Evaluation of Water Quality in Urban Delhi Stretch of River Yamuna using Statistical Methods

Thesis submitted in partial fulfillment of the requirements for the degree of

Master of Technology
in
Environmental Engineering

by

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CERTIFICATE

This is to certify that the research work embodied in this dissertation entitled “**Evaluation of Water Quality in Urban Delhi Stretch of River Yamuna using Statistical Methods**” has been carried out in the Department of Environmental Engineering, Delhi Technological University, New Delhi. This work is original and has not been submitted in part or full for any other degree or diploma to any university or institute.

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Date: .07.2014

Place: Delhi

Dedicated

To

My Late Grand Parents

ACKNOWLEDGEMENT

I would like to express my gratitude and appreciation to all those who gave me the possibility to complete this report. A special thanks to my guide, Dr. S. K. Singh, whose help, stimulating suggestions and encouragement, helped me to coordinate my project especially in writing this report.

I would also like to acknowledge with much appreciation the crucial role of the staff of Environmental Laboratory, who gave the permission to use all required machinery and the necessary material to complete the project.

Special thanks go to my HOD Dr. S K Singh, who help me to assemble the parts and gave suggestion about the project. I also thank the scientists at CPCB for providing data and continuous guidance and advise.

Last but not least, many thanks go to my family who has given his full effort in guiding me in achieving the goal as well as their encouragement to maintain our progress in track. I would like to appreciate the guidance given by other supervisors as well as the friends especially in my project presentation that has improved our presentation skills by their comment and tips.

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DECLARATION

I, hereby declare that the work being presented in the Project Report entitled **“Water quality evaluation in an urban Delhi stretch of the Yamuna river using regression analysis”** is my original work and an authentic report carried out during the period of 4th Semester as a part of my major project.

The contents of this report has not been previously formed the basis or the award of any degree, diploma or other similar title or recognition and is being utilized by me for the submission of my Major Project Report to complete the requirements of Master’s Degree of Examination in Environmental Engineering, as per Delhi Technological University curriculum.

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SYNOPSIS

The present study deals with the variation of water quality characteristics over an urban stretch of the Yamuna River covering areas upstream, downstream and the entire length of the Delhi city. The study has been conducted over a period of six months. Water samples collected systematically from nine sites during October to February and examined for water quality evaluation through application of Regression analysis models. A regional perspective is provided with river water quality being interpreted in relation to catchment geography and to the observed point and non-point source inputs to the catchment. For many determinants, both diffuse and point sources appear to contribute to the riverine load in the study area. Point source inputs are important for phosphate, nitrate and micro-organic pollutants. Diffuse agricultural sources are particularly important in upstream arable areas, e.g. for nitrate, phosphate and micro-organics. In addition, widespread background geological sources contribute to loads of sulfate and phosphate. Sewage effluent is the most widespread and most significant point source of many pollutant chemicals in the study area. Low biochemical oxygen demand, nitrate, chloride and phosphate result from domestic effluent and commercial inputs, e.g. from sectors such as public places and fishery. Fish farms cause depletion in dissolved oxygen but on the whole, these changes were not observed to cause problems on a wider scale as of now. From the findings, a subset was selected for the water quality indices (WQI) analysis. Water quality of the Yamuna River at different points assessed by the WQI was compared. According to the quality indices during the study period, water quality in the study area of the river was average to good. To support and strengthen the findings, an analyses of the data based on multiple regression was done to examine whether seasonal or spatial variation in different parameters can be explained and predicted based upon their interrelationships in terms of source and mobility.

Key words: River water, water quality, water quality index, regression analysis.

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Chapter 1

Introduction

Chapter 1
INTRODUCTION

In the study of natural ecosystems, often many variables simultaneously change with time and location due to anthropogenic influences (urban, industrial and agricultural activities, increasing consumption of water resources) as well as natural processes (changes in precipitation inputs, erosion, weathering or mineral dissolutions), systematically or otherwise. By measuring as many parameters as possible that define the system, it may be possible to understand their interactions and to assess the sustainability of the environment (Hopke, 1985). The long and short- term safety and health effects on humans and livestock depend upon the physical and chemical characteristics of the pollutants and level of exposure to such polluted water systems. Data collected by state, local or national agencies and private entities are needed to build the assessment that we need to make better pollution control decisions. Without data, we simply cannot know where pollution problems exist, where we need to focus our pollution control energies or where we have made progress.

1.1 Water Quality

The suitability of water for a use depends on the type and amounts of some specific impurities present that will in some way affect the desired use. The assigning of a class to a river reach is not simple. Only in rare cases are all the relevant variables found to be within the permissible limits of a given class. In other words, in most cases, the river water would be classified into one grade with regard to one set of variables and into another class with regard to another variable or set of variables. In this view, it would be appropriate to base river classification on the ranges of an index representing the integrated effect of the concentrations and importance values of the relevant variables for a use.

1.2 Water Quality of Delhi

The water Quality of Delhi is primarily based upon river Yamuna. The River Yamuna which is an important tributary of River Ganges , is one of the most important rivers in India and supports the life of millions of people particularly in Delhi. The river receives domestic effluents without primary treatment from the towns situated on both the sides of River. In view of the above , there is a need for accurate and reliable estimate of River water Quality and for keeping Yamuna free of Pollution.

1.3 Objectives of the Present Investigation

1. To characterize water quality of River Yamuna in Delhi Urban Stretch .
2. To study changes or trends in water quality over time.
3. To estimate River water Quality by use of a software called Aq.Qa
4. To identify specific existing or emerging water quality problems based on analysis of the data using WQI and multiple regression analysis .

Chapter 2

Literature Review

Chapter 2
LITERATURE REVIEW

2.1. Introduction

The use of Regression Analysis and WQI could be of particular interest for developing countries, because they provide cost-effective water quality assessment as well as the possibility of evaluating trends (Silvia., et al., 1999). The first WQI was developed in the United States by Horton (1965) and applied in Europe since the 1970s, initially in the United Kingdom. It has also found applicability in Africa and Asia (Shoji, et al., 1966; Handa, 1981; Suki, et al., 1988; Bhargava, 1987; Al-Ami, et al., 1987; Zou, et al., 1988; Sahu, et al., 1991; Erondu and Nduka, 1993; Palupi, et al., 1995). In order to assess the present water quality and the future uses of the water of the Yamuna River, a WQI was applied to a data set collected for this study. Water quality indices are intended to provide a simple and understandable tool for managers and decision makers on the quality and possible uses of a given water body. Basically, a water quality index (WQI) attempts to provide a mechanism for presenting a cumulatively derived, numerical expression defining a certain level of water quality (Miller et al., 1986).

2.2 Yamuna River

Yamuna, the main river in the Northern part in India, arises in the Himalayas (56.12°S, 12.34°E, altitude 5300m), flows east wards followed by west wards with a total length of 2900 km. Its main source is in a great glacier-mass of the northernmost chain of the Himalayas, called Kubigangri, about 82°N and it receives various tributaries including one formerly regarded as the true source from the pass of Mariam La (15,500 ft.), which separates its basin from the eastern affluent of the Mansarowar lakes, at least 100 m. south-east of those of the Indus.

Linear regression shows that chlorides, nitrates and ammonium concentrations significantly increased over time. Casey and Clarke, (1979) carried out statistical analysis for 11 years (1965-1975) of weekly data of nitrate concentrations and discharge values from the river

Frome (Dorset). The results show a trend over the 11-year period with nitrate concentrations increasing by 0.11mg NO3 -N/L/year. Bhargava, D. S., (1983) did the classification and zoning of Ganga River using water quality index (WQI). Criteria and methodology for evolving such quality indices and limits of significant variables for the different grades of the various beneficial uses of a water were used. He used the simplified model for the Water Quality Index (WQI) to evaluate the WQI values of the River Ganga and tributaries for its various uses. The use of WQI was exploited for the classification and zoning of Ganga. Based on the investigation he found that the river standards for pollution control and water quality management could also be prescribed in terms of the WQI. Van Belle and Hughes., (1984) analyzed the non-uniformly sampled biochemicaloxygen demand (BOD) data set from two stations on Willamette River (Oregon) by trend detection method. The data spanned an 11-year period (1970-1981) with only few gaps. BOD has decreased over the period but no evidence on trend heterogeneity is found either between seasons or between stations by the modified Kendall's tau test .

Jose, (1989) presented data for the river Trent basin (Nottingham) indicating that as for rivers draining other areas of the United Kingdom, upward trends in both nitrate concentration and load were evident. The data indicated a distinct contrast between the rate of nitrate concentration increase in the urbanized and rural sub-catchments. Long-term nitrate loads have been calculated from irregular data of variable sampling frequency for the river using a discharge weighted mean interval method. Nevertheless, no statistical information is given on trends or sudden changes during the 1960-1985 periods. Andreja, D., and Jana, Z. K., (1995) investigated the water quality of the river Sava nearby Ljubljana, Slovenia. Based on the data, they found that discharge of organic, degradable wastewater into the river Sava resulted in a decrease of dissolved oxygen concentration. A surface water quality model, QUAL2E, developed by United States Environmental Protection Agency, was applied to estimate the impact of discharged wastewater on quality of the river Sava. QUAL2E model was modified and sensitivity analysis was performed to determine the most important factors, which affect dissolved oxygen concentration in river water. The model was calibrated and validated according to the field measurements. The Yamuna River water is often used for irrigation and as the main drinking water source. A systematic study on the river water quality is of great necessity and significance.

This report presents the results of studies on some major chemical parameters of the Yamuna water system for a six months study period.

Few Researchers investigated the seasonal variation of water quality indices of dissolved oxygen, biological oxygen demand (BOD),turbidity, total solids, nitrates, phosphates, pH, temperature and fecal coliforms of the Warri River at five points from July 1981 to July 1982. Based on the data, it was found that with respect to different parameters, the variation of the change in water quality was different. After applying the weighted mean index to all nine parameters, they found that the quality of the Warri River water was medium to good and the immediate source of pollution was sewage rather than industrial.

In order to monitor the trends of river pollution, hydrobiological investigations of nine selected parameters were carried out from September 2013 to February 2014 and the multiplicative weighted index applied. Besides trend analysis and WQI studies, statistical studies like Kriging and regression analyses were applied to the dataset for an enhanced understanding through diverse interpretation tools. The water quality index (WQI) is represented by a number between 0 and 100. Rivers with WQI values between 0-25, 26-50 and 51-70 are grouped as very bad, bad and medium, respectively, while waters of good and excellent quality have WQI values of 71-90 and 91-100, respectively.

Figure 1.1:Yamuna River

2.3 Water quality review

In research of water quality , there is increasing interest in the analysis of time series in relation to environmental degradation, which is one of the most important concerns of regulatory agencies who are responsible for the management of water resources. A prime question is whether or not the quality of water has changed over time or space. Edward and Thomas, (1973) used regression, spectral and cross-spectral techniques to examine the trends and periodicity in a 20-year records period (1951-1970) of weekly observations of eight water quality variables in the river Stour (Eastern England). On the basis of the model predictions it was estimated that in time when summer river low flow period occurs, wastewater should be treated to reach BOD value under 30 mg/l so that Slovenian water quality standards will not be violated. Barros, M. C., et al., (1995) analyzed the surface water quality in Portugal during a drought periodThey did the statistical analysis for possible correlation between concentrations and time or storage volume since 1989. Based on the analysis, they concluded that there was a tendency towards further deterioration of water quality in some of the reservoirs. . They studied to ascertain the possible relationship between water quality, flow and storage. Based upon the existing Water Quality Network, fifteen reservoirs, representative of different regions were selected, and analytical data on water quality parameters that are significant for each station, collected since 1989, were evaluated.

