V. K. (2020). Is the transmission of novel coronavirus disease (COVID-19) weather dependent? *Journal of the Air and Waste Management Association*, 70(11), 1061–1064. <https://doi.org/10.1080/10962247.2020.1823763>
- Sharma, S., Zhang, M., Anshika, Gao, J., Zhang, H., & Kota, S. H. (2020). Effect of restricted emissions during COVID-19 on air quality in India. *Science of the Total Environment*, 728, 138878. <https://doi.org/10.1016/j.scitotenv.2020.138878>
- Srivastava, A. N., & Chakma, S. (2020). Quantification of landfill gas generation and energy recovery estimation from the municipal solid waste landfill sites of Delhi, India. *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, 00(00), 1–14. <https://doi.org/10.1080/15567036.2020.1754970>
- Srivastava, S., Kumar, A., Bauddh, K., Gautam, A. S., & Kumar, S. (2020). 21-Day Lockdown in India Dramatically Reduced Air Pollution Indices in Lucknow and New Delhi, India. In *Bulletin of Environmental Contamination and Toxicology* (Vol. 105, Issue 1, pp. 9–17). <https://doi.org/10.1007/s00128-020-02895-w>
- Sughosh, P., Anusree, ; N, Prathima, ; B, & Sivakumar Babu, G. L. (n.d.). *Estimation of Landfill Gas Emissions and Energy Recovery Potential from Landfills of Bangalore and Mysore: A Case Study*.
- Wedaa, S. A. M., Abuelnuor, A. A. A., Muawad, S. A. T., Ali, A. M., Omara, A. A. M., & Elemam, A. E. (2021, February 26). Estimation of Methane Emissions and BioEnergy Recovery Potential from a Sanitary Landfill Using FOD, DM and LandGEM models. *Proceedings of: 2020 International Conference on Computer, Control, Electrical, and Electronics Engineering, ICCCEEE 2020*. <https://doi.org/10.1109/ICCCEEE49695.2021.9429622>
- Yu, Y., Yu, Z., Sun, P., Lin, B., Li, L., Wang, Z., Ma, R., Xiang, M., Li, H., & Guo, S. (2018). Effects of ambient air pollution from municipal solid waste landfill on children's non-specific immunity and respiratory health. *Environmental Pollution*, 236, 382–390. <https://doi.org/10.1016/j.envpol.2017.12.094>
- Załoska, M., & Gładyszewska-Fiedoruk, K. (2020). Regression model of PM_{2.5} Concentration in a single-family house. *Sustainability (Switzerland)*, 12(15). <https://doi.org/10.3390/su12155952>

VITAE

NAME	CONTACT	PICTURE
<p>ADARSH KHARE</p> <p>Area of Interest: Air Pollution, Climate Change, Sustainability and water and wastewater engineering.</p>	<p>adarshkhare.jhs@gmail.com</p>	
<p>Mr. ANUNAY A. GOUR Assistant Professor, Department of Environmental Engineering, DTU</p> <p>Area of Interests: Environmental Engineering, Water & Wastewater Engineering, Air Pollution, Environmental Impact Assessment, System Simulation & Modeling</p> <p>Specialization: Environmental Engineering</p>	<p>anunaygour@dtu.ac.in</p>	