Shu Tao, (1997) investigated the spatial and temporal variations in the concentration and flux of the dissolved organic carbon (DOC) in the Yichun River, China. It was found that in the summer, DOC in the river water originated primarily from allochthonous sourcesTwo equations were derived to estimate DOC levels based on flow rate in the summer and winter, respectively. Spatially, the DOC increased downstream throughout the year. The annual DOC flux from the Yichun River drainage basin was calculated to be 7113 ton/a or 2.88 gC/m^2.a, among which over 87% occurred during 4 months of the wet season from June to September.

Nives, S. Tambuk-Giljanovic., (1999) determined water quality indices (WQI) for Dalmatian County waters as well as the results of the application of the index for water evaluation in Dalmatia (Southern Croatia) for a three-year period (1995, 1996 and 1997). For that nine parameters were included. Based on the nine parameters, the overall WQI were calculatedAfter the analysis, he found that the spring and river waters in Dalmatia, which contained low sulfate and chloride concentrations, were of high sanitary quality. This quality could be estimated by the WQI, which varied around 1. The increase of sulfate as well as chloride in springs, rivers and underground waters decreased the WQI value; in fact, it caused deterioration of the water quality with respect to the established standard for drinking water. . The WQI was obtained so that the water quality evaluation (WQE) could be divided by water quality evaluation (WQE)MAC that satisfied the maximum admissible concentration (MAC) of first class water. It included both underground and surface water, which could be used in its natural state or after being disinfected for drinking water.

Silvia, F. Pesce and Daniel, A. Wunderlin, (1999) verified the usefulness of water quality indices (WQI) to assess the water quality from multiple measured parameters, and to evaluate spatial and temporal changes. As a case study, they reported on the use of WQI from the Suquia River in Cordoba City (Argentina) and nearby locations. Two WQI (subjective and objective - WQIsub and WQIobj) take into consideration 20 parameters. Another index (minimal - WQImin) was developed considering only three parameters: turbidity, dissolved oxygen, and either conductivity or dissolved solids. WQIsub tends to overestimate the pollution due to the use of a subjective constant, which is not necessarily correlated with the measured parameters. WQImin shows a similar trend to WQIsub and WQIobj at a lower analytical cost; however, it should be combined with WQIobj to corroborate the results. In case of Suquia River, they concluded that the city urban activity produces a serious and negative effect on the water quality; this is particularly severe in locations following the city sewage discharge. The dry season shows the worst water quality. Alberto, W. D., et al., (2000) reported a comparative study using three different chemometric techniques to evaluate both spatial and temporal changes in water quality of Suquia River (Cordoba, Argentina), with a special emphasis on the improvement obtained using discriminant analysis for such evaluation. They monitored 22 parameters at different stations from the upper, middle, and beginning of the lower river basin during at least two years including 232 different samples.They obtained a complex data matrix, which was treated using the pattern recognition techniques of cluster analysis (CA), factor analysis/principal components (FA/PCA), and discriminant analysis (DA). DA technique shows the best results for data reduction and pattern recognition during both temporal and spatial analysis. DA allowed us to greatly reduce the dimensionality of the starting data matrix, pointing out to a few parameters that indicate the biggest changes in water quality as well as variation patterns associated with seasonal variations, urban run-off, and pollution sources, presenting a novel approach for water quality assessments.

Takanashi, H., et al., (2000) proposed a method of novel water quality index, for measuring the mutagen formation potential (MFP) on chlorination as a new water quality index. The main application of this index was to use in evaluation of the quality of drinking water, which may contain pollutants capable of forming mutagens when chlorinated under the conditions used in water purification processes. White, C. C., Smart, R., and Cresser, M. S., (2000) evaluated the effectiveness of the approach for protecting all the waters of the complex river network of a major catchment in N.E. Scotland, under high and low flow regimes. They also examined the relationship between the concentrations of major ions, trace elements (in dissolved and acid-available particulate forms) and flow, and a simple two-component end member mixing analysis performed to link river water chemistry to catchment sources, to identify whether within-river processes modify concentrations to produce non-conservative behaviour. They analyzed the samples, which were collected over a period of one year, at intervals of two weeks, from 59 sub-catchments of the River Dee catchment. They investigated the discharge effect also, from where they concluded that the system used in the UK is generally very effective for protection of rivers, but only under low flow conditions . Jarvie, P. H., et al., (2000) examined spatial and temporal variability in freshwater inputs of trace elements and major ions to the tidal reaches of the River Tweed. Based on the findings, they suggested that the variability in concentration of most dissolved trace elements and major ions in the lower Tweed can be modeled using simple mixing relationships.

Egborge, A. B. M., and Benka-Coker, J., (1986) investigated the seasonal variation of water quality indices of dissolved oxygen, biological oxygen demand (BOD),turbidity, total solids, nitrates, phosphates, pH, temperature and fecal coliforms of the Warri River at five points from July 1981 to July 1982. Based on the data, it was found that with respect to different parameters, the variation of the change in water quality was different. After applying the weighted mean index to all nine parameters, they found that the quality of the Warri River water was medium to good and the immediate source of pollution was sewage rather than industrial.

Jonnalagadda and Mhere, (2001) analyzed the water quality of the Odzi River in the eastern highlands of Zimbabwe. Over a span of 9 months, the river water samples collected at six selected sites were analyzed for various physical and chemical parameters namely temperature, conductance, pH, total suspended and dissolved solids, BOD, total phosphate and nitrate levels. Water quality of the Odzi River at different points assessed by the water quality indices (WQI) was compared. According to the quality indices during the study period, water quality in the upper reaches of the river was medium to good. It dwindled in the plains due to the seepage from abandoned mine dumps and discharges from the farm-lands. .

Bordalo, A. A., et al., (2001) analyzed the water quality index for the Bangpakong River (Eastern Thailand). They did the sampling from June 1998 to May 1999 at 11 sites along a 227 km gradient, covering the wet season (June–November) and the dry season (December–May). Surface water was collected at three different stations per site (close to the banks and in the middle of the river), and analyzed for different parameters. The Scottish water quality index (WQI) was adapted to the tropical environment. The averaged WQI was low (41%) and quality declined significantly during the dry season. Although the quality raised somewhat at middle sites, only 27% of the WQI values during wet season and 2.5% during dry season were higher than 50%, denoting poor environmental quality. Based on the seasonal results they concluded that the river was suitable only for tolerant fish and wildlife species and was of doubtful use for potable water supply during the dry season. As quality improves during the wet period, water could be used for the production of potable water, but only with advanced treatment, and for indirect and non-contact recreational activities.

Simeonov, V., et al., (2003) presented the interpretation of a large and complex data matrix obtained during a monitoring program of surface waters in Northern Greece. The data set consists of analytical results from a 3-yr survey conducted in the major river systems (Aliakmon, Axios, Gallikos, Loudias and Strymon) as well as streams, tributaries and ditches. Twenty-seven parameters have been monitored on 25 key sampling sites on monthly basis (total of 22,350 observations). The dataset was treated using cluster analysis (CA), principal component analysis and multiple regression analysis on principal components. Six latent factors were identified as responsible for the data structure explaining 90% of the total variance of the data set and are conditionally named organic, nutrient, physicochemical, weathering, soil leaching and toxic-anthropogenic factors. A multivariate receptor model was also applied for source apportionment estimating the contribution of identified sources to the concentration of the physicochemical parameters. This study presents the necessity and usefulness of multivariate statistical assessment of large and complex databases in order to get better information about the quality of surface water, the 9 design of sampling and analytical protocols and the effective pollution control/management of the surface waters.

Pekey, P., Karaka, D., and Bakoglu, M., (2004) investigated the concentrations of trace metals in the surface water samples collected twice along the Dil Deresi stream. Based on the investigation, they determined the status of the pollution and the stream and to estimate the contributions of the pollution sources using multivariate statistical analysis. They found the concentrations of almost all of the elements were log normally distributed having similar origin showed high inter-elemental correlations. Solidoro, S., et al., (2004) presented the results of the statistical analysis of a set of seven water quality parameters which were collected in 2001 within the frame of a more comprehensive monitoring program of the lagoon of Venice. The program included the monthly sampling of 32 water quality parameters in 30 stations. They used the multivariate techniques and gridding methods for investigating the spatial and seasonal validity of the data and for characterizing the trophic evolution of the basin in 2001. Based on the results, they classified the stations into different groups. Further, they found that the relative magnitude of the nutrient–flow relationship was found to vary seasonally for both phosphorus and nitrogen. Nutrient concentrations during high flows in summer and autumn were significantly higher than during winter and spring. They suggested that the disproportionate risk to surface water quality during summer high flow events owe to high potential growth rates of algal communities.

Singh, K. P., et al., (2004) applied different multivariate statistical techniques for evaluation of temporal and spatial variations and interpretation of a large complex water quality data set obtained during monitoring of Gomti River in Northern part of India. Water quality of the Gomti River was monitored at eight different sites selected in relatively low, moderate and high pollution regions, regularly over a period of 5 years (1994–1998) for 24 parameters. The complex data matrix (17,790 observations) was treated with different multivariate techniques such as cluster analysis, factor analysis/principal component analysis (FA/PCA) and discriminant analysis (DA). Cluster analysis (CA) showed good results rendering three different groups of similarity between the sampling sites reflecting the different water-quality parameters of the river system. Discriminant analysis showed the best results for data reduction and pattern recognition during both temporal and spatial analysis. Discriminant analysis showed five parameters (pH, temperature, conductivity, total alkalinity and magnesium) affording more than 88% right assignations in temporal analysis, while nine parameters (pH, temperature, alkalinity, Ca-hardness, DO, BOD, chloride, sulfate and TKN) to afford 91% right assignations in spatial analysis of three different regions in the basin. Thus, DA allowed reduction in dimensionality of the large data set, delineating a few indicator parameters responsible for large variations in water quality. This study presents necessity and usefulness of multivariate statistical techniques for evaluation and interpretation of large complex data sets with a view to get better information about the water quality and design of monitoring network for effective management of water resources.

The literature survey reveals that in recent times, a number of researchers/ scientists have studied various water bodies to evaluate critical threat towards their municipal and other uses. The present work is being attempted keeping in perspective all these knowledge gained, as no previous study exists for one of the most stressed urbanized reach of the river Brahmaputra. While the methods used in the current study are those demonstrated to be some of the dependable ones, the findings have been further illustrated by the Aq.Qa based on the data obtained from WQI and regression analysis.

Chapter 3

Study Area

Chapter 3

STUDY AREA

Yamuna starts from Yamunotri and passes through Delhi and ends at Allahabad where it meets River Ganga. The region of sampling covers a wide range of catchments and surface water types river, tributaries, ditches etc.). The main pollutant loads include domestic wastewaters, agricultural runoff, animal husbandry, industrial effluents and fishery. Yamuna is the longest river in India with a total length of nearly 2900 km and the average annual discharge 51.0450 million cubic meters (CPCB, 2000). The area of Yamuna basin is 580000 Km^2. An enormous development of agricultural resources has taken place within the Yamuna basin of late years, chiefly in the

direction of tea cultivation, as well as in the production of jute and silk. During the rains the Yamuna floods hundreds of square miles of country, reaching a height of 30 to 40 ft. above its usual level.

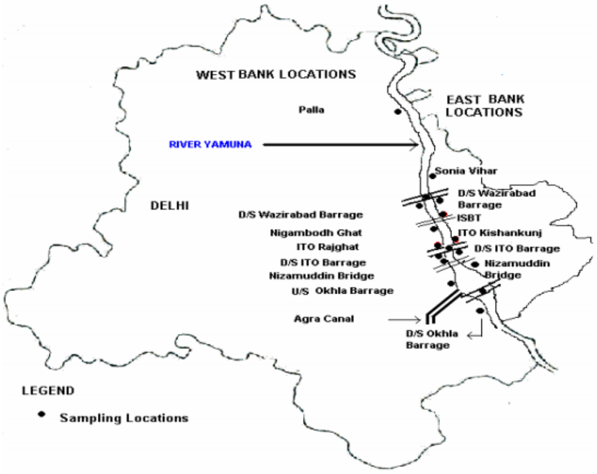

Fig. 3.1: Map of the Yamuna river adjoining Delhi city

Fig. 3.1 shows the map of the study area comprising the part of the Yamuna river adjoining Delhi city along with location of the sampling sites. Nine sampling points were chosen for the study after careful consideration**.**

1. Palla
2. Surajghat
3. Khajori Paltoon Pool
4. Kudesia Ghat
5. ITO Bridge
6. Nizamuddin Bridge
7. Agra Canal Okhla
8. Shahdara Drain
9.Agra Canal Jaitpur

It is expected to provide the cumulative assessment of any pollutant load downstream of the city area as a whole along with possible recovery due to attenuation by the assimilative capacity of the huge water mass of the main river.

Source : CPCB

Figure 3.2: Map of the Yamuna River adjoining Delhi city

Fig. 3.3 Map of Yamuna River in Delhi (Source : CPCB)

Chapter 4

Materials and Methodology

Chapter 4
MATERIALS AND METHODOLOGY

Data for Water Sample analysis of River Yamuna of study area was collected from Central Pollution Control Board . Methods of sampling and analysis of result was discussed with the scientists of CPCB . Interpretations of all the analyses results obtained in the second phase were performed using three different techniques:

1. Regression Analysis
2. Aq.Qa Software Analysis

Details of these have been elaborated in the later part of this chapter.

4.1 Sampling Strategy

The sampling strategy of CPCB was discussed with scientists and engineers of CPCB . The sampling strategy was designed to cover a range of determinants at key sites that accurately represent the water quality of the river system in Delhi city. Monthly sampling was carried out to monitor changes caused by the seasonal hydrological cycle. Sampling, preservation and analytical protocols were conducted by standard methods for surface waters (APHA., et al., 1998). The measured parameters include temperature, pH, electrical conductivity (EC), turbidity, total dissolve solids (TDS), hardness, dissolved oxygen (DO), biochemical oxygen demand (BOD5), chemical oxygen demand (COD), fecal coliform, alkalinity (HCO3-), nitrate (NO3--N), total phosphate (PO4-3-P), fluoride (F-), chloride (Cl-), sulfate (SO4-2),sodium (Na+), potassium (K+), calcium (Ca+2), and magnesium (Mg+2). Temperature of water samples was measured in the field using a thermometer. The sample bottles were rinsed three times before a final sample was collected and care was taken to throw the rinsed water downstream of where the sample was to be collected. The sample bottles were labeled with the date, time and site number. No preservatives were added to the samples before analysis but these were refrigerated within 24 hours of collection from the site.

4.2 Analytical Procedures

Particularly nine parameters were analyzed keeping in mind there requirements for calculating the WQI - temperature, dissolved oxygen (D.O), turbidity, pH, total dissolved solids (TDS), biochemical oxygen demand (BOD5), fecal coliform, total phosphate (PO4 -3-P) and nitrate (NO3--N). In addition, electrical conductivity (EC), sulfate (SO4-2), sodium (Na+), potassium (K+), calcium (Ca+2), hardness and alkalinity (HCO3-) were also determined for regression analysis. Standard methods were applied for estimation of parameters.

4.3 Water Quality Indices (WQI)

A water quality index is a means to summarize large amounts of water quality data into simple terms (e.g., good, medium, fair, etc.) for reporting to management and the public in a consistent manner. It expresses overall water quality at a certain location and time based on several water quality parameters.**No table of contents entries found.** It can tell us whether the overall quality of water bodies poses a potential threat to various uses of water, such as habitat for aquatic life, irrigation water for agriculture and livestock, recreation and aesthetics, and drinking water supplies. The use of an index to grade water quality is a controversial issue among water quality scientists. However, a water index based on some very important parameters can provide a simple indicator of water quality. It gives the public a general idea the possible problems with the water in the region. A commonly used water quality index (WQI) was developed by the US National Sanitation Foundation (NSF) in 1970 (Brown and others, 1970). The NSF WQI was developed to provide a standardized method for comparing the water quality of various bodies of water. Nine water quality parameters were selected to include in the index. These parameters are Biochemical oxygen demand (BOD5), Dissolved oxygen (DO), Fecal coliform (FC), Nitrates (NO3--N), pH, Temperature change, Total dissolved solids (TDS), Total phosphate (PO4-3-P) and Turbidity.

Then the graphs indicating the level of water quality ranging from 0 (worst) to 100 (best) from the raw data (e.g., pH values 2-12) were prepared to obtain a weighting curve for each parameter. Results of the nine parameters are compared to the curves and a numerical value, or *Q*-value, which indicates the level of water quality, has been obtained.

After the obtaining *Q*-value, it has been multiplied by a weighting factor, based on that test's importance in water quality. The weighting factors for nine parameters are shown in Table II.1 given in the appendix II. The nine resulting values are then added to arrive at an overall water quality index (WQI). The Water Quality Index uses a scale from 0 to 100 to rate the quality of the water, with 100 being the highest possible score and 0 is the lowest. Once the overall WQI score is known, it can be compared against the following scale to determine how healthy the water is on a given day. The WQI ranges, which are given in Table II.2 (Appendix II), also have been defined as following (Brown and others, 1970): Water supplies with ratings falling in the good or excellent range would able to support a high diversity of aquatic life. In addition, the water would also be suitable for all forms of recreation, including those involving direct contact with the water. Water supplies achieving only an average rating generally have less diversity of aquatic organisms and frequently have increased algae growth. Water supplies falling into the fair range are only able to support a low diversity of aquatic life and are probably experiencing problems with pollution. Water supplies that fall into the poor category may only be able to support a limited number of aquatic life forms, and it is expected that these waters have abundant quality problems. A water supply with a poor quality rating would not normally be considered acceptable for activities involving direct contact with the water, such as swimming.

4.4 Kriging

Kriging is a statistical method of interpolation, which predicts unknown values from data observed at known locations. This method uses variogram to express the spatial variation, and it minimizes the error of predicted values, which are estimated by spatial distribution of the predicted values. The potential of GIS for various spatial analyses to get a scenario can be easily comprehended to arrive at a proper decision (Priyakant, 2000). Kriging is also the method that is associated with the acronym B.L.U.E. (best linear unbiased estimator). It is linear since the estimated values are the weighted linearcombinations of the available data. It is unbiased because the mean of error is 0. It is best since it aims at minimizing the variance of the errors. The difference of kriging and other linear estimation method is its aim of minimizing the error variance.

4.5 Regression Analysis

Regression analysis is used for explaining or modeling the relationship between a single variable *y*, called the response, an output or dependent variable, and one or more predictor, input, independent or explanatory variables, *x1*, ………, *xp*. When $p = 1$, it is called simple regression, but when $p > 1$ it is called multiple regression or sometimes multivariate regression. When there is more than one *y*, then it is called multivariate multiple regression. Regression analyses have several possible objectives including (Faraway 2002):

1. Prediction of future observations.
2. Assessment of the effect of, or relationship between, explanatory variables on the response.
3. A general description of data structure.

It can be linear as well as non-linear. The simplest multiple linear regression equation becomes:

$\Sigma = a + \varepsilon_i + \sum_{i=1}^{i=n} b_i \, x_i$

0where, quantities *b1, b2, …,bn* are termed partial regression coefficient. In multiple regression, as Type equation here.we are concerned with several variables, we can measures the effect of variations in the independent variable on those in the dependent variable by calculating an analogous measure *r*. This is called the coefficient of multiple determination. It can vary between -1 and 1 and it tells us what proportion of the observed variance of *y* is due to variations in *x1, x2, …, xn*. In other words, if the variance of all *n* independent variables fell to zero, then the variance of *y* would fall to a fraction *1- r* of its value. The magnitude of the regression coefficient denotes how strongly the *k* independent variables taken as a whole affect the independent variable *y*, and how strong their individual effects are relative to each other. The magnitude of the regression coefficients depends on the magnitude of the observations and thus on the units that we use to measure them. So, to compare coefficients for variables measured in different units, we can do this by using the method of standardization to calculate what are known as beta coefficients. For any given independent variable *xi* these are obtained by subtracting the average value of *xi* and then dividing the result by the standard deviation (σ *x*) of *x*.

So,

$$\beta_i = \{(x_i - x) \div \sigma_x\}$$

In some cases no appropriate transformation can be found, or it is necessary to examine the structure of the relationship between the variables in more detail. In these cases, the multiple non-linear regression method can be applied. The general form of multiple non-linear regression equation becomes:

$$y_i = a + \varepsilon_i + \sum_{i=1}^{n} b_i x_i^{c^1}$$

where, y for observation i 1, 2,3, , n i = μ +ε i = L and *i c* any real coefficient.

The criterion for estimating μ from the data is to determine the value of μ that minimizes the sum of squares:

$$\sum_{i=1}^{n} (y_i - \mu)^2$$

4.5.1 Justification of the Analysis

The accuracy and precision of the model results were validated by comparing predicted values to observed values and the results were evaluated using three different statistical procedures (Kreuger and Tornqvist, 1998), which are given below:

1. The correlation coefficient (*r*); a measure of the strength of the linear relationshipbetween the two variables, i.e. the degree of association between predicted and observed values, but not necessarily of their agreement (an r value close to 1.0 may occur even if the predicted values are twice as large as the observed values).

2. The mean difference (*M*) between observed and predicted values, along with the standard error of *M* (*SEM*); a measure of the degree of agreement, but not necessarily of their association (a perfect fit between observed and predicted values would result in a value of zero, but it may be positive or negative indicating a general tendency of the model for underpredicting or overpredicting the true values).1

$$M = \frac{1}{N}\sum_{i-1}^{N}(observed_i - predicted_i)$$

where, *N* is the number of pairs and the observedi and predictedi represent the individual data points.

3. The model efficiency (*ME*); an indicator of the overall agreement between predicted and observed data (a perfect fit would result in a value of 1.0, but a value greater than 0.5 can be said to be acceptable, while a negative value indicates an unacceptably poor fit where the model-predicted values are worse than simply using the observed mean).

$$ME = 1 - \frac{\sum(observed_i - predicted_i)^2}{\sum(observed_i - \bar{O})^2}$$

where, *O* represent the mean observed values.

Chapter 5

Results & Discussions

Chapter 5
RESULTS AND DISCUSSIONS

The set of data collected from CPCB was analysed and then the quality of River Yamuna was deduced . For a better understanding, each of the months has been denoted by a legend based on the prevailing climatic conditions. The legends and corresponding months are given in Table 5.1.

Table 5.1: Legends for the sampling months with corresponding seasons

S.No	Month	Legend
1	October	Receding Monsoon
2	December	Winter Season
3	February	Receding Winter Season

Use based classification of surface waters in India

The water quality management in India is performed under the provision of Water (Prevention and Control of Pollution) Act, 1974. The basic objective of this Act is to maintain and restore the wholesomeness of national aquatic resources by prevention and control of pollution. The Act does not define the level of wholesomeness to be maintained or restored in different water bodies of the country. The Central Pollution Control Board (CPCB) has tried to define the wholesomeness in terms of protection of human uses, and thus, taken human uses of water as base f or identification of water quality objectives for different water bodies in the country.
Thus, a concept of "designated best use" (DBU) was developed. According to this concept, out of several uses a water body is put to, the use which demands highest quality of water is termed as "designated best use", and accordingly the water body is designated. Primary water quality criteria for different uses have been identified. A summary of the use based classification system is presented in table -5.2.

S.No	Designated-Best-Use Criteria	Class of Water	Criteria
1	Drinking Water Source without conventional treatment but after disinfection	A	1. Total Coliforms OrganismMPN/100ml shall be 50 or less 2. pH between 6.5 and 8.5 3. Dissolved Oxygen 6mg/l or more 4. Biochemical Oxygen Demand 5 days 20o C 2mg/l or less
2	Outdoor bathing (Organised)	B	1. Total Coliforms Organism MPN/100ml shall be 500 or less 2. pH between 6.5 and 8.5 3. Dissolved Oxygen 5mg/l or more 4. Biochemical Oxygen Demand 5 days 20o C 3mg/l or less
3	Drinking water source after conventional treatment and disinfection	C	1. Total Coliforms Organism MPN/100ml shall be 5000 or less 2. pH between 6 to 9 3. Dissolved Oxygen 4mg/l or more 4. Biochemical Oxygen Demand 5 days 20o C 3mg/l or less
4	Propagation of Wild life and Fisheries	D	1. pH between 6.5 to 8.5 2. Dissolved Oxygen 4mg/l or more 3. Free Ammonia (as N) 1.2 mg/l or less
5	Irrigation, Industrial Cooling,	E	1. pH between 6.0 to 8.5

	Controlled Waste disposal		2. Electrical Conductivity at 25o C micro mhos/cm Max.2250 3. Sodium absorption Ratio Max. 26 4. Boron Max. 2mg/l

Depending upon Designated best use , the nine stations of River Yamuna has been categorized in classes in table 5.3 below .

S.No	Station	Class
1	Palla	B
2	Surajghat	C
3	Khajori Paltoon Pool	A
4	Kudesia Ghat	C
5	ITO Bridge	A
6	Nizamuddin Bridge	D
7	Agra Canal Okhla	E
8	Shahdara Drain	B
9	Agra Canal Jaitpur	C

5.1 Seasonal and Spatial Variations of Parameters

Table 5.2 summarizes the analyses results and basic statistics of the dataset. Further, the analytical results are also illustrated from Fig. 3.1(a) to Fig. 3.1(q), depicting the seasonal and spatial variations of selected parameters at the sampling sites. Seasonal variations were predominant for some of the parameters like conductivity, turbidity, hardness, dissolved oxygen, alkalinity, nitrate, and potassium, whereas the spatial variations were predominant for total dissolved solids and biochemical oxygen demand but there were few parameters like pH, phosphate, calcium and magnesium, for which the variations have been observed seasonally as well as spatially.

Table 5.4: Summary of Water Sample Analyses and Basic Statistics (concentration units in mgL^{-1}; conductivity in µS cm-1) of October 2013

Sampling Point	Basic Statistics	pH	EC	TDS	Hard-Ness	DO	BOD$_5$	HCO$_3^-$	Alka-Linity	Turb-Idity	PO$_4^{3-}$	Ca^{2+}	Mg^{2+}
1	A	8	153	166	45	6.6	0.2	78	189	9	0.34	14.4	3.4
	B	8.6	224	245	21	7.8	0.2	45	231	11.2	1.2	6.7	1.2
	C	7.2	145	103	11	9	0.24	78	212	11.4	0.6	11.2	2.2
	Avg	7.93	174	242.4	25.6	7.8	0.12	67	210.6	10.5	0.7	10.7	2.2
	Std Dev	0.57	35.5	136.2	14.2	0.9	0.05	15.5	17.1	1.0	0.3	3.1	0.8
2	A	7.1	244	221	33	5.4	0	67	221	11.2	1.4	12.3	1.5
	B	8.3	134	111	32	9.9	0.1	89	312	20	0.6	7.8	3.4
	C	8.2	223	50	54	8.9	0.06	67	123	18	0	14.4	1.2
	Avg	7.86	200.3	127.3	39.6	8.1	0.2	74.3	218.6	16.4	0.6	11.5	2.0
	std dev	0.54	47.6	70.7	10.1	1.9	0.1	10.3	77.1	3.7	0.5	2.7	0.9
3	A	7	234	221	21	10	0.6	15	310	9.6	0.6	14.6	3.6
	B	8	222	67	46	11.5	0.5	87	289	11.5	0.2	4.6	3.4
	C	8.2	123	133	23	7.8	0.2	76	213	15.5	1.5	9.4	3.3
	Avg	7.73	193	140.3	30	9.7	0.4	59.3	270.6	12.2	0.7	9.5	3.4
	std dev	0.52	49.7	63.0	11.3	1.5	0.1	31.6	41.6	2.4	0.5	4.0	0.1

Sampling Point	Basic Statistics	pH	EC	TDS	Hard-Ness	DO	BOD$_5$	HCO$_3^-$	Alka-Linity	Turb-Idity	PO$_4^{3-}$	Ca^{2+}	Mg^{2+}
4	A	7.8	247	124	22	4.6	0.8	88	211	14.8	0.45	12.3	1.2
	B	7.6	189	213	55	5.8	0	67	112	17.3	1.5	7	2.3
	C	8.8	222	89	25	7.8	0.1	35	230	12.3	0.23	11.2	3.1
	Avg	8.06	219.3	142	34	6.1	0.3	63.3	184.3	14.8	0.7	10.1	2.2
	std dev	0.52	23.7	52.1	14.8	1.3	0.3	21.7	51.7	2.1	0.5	2.2	0.7
5	A	6.6	123	222	22	8.8	0.2	54	175	11	0.89	14.4	1.2
	B	7.1	223	123	45	3.5	0.5	77	221	13.3	0.54	12.3	1.3
	C	7.6	165	103	12	6.9	0.24	54	212	16.2	1.3	6.6	2
	Avg	7.1	170.3	149.3	26.3	6.4	0.3	74.9	202.6	13.5	0.91	11.1	1.5
	std dev	0.40	40.9	52.0	13.8	2.1	0.1		19.9	2.1	0.3	4.2	0.3
6	A	7.8	239	108	13	7.1	0.5	45	123	11.2	1.4	12.3	3.3
	B	8.6	138	68	45	3.6	0	66	231	12.3	0.5	11.4	3.3
	C	7.8	231	231	23	6.7	0.6	77	246	11.2	0	4.8	1.2
	Avg	8.06	202.6	114.7	27	5.8	0.3	62.6	200	11.5	0.6	9.5	2.6
	std dev	0.37	45.8	70.1	13.3	1.5	0.2	14.2	54.7	0.5	0.5	3.3	0.9
7	A	6.6	213	156	21	4.9	0.12	89	121	17.7	1.2	12.3	1.2
	B	7.4	124	234	45	5.8	0.09	34	175	18.9	0.6	14.4	2.3
	C	7.5	265	18	13	7.8	0.45	78	189	19	0.2	10	2.1
	Avg	7.16	200.6	136	26.3	8.7	0.22	67	161.6	18.5	0.6	12.2	1.8

Sampling Point	**Basic Statistics**	**pH**	**EC**	**TDS**	**Hard-Ness**	**DO**	**BOD_5**	**HCO_3^-**	**Alka-Linity**	**Turb-Idity**	**PO_4^{3-}**	**Ca^{2+}**	**Mg^{2+}**
8	std dev	0.40	58.2	89.3	13.5	1.7	0.1	23.7	29.3	0.5	0.4	1.7	0.4
	A	8.3	145	234	13	6.8	0.23	67	212	11.2	1.8	13.3	1.2
	B	8.4	123	22	44	7.8	0.56	54	222	11.3	0.4	6.5	1.3
	C	7.6	223	170	34	6.1	0.01	13	234	14.4	1.2	8.7	4.2
	Avg	8.1	163.6	142	30.3	6.9	0.5	72.8	222.6	12.3	1.1	9.5	1.9
	std dev	0.35	42.9	88.7	12.9	0.6	0.2	26.9	8.9	1.4	0.5	2.8	0.9
9	A	8.5	222	211	11	7.1	0.2	78	133	10	1.2	14.8	1
	B	7.3	188	109	46	2.8	0.6	56	123	9.9	0.3	13.3	1.8
	C	7.8	223	48	32	5.9	0.4	33	145	9.8	0.5	11.2	1.9
	Avg	7.86	211	122.6	29.6	5.2	0.4	55.6	133.6	9.9	0.6	13.1	1.5
	std dev	0.49	16.2	67.2	14.3	1.8	0.1	18.3	8.9	0.1	0.3	1.4	0.4

Table 5.5: Summary of Sample Analyses & Basic Statistics (concentration in mgL^{-1}; conductivity in µS cm^{-1}) of December 2013

Sampling Point	Basic Statistics	pH	EC	TDS	Hard-Ness	DO	BOD$_5$	HCO$_3^-$	Alka-Linity	Turb-Idity	PO$_4^{3-}$	Ca^{2+}	Mg^{2+}
1.0	A	6.5	156.0	170.0	46.0	7.0	0.2	76.0	190.0	10.9	0.3	14.9	4.3
	B	8.4	189.0	244.0	13.0	7.7	0.2	46.0	232.0	11.4	1.3	7.1	1.5
	C	7.2	187.0	135.0	23.0	8.6	0.2	77.0	210.0	11.6	0.9	11.4	2.5
	Avg.	7.4	177.3	183.0	27.3	7.8	0.2	66.3	210.7	11.3	0.8		2.8
	std dev	0.8	15.1	45.4	13.8	0.7	0.0	14.4	17.2	0.3	0.4		1.2
2.0	A	8.3	232.0	225.0	37.0	6.0	0.3	76.0	222.0	11.2	1.5	14.2	1.5
	B	8.2	213.0	123.0	31.0	10.0	0.1	90.0	311.0	21.0	0.9	8.2	3.6
	C	8.4	123.0	89.0	54.0	7.0	0.1	61.0	134.0	18.9	0.8	14.5	1.3
	Avg.	8.3	189.3	145.7	40.7	7.7	0.2	75.7	222.3	17.0	1.1	12.0	2.1
	std dev	0.1	47.5	57.8	9.7	1.7	0.1	11.8	72.3	4.2	0.3	2.7	1.0
3.0	A	6.8	234.0	133.0	23.0	12.0	0.1	16.0	310.0	9.4	0.7	14.2	3.9
	B	7.2	127.0	56.0	43.0	10.0	0.4	67.0	289.0	11.5	0.2	4.3	4.2
	C	8.2	129.0	123.0	34.0	7.8	0.3	89.0	215.0	15.5	1.4	9.7	3.1
	Avg.	7.4	163.3	104.0	33.3	9.9	0.3	57.3	271.3	12.1	0.8	9.4	3.4
	std dev	0.6	50.0	34.2	8.2	1.7	0.1	30.6	40.7	2.5	0.5	4.0	0.4

Sampling Point	**Basic Statistics**	**pH**	**EC**	**TDS**	**Hard-Ness**	**DO**	**BOD$_5$**	**HCO$_3^-$**	**Alka-Linity**	**Turb-Idity**	**PO$_4^{3-}$**	**Ca^{2+}**	**Mg^{2+}**
4.0	A	8.8	176.0	145.0	23.0	4.6	1.0	87.0	217.0	15.6	0.5	13.3	1.5
	B	6.7	234.0	223.0	52.0	6.1	0.2	76.0	113.0	14.5	1.8	7.6	2.2
	C	7.3	222.0	176.0	26.0	7.4	0.3	35.0	231.0	12.3	0.3	11.2	3.6
	Avg.	7.6	210.7	181.3	33.7	6.0	0.5	66.0	187.0	14.1	0.9	10.7	2.4
	std dev	0.9	25.0	32.1	13.0	1.1	0.4	22.4	52.6	1.4	0.7	2.4	0.9
5.0	A	7.6	145.0	123.0	22.0	9.0	0.2	54.0	156.0	11.4	0.9	15.6	1.6
	B	6.7	135.0	342.0	54.0	4.0	0.5	51.0	227.0	12.9	0.5	11.9	1.4
	C	7.6	145.0	111.0	20.0	6.9	0.3	33.0	221.0	16.5	1.2	7.0	1.9
	Avg.	7.3	141.7	192.0	32.0	6.6	0.3	46.0	201.3	13.6	0.9	11.5	1.6
	std dev	0.4	4.7	106.2	15.6	2.0	0.1	9.3	32.1	2.1	0.3	3.5	0.2
6.0	A	8.3	233.0	89.0	14.0	7.2	0.5	31.0	134.0	11.7	1.3	11.4	4.2
	B	8.5	233.0	98.0	16.0	4.0	0.0	60.0	231.0	12.0	0.9	12.3	3.3
	C	7.4	231.0	134.0	23.0	6.8	0.5	7.0	245.0	11.0	0.3	5.0	1.5
	Avg.	8.1	232.3	107.0	17.7	6.0	0.3	32.7	203.3	11.6	0.8	9.6	2.7
	std dev	0.5	0.9	19.4	3.9	1.4	0.2	21.7	49.4	0.4	0.4	4.2	0.8

Sampling Point	**Basic Statistics**	**pH**	**EC**	**TDS**	**Hard-Ness**	**DO**	**BOD$_5$**	**HCO$_3^-$**	**Alka-Linity**	**Turb-Idity**	**PO$_4^{3-}$**	**Ca^{2+}**	**Mg^{2+}**
7.0	A	7.0	213.0	23.0	22.0	4.7	0.1	87.0	122.0	16.7	1.3	13.4	1.6
	B	7.6	145.0	56.0	43.0	6.0	0.1	32.0	173.0	18.9	0.7	14.2	1.7
	C	7.6	276.0	21.0	15.0	6.7	0.5	80.0	171.0	18.0	0.2	9.7	3.4
	Avg.	7.4	211.3	33.3	26.7	5.8	0.2	66.3	155.3	17.9	0.7	12.4	2.2
	std dev	0.3	53.5	16.0	11.9	0.8	0.2	24.4	23.6	0.9	0.4	2.0	0.8
8.0	A	8.9	213.0	234.0	14.0	6.8	0.5	60.0	231.0	11.3	1.0	12.9	1.1
	B	8.7	234.0	22.0	43.0	7.6	0.5	41.0	242.0	12.3	1.4	6.9	1.4
	C	7.6	223.0	170.0	33.0	6.1	0.2	13.0	234.0	15.1	1.2	8.3	3.3
	Avg.	8.4	223.3	142.0	30.0	6.8	0.4	38.0	235.7	12.9	1.2	9.4	1.9
	std dev	0.6	8.6	88.8	12.0	0.6	0.2	19.3	4.6	1.6	0.2	2.6	1.0
9.0	A	7.1	189.0	211.0	11.0	7.0	0.3	71.0	133.0	10.0	1.3	15.0	0.9
	B	7.3	188.0	109.0	44.0	2.9	0.4	54.0	123.0	9.9	0.4	13.4	2.0
	C	7.8	199.0	48.0	32.0	6.0	0.5	34.0	145.0	9.8	0.5	12.3	1.8
	Avg.	7.4	192.0	122.7	29.0	5.3	0.4	53.0	133.7	9.9	0.7	13.6	1.6
	std dev	0.3	5.0	67.2	13.6	1.7	0.1	15.1	9.0	0.1	0.4	1.1	0.5

Table 5.6: Summary of Sample Analyses & Basic Statistics (concentration: mgL-1; conductivity in µS cm-1) of February 2014

Sampling Point	Basic Statistics	pH	EC	TDS	Hard-Ness	DO	BOD$_5$	HCO_3^-	Alka-Linity	Turb-Idity	PO_4^{3-}	Ca^{2+}	Mg^{2+}
1.0	A	8.1	153.0	118.0	53.0	6.6	0.3	68.0	198.0	9.0	0.3	13.4	4.2
	B	7.8	189.0	245.0	23.0	7.8	0.2	45.0	243.0	11.2	1.1	7.6	1.3
	C	7.2	145.0	132.0	12.0	9.0	0.4	35.0	221.0	11.4	0.6	11.2	4.2
	Avg.	7.7	162.3	165.0	29.3	7.8	0.3		220.7	10.5	0.7		
	Std. Dev	0.4	19.1	56.9	17.3	1.0	0.1		18.4	1.1	0.3		
2.0	A	6.9	244.0	222.0	33.0	5.4	0.0	67.0	131.0	11.2	1.4	14.2	1.5
	B	8.8	134.0	112.0	33.0	9.9	0.0	78.0	312.0	20.0	0.6	7.8	4.3
	C	8.8	223.0	54.0	52.0	8.9	0.1	34.0	231.0	18.0	1.1	14.4	1.1
	Avg.	8.2	200.3	129.3	39.3	8.1	0.0	59.7	224.7	16.4	1.0	11.8	2.3
	Std. Dev	0.9	47.7	69.7	9.0	1.9	0.0	18.7	74.0	3.8	0.3	2.9	1.4
3.0	A	7.3	123.0	224.0	21.0	10.0	0.6	15.0	312.0	9.6	1.6	14.6	3.6
	B	7.9	222.0	62.0	46.0	11.5	0.0	65.0	222.0	11.5	0.2	5.4	4.0
	C	8.2	134.0	123.0	23.0	7.8	0.2	76.0	213.0	15.5	1.5	9.4	3.3
	Avg.	7.8	159.7	136.3	30.0	9.8	0.3	52.0	249.0	12.2	1.1	9.8	3.6
	Std. Dev	0.4	44.3	66.8	11.3	1.5	0.2	26.5	44.7	2.5	0.6	3.8	0.3
4.0	A	8.1	321.0	145.0	22.0	4.6	0.9	11.0	211.0	14.8	1.5	12.3	1.2
	B	7.9	198.0	234.0	55.0	5.8	0.0	67.0	121.0	17.3	0.5	8.1	5.0
	C	8.2	234.0	98.0	25.0	7.8	0.2	35.0	312.0	12.3	0.2	9.0	3.6
	Avg.	8.1	251.0	159.0	34.0	6.1	0.4	37.7	214.7	14.8	0.7	9.8	3.3
	Std. Dev	0.1	51.6	56.4	14.9	1.3	0.4	22.9	78.0	2.0	0.5	1.8	1.6

Sampling Point	**Basic Statistics**	**Ph**	**EC**	**TDS**	**Hard-Ness**	**DO**	**BOD$_5$**	**HCO$_3^-$**	**Alka-Linity**	**Turb-Idity**	**PO$_4^{3-}$**	**Ca^{2+}**	**Mg^{2+}**
5.0	A	6.6	167.0	222.0	22.0	8.8	0.2	11.0	178.0	11.0	1.0	14.4	1.2
	B	7.6	254.0	132.0	45.0	3.5	0.5	78.0	221.0	13.3	0.5	14.2	1.3
	C	7.6	176.0	134.0	12.0	6.9	0.3	53.0	213.0	16.2	2.3	7.6	2.6
	Avg.	7.3	199.0	162.7	26.3	6.4	0.3	47.3	204.0	13.5	1.3	11.7	1.7
	Std. Dev	0.5	39.1	42.0	13.8	2.2	0.1	27.6	18.7	2.1	0.7	3.0	0.6
6.0	A	8.1	239.0	181.0	13.0	7.1	0.1	42.0	134.0	11.2	1.4	12.3	3.3
	B	8.9	156.0	68.0	45.0	3.6	0.0	65.0	321.0	12.3	0.8	11.4	3.8
	C	7.8	213.0	201.0	23.0	6.7	0.5	77.0	246.0	11.2	0.0	0.0	2.1
	Avg.	8.3	202.7	150.0	27.0	5.8	0.2	61.3	233.7	11.6	0.7	7.9	3.1
	Std. Dev	0.5	34.7	58.6	13.4	1.6	0.2	14.5	76.8	0.5	0.6	5.6	0.7
7.0	A	6.6	203.0	143.0	21.0	4.9	0.2	90.0	131.0	17.7	1.2	12.3	2.2
	B	7.6	134.0	213.0	45.0	5.8	0.1	30.0	185.0	18.9	0.5	13.0	2.3
	C	7.9	245.0	81.0	13.0	7.8	0.1	78.0	189.0	19.0	0.3	10.0	2.5
	Avg.	7.4	194.0	145.7	26.3	6.2	0.1	66.0	168.3	18.5	0.7	11.8	2.3
	Std. Dev	0.6	45.8	53.9	13.6	1.2	0.1	25.9	26.4	0.6	0.4	1.3	0.1
8.0	A	8.3	145.0	213.0	13.0	6.8	0.2	61.0	231.0	11.2	1.8	14.0	1.6
	B	7.2	233.0	220.0	44.0	7.8	0.6	51.0	234.0	11.3	1.3	6.5	1.3
	C	8.9	123.0	170.0	34.0	6.1	0.0	23.0	234.0	14.4	1.3	9.0	3.9
	Avg.	8.1	167.0	201.0	30.3	6.9	0.3	45.0	233.0	12.3	1.5	9.8	2.3
	Std. Dev	0.7	47.5	22.1	12.9	0.7	0.2	16.1	1.4	1.5	0.2	3.1	1.2

Sampling Point	Basic Statistics	pH	EC	TDS	Hard-Ness	DO	BOD_5	HCO_3^-	Alka-Linity	Turb-Idity	PO_4^{3-}	Ca^{2+}	Mg^{2+}
9.0	A	8.5	231.0	112.0	11.0	7.1	0.2	76.0	143.0	10.0	0.0	14.8	1.0
	B	8.5	155.0	214.0	46.0	2.8	0.2	54.0	145.0	9.9	12.0	15.9	1.9
	C	8.7	221.0	84.0	32.0	5.9	0.4	35.0	154.0	9.7	1.4	12.2	1.9
	Avg.	8.6	202.3	136.7	29.7	5.3	0.3	55.0	147.3	9.9	4.5	14.3	1.6
	Std. Dev	0.1	33.7	55.9	14.4	1.8	0.1	16.8	4.8	0.1	5.4	1.6	0.4

5.1.1 Temperature

The measured temperature of the water reflected the changes corresponding to the altitude of the sites and the sampling seasons. Temperature profiles of the water at the sampling sites were similar and varied in the range 18°C (minimum) and 27°C (maximum). Always, sampling was done at the Delhi city side in the morning hours till noon; following an identical water stage and time of the day along

5.1.2 pH

Although not definitive, pH of the aquatic systems is an important indicator of water quality and extent of pollution. Geology of the watershed and original source of the water determine its initial pH. The greatest natural cause for change in pH in a stream is the seasonal and daily variation in photosynthesis. Fig. 3.1 illustrates the variation of pH at nine sites along the river.

Most of the water samples had a pH between 7 and 8 except receding monsoon and post monsoon period. During lean flow, the pH values were more or less consistent throughout, but during high flow it was fluctuating in nature. In all the sampling periods, at station 9 and further downstream the pH reduced abruptly. The seasonal variation of pH was clear. From monsoon period, the pH increased till the leanest flow period within a range between 7 and 8.8. The pH values of 7 to 8.8 indicate the alkaline nature of the water for all the sampling periods. In the leanest flow period, the value was at the highest and in pre monsoon period, it was again reduced due to the rise in discharge of flow. Some differences in pH values were observed over all seasons, between the points of entry and exit of the study area. **Subramanian (1979)** reported that an increase in alkalinity downstream for most Indian River irrespective of basin characteristics.

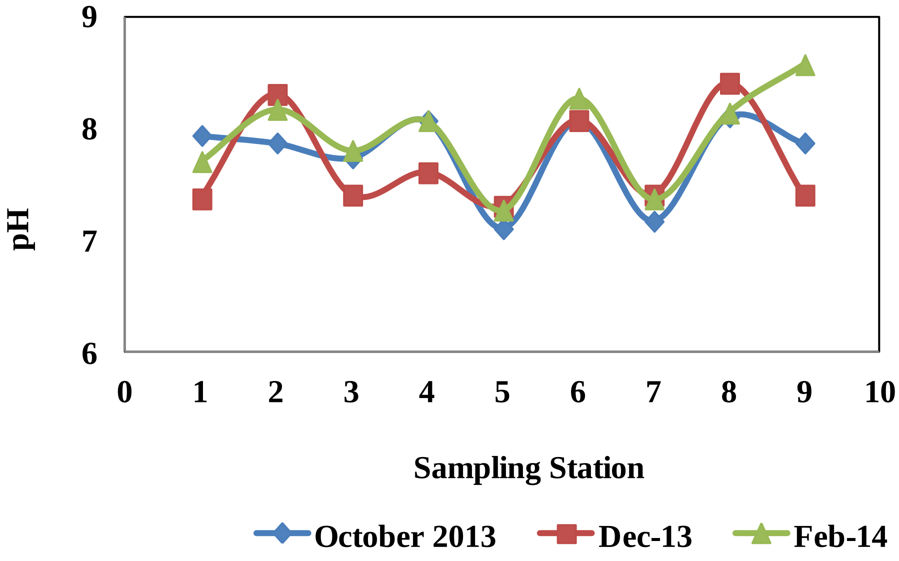

Figure 5.1: Seasonal variation of pH in the study area along downstream

5.1.3 Electrical Conductivity

Conductivity qualitatively reflects the status of inorganic pollution. The conductivity depends mainly on the solubility of rocks and soils that the water contacts. For instance, water that flows through limestone and gypsum dissolves calcium, carbonate and sulfate resulting in high levels of total dissolved solids. A failing sewage system could raise the conductivity because of the presence of chloride, phosphate and nitrate. Figure 4.2 illustrates the variation of conductance. Clearly, the conductivity of the different sets of samples was much different. Influences of city inputs were responsible for further variation in conductivity levels, particularly from location 7 onwards.

The relatively higher conductance values recorded during monsoon at site 5 could be due to the pollutants from the refinery sector-2 and fisheries. The sudden changes of 34 conductivity were observed at station point 10 during post monsoon and early dry season. The high ionic concentrations of waste discharge coming from Delhi city was mixed with river flow and showed the change of conductivity at the next downstream station points. But from the dry season onwards as the flow of the river was quite lean, similar changes commenced only at the station point 9 instead of 10. The highest value of conductivity was about 650µScm-1 during the leanest flow period and the lowest was 131µScm-1 during the receding monsoon period. An increase in conductivity suggests an increase in the ionic strength of the solution, which invariably indicates an increased concentration of major ions, often governed by concentrating or diluting effects of inflows with high or low TDS. The major direct concern associated with high dissolved salt concentrations relates to direct effects on the health of fish and other aquatic organisms. The average value of conductivity during the last sampling suddenly fell down (191µScm-1) comparative to earlier four samplings due to dilution by local precipitation during the last sampling.

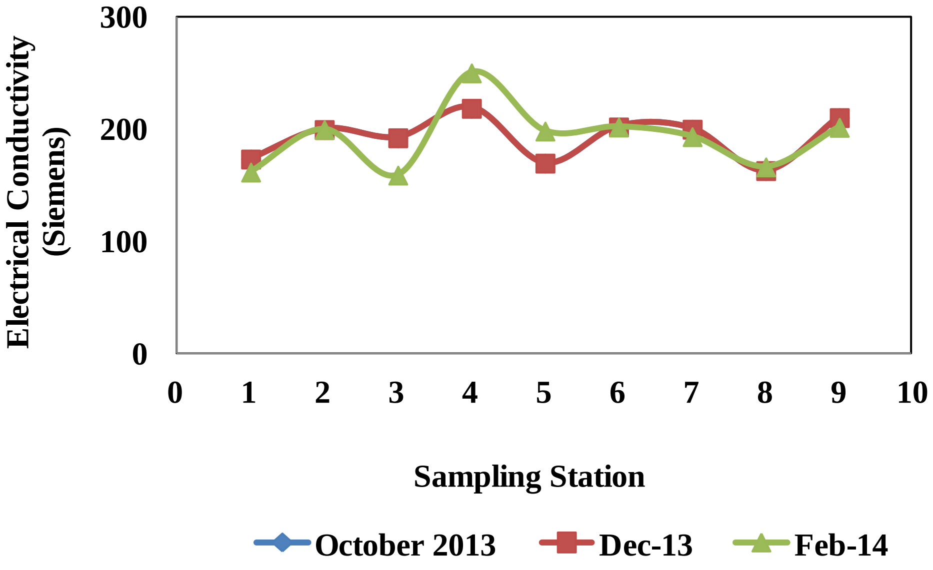

Figure 5.2: Seasonal variations of conductivity in the study area along downstream

5.1.4 Turbidity

Turbidity can be caused by soil erosion, waste discharge, urban runoff, bottom feeders like carp that stir up sediments, household pets playing in the water, and algal growth. Turbidity may be composed of organic and or inorganic constituents. Figure 3.3 illustrates the variation of turbidity values

The relatively high turbidity values were recorded during the monsoon and also in the receding monsoon period. This could be due to a high rainfall and the wash out accumulation from the large fallow land adjoining the upstream portion of the river. But in the lean flow period October to February), it showed a lesser turbidity values. Turbid waters become warmer as suspended particles absorb heat from sunlight, causing oxygen levels to fall. Photosynthesis decreases with lesser light, resulting in even lower oxygen levels.

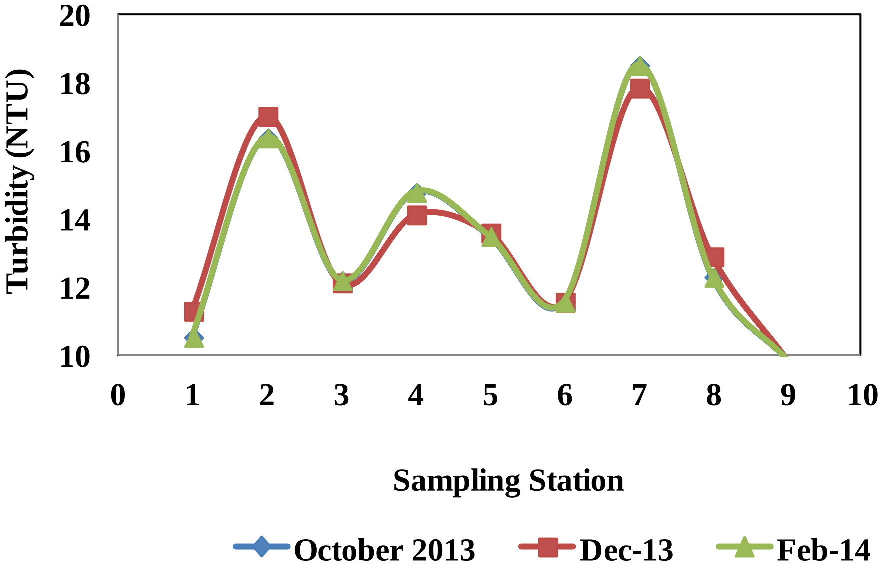

Fig. 5.3: Seasonal variations of TDS in the study area along downstream

5.1.5 Total Dissolved Solids (TDS)

Total dissolved solids may come from organic sources such as leaves, silt, plankton, and industrial waste and sewage. Other major sources are runoff from urban areas, and fertilizers and pesticides used on lawns and farms. Fig. 3.4 illustrates the variation of total dissolved solids

(TDS) concentration. The upstream sampling sites recorded relatively more TDS concentration for all the sampling periods. More initial dissolved inorganic materials could be due to soil erosion from the large fallow land. In the downstream sites, the reasons behind the less TDS values could be relatively less inorganic matter coming through the predominant by organic waste load containing raw sewage from the city compared to the original river concentration. During the monsoon period, at the stations 10, the TDS concentration is higher than the others stations because of the high inflow of sewage discharge coming from the city.

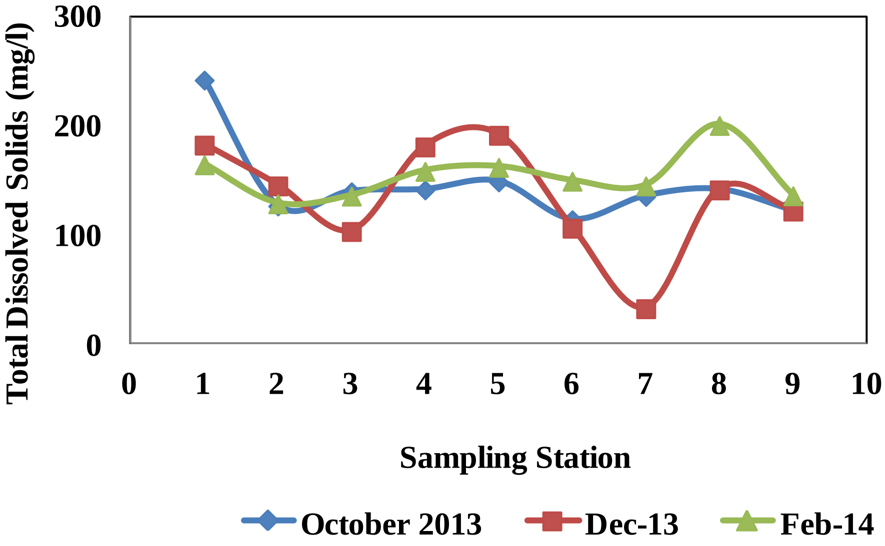

Fig. 5.4: Seasonal variations of TDS in the study area along downstream

5.1.6 Hardness

The hardness in water is derived largely from contact with soil and rock formations. Rainwater as it falls upon the earth is incapable of dissolving the tremendous amounts of solids found in many natural waters. In general, hard waters originate in areas where the topsoil is thin and limestones are sparse or absent. Figure 3.5 illustrates the variation of hardness. For the monsoon and receding monsoon periods, the total hardness varied in similar manner and at time the variation for all the station points were almost same because of very high flow.

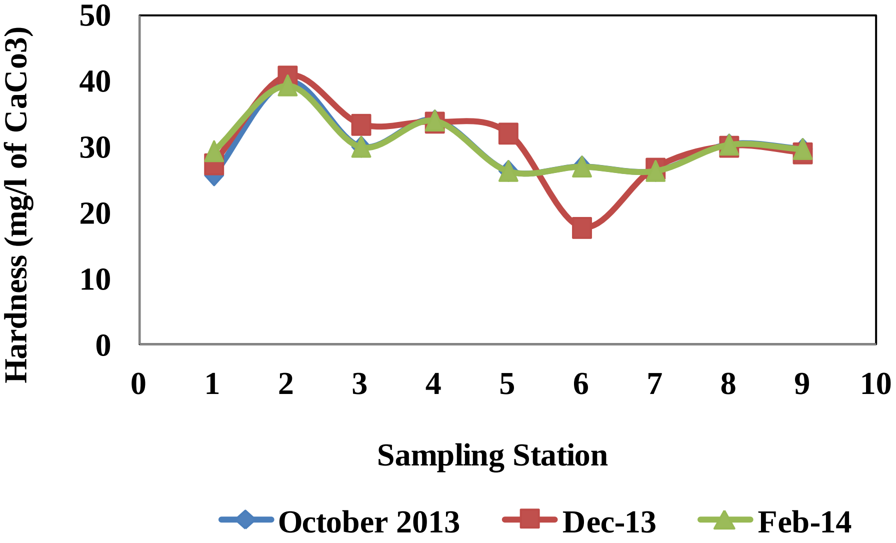

Fig. 5.5: Seasonal variations of hardness in the study area along downstream

For the remaining sampling periods the hardness varied in another similar pattern. It has been observed that the concentration of hardness increased up to the dry season with a maximum concentration of 45 mg/l as $CaCO_3$. During the leanest flow and pre monsoon, the concentration was reduced a little. The reason behind that could be due to addition of a little rainfall occurred in that period. In post monsoon, early dry season and dry season, the variations were almost consistent in nature because of the low flow in the river. During the last three sampling times (January to March) the abrupt change of hardness was observed at the station point 9 where the sewage was coming from Delhi city. The change of concentration has been observed clearly because of the lean flow. In the early dry season, this effect was observed at station 10 instead of 9, because of quite high flow. Though hard waters are as satisfactory for human consumption as soft waters, hardness does have an impact on the toxicity of other dissolved substances in the water, such as heavy metals, nutrients and low pH tolerance (**Sigma, 1983)**.

5.1.7 Dissolved Oxygen (DO)

In streams where a large portion of the organic matter is brought in from outside the stream, oxygen production and oxygen consumption are not balanced and low DO may become even more of a problem. Figure 3.6 illustrates the variation of dissolved oxygen. It is clear that the dissolved oxygen concentration has increased up to till dry season. It could be due to the plenty of photosynthesis in shallow depth river.

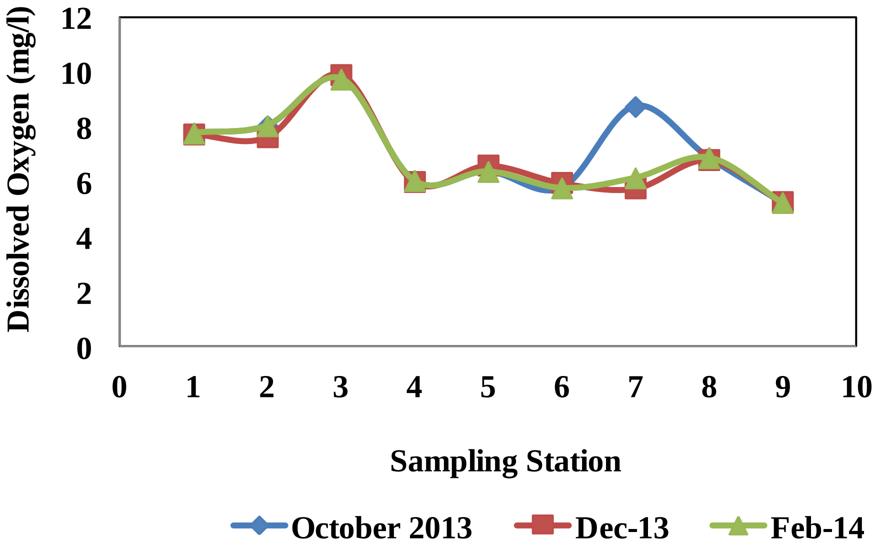

Fig. 5.6: Seasonal variations of DO in the study area along downstream

During leanest flow period and pre monsoon periods, the concentration reduced somewhat may be due to lesser precipitation. During the high flood period, the discharge was high, so the pollutants from different sources were thoroughly mixed. So, in the monsoon and receding monsoon period, the dissolved oxygen concentrations for all the sampling stations were almost same.

5.1.8 Biochemical Oxygen Demand (BOD_5)

Fig. 5.7 illustrates the variation of BOD_5. For all the sampling periods, BOD_5 values were generally negligible except for the station 7. It reflects very low burden of organic pollution on the particular stretch of the Yamuna River

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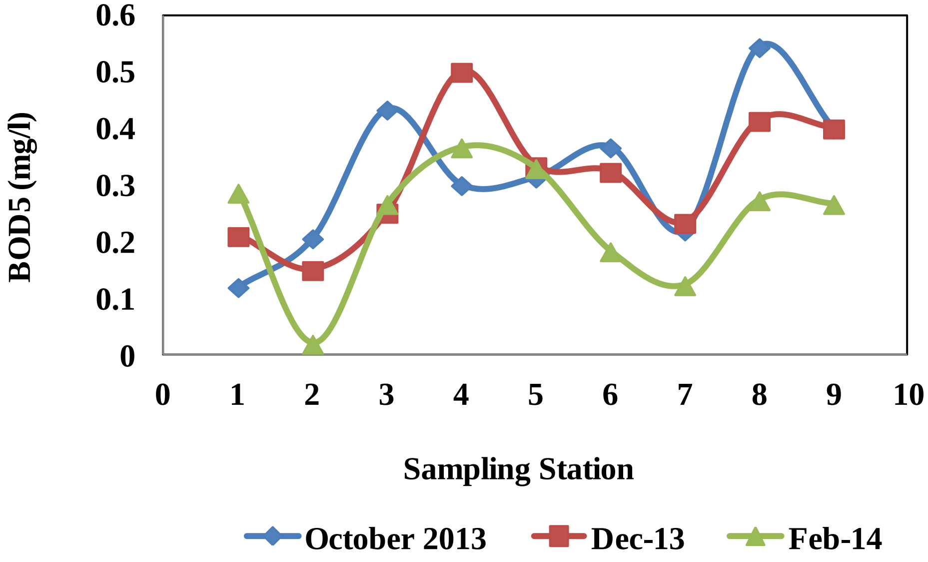


Figure 5.7: Seasonal variations of BOD_5 in the study area along downstream

As compared to high discharge of the main river during monsoon, the wastewater coming from Delhi city being negligible, the degree of pollution in respect to BOD5 is negligible. But from post monsoon period onwards the impact of sewage coming from Delhi city through Okhla was visible with peak value during the leanest flow period due to low dilution by a relatively lesser discharge in the main river. At Okhla confluence with high BOD5 levels, much of the available dissolved oxygen is consumed by aerobic bacteria, robbing other aquatic organisms of the oxygen they need to live. Organisms that are intolerant of low oxygen levels, such as caddishly larvae, mayfly nymphs and stonefly nymphs will not survive.

5.1.9 Alkalinity

In surface water, if there is algae growth, it contains appreciable quantities of carbonate and hydroxide alkalinity. Figure 3.8 illustrates the variation of alkalinity. All sampling sites recorded almost same alkalinity values. The concentration of alkalinity increased up to the early dry season. In early dry season and dry season, the average value of alkalinity was almost same and that was the highest observed (97mg/l as $CaCO_3$). The reflections due to addition of wastewater coming from Delhi city were observed from post monsoon period onwards.

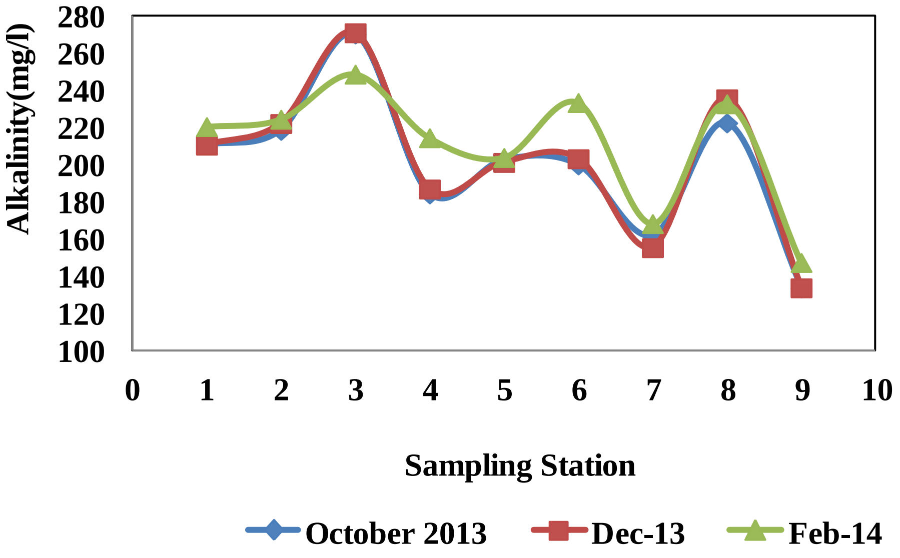


Fig. 5.8 : Seasonal variations of alkalinity in the study area along downstream

The concentration in the most upstream point was slightly higher than the most downstream point. It could be due to some addition coming from the large fallow land adjoining the upstream points. Alkalinity in excess of alkaline earth metal concentrations is significant in determining the suitability of water for irrigation. Highly alkaline waters are usually unpalatable.

5.1.10 Phosphate

The concentration of nutrients and the form those are found in, changes continually. First, the total input of nutrients varies depending upon land use and other factors. During the summer, nutrient input may increase due to fertilization of cropland and gardens. During the monsoon, high rainfall causes increased wash-off of organic matter such as leaves, twigs, grass and other debris.

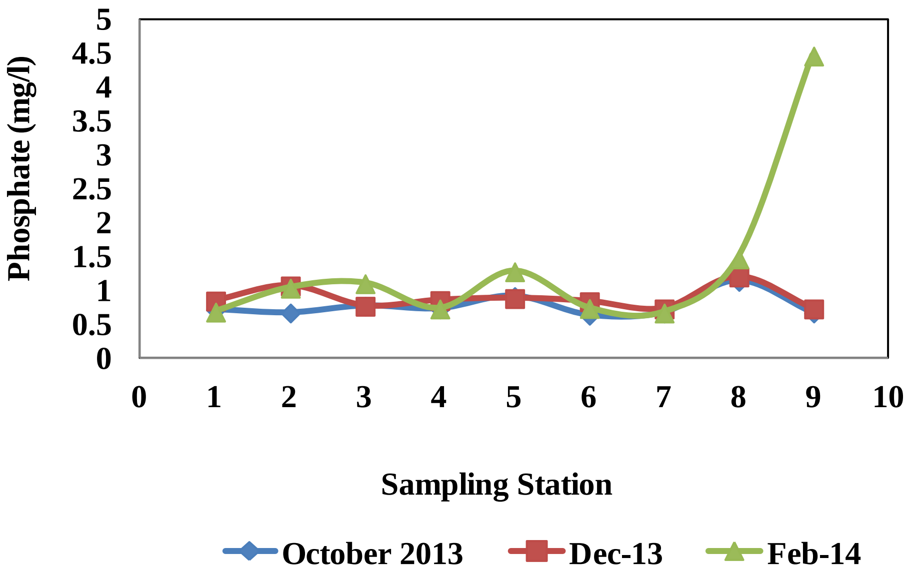


Fig. 5.9 : Seasonal variations of phosphate in the study area along downstream

In case of phosphate, During the receding monsoon period, the average concentration was observed relatively higher. The higher values were mainly observed in the upstream side. The reason could be similar to that for nitrate. During warmer month, nutrients entering the system, as intact organic matter would be decomposed relatively quickly as compared to cold, wet-weather months when decomposition is slow.

5.1.11 Calcium

Calcium is dissolved from most soils and rocks, especially limestone, dolomite and gypsum. It is sometimes referred to as lime. It is most commonly found in milk and milk products but also in vegetables, nuts and beans. Fig. 3.10 illustrates the variation of calcium concentrations. In all the sampling periods, the levels of calcium varied in a large scale i.e. between 8 - 15mg/L for most of the points. During monsoon and receding monsoon periods, the variation of concentration was in a erratic likely due to excessive flood. But from post monsoon onwards, it showed a consistent variation all along the stretch.

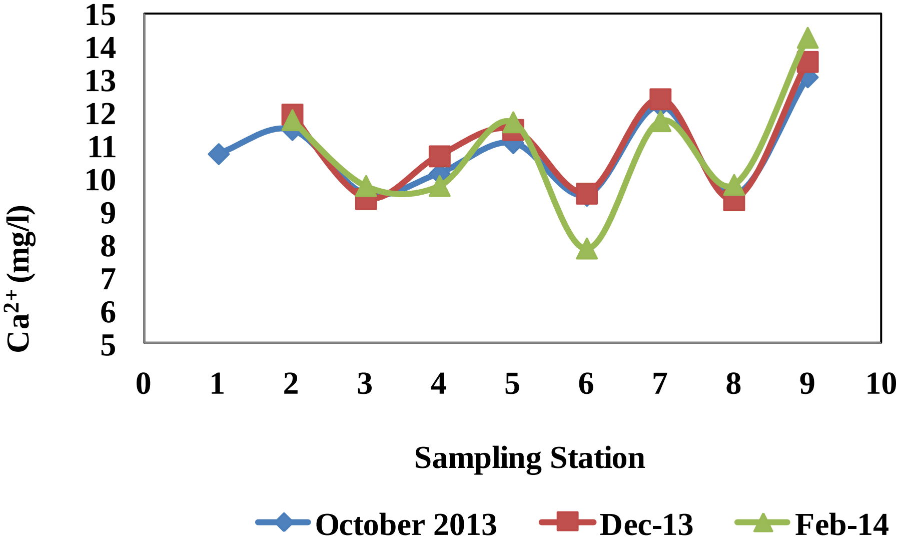


Figure 5.10: Seasonal variations of calcium in the study area along downstream

5.1.12 Magnesium

Magnesium is found as dissolved from most soils and rocks, especially limestone, dolomite and gypsum. Ca and Mg are found in some brine. Fig. 3.11 illustrates the variation of magnesium concentrations. From the graph, it has been observed that in the receding monsoon and the post monsoons, the levels of magnesium concentration were relatively higher than the other sampling. The minimum magnesium concentration was observed in the leanest flow period, as the main source of magnesium is soil and rocks. So in the lean flow period, the dissolution was lesser.

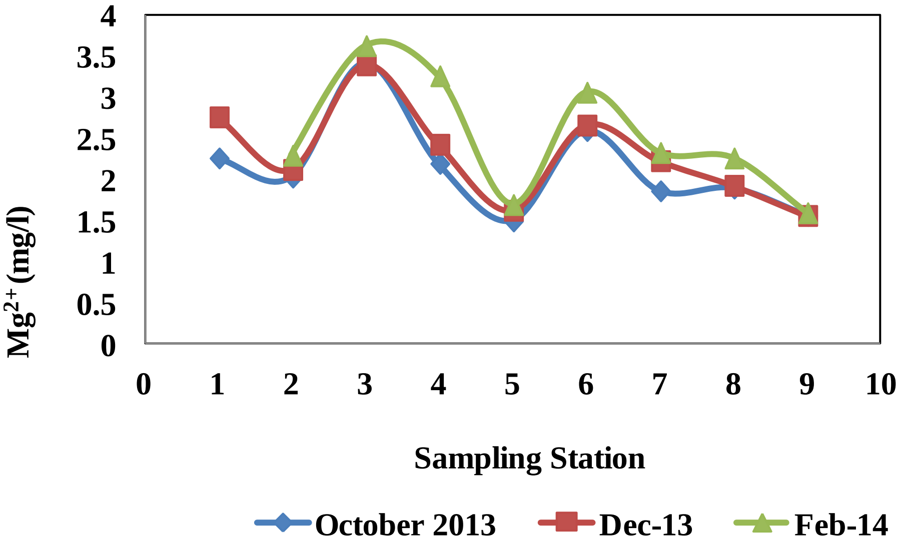


Fig. 5.11: Seasonal variations of magnesium in the study area along downstream

5.1.13 Discussion on Results

Considering all the parameters evaluated and their respective trends through different seasons from upstream to downstream, it can be concluded that though there have been local water quality perturbations due to waste water drainage from the city area, there has been little change between the first and the last sampling points due to natural dilution and attenuation of these additional inputs. However, water quality indicators like alkalinity and dissolved phosphates were apparently more impacted resulting in relatively erratic trends in the study area. All throughout, the inputs of the Okhla wastewater channel were clearly discernible, which was the main agent of localized quality degradation.

5.2 Analysis of the Observed Data, Based on Multiple Regressions

A range of water quality data were generated and examined in the present work for a comprehensive water quality evaluation. However as required, only a subset was selected for the WQI analysis. Now, to support and strengthen the findings so far, an analysis of the data, based on multiple regression, was attempted. This was done to examine whether seasonal or spatial variation in different parameters can be explained and predicted based upon their interrelationship in terms of source and mobility.

From analysis point of view, twelve parameters were selected to set up the regression model. The dependent variable was Electrical Conductivity (EC) and the independent variables were TDS, Na^+, K^+, Ca^{+2}, NO_3-, HCO_{3-}, $SO4^{-2}$, pH, $PO4^{-3}$, DO, and Hardness. The modeling has been done based on three different approaches:

5.3.1 Model: October

In this model the approach was to consider all the twelve parameters and all the sampling data for the entire study period. Based on that approach, the multiple linear regressions as well as the multiple non-linear regression analysis has been done. The final empirical equations observed from this model are given below:

$$\mathbf{EC = (253.8 + (0 \times pH) - (0.2 \times TDS) + (0.6 \times Hardness) - (14 \times DO) + (0 \times BOD_5) - (3.5 \times HCO_3\text{-}) + (0.49 \times Alkalinity) + (8.9 \times Turbidity) + (0 \times PO_4^{3-}) + (6.6 \times Ca^{2+}) + (0 \times Mg^{2+}))}$$

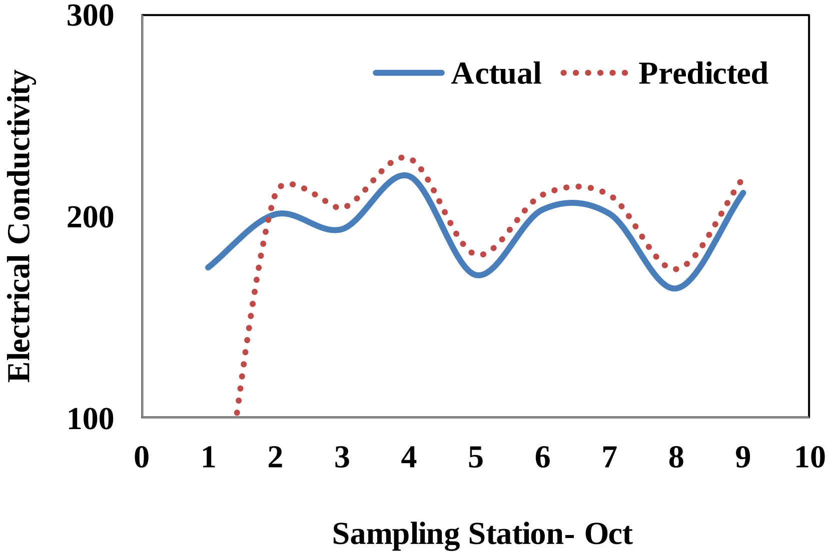


Figure 5.12: Comparison of actual and predicted data of electrical conductivity for October season

5.3.2 Model : November

In this model the approach was to consider all the twelve parameters and all the sampling data for the entire study period. Based on that approach, the multiple linear regression as well as the multiple non-linear regression analysis has been done. The final empirical equations observed from this model are given below:

$$\mathbf{EC = (326.5 + (49 \times pH) - (0.26 \times TDS) + (1.01 \times Hardness) + (0 \times DO) + (0 \times BOD_5) + (0.7 \times HCO_3^-) - (1.1 \times Alkalinity) - (2.3 \times Turbidity) + (0 \times PO_4^{3-}) - (27 \times Ca^{2+}) + (0 \times Mg^{2+}))}$$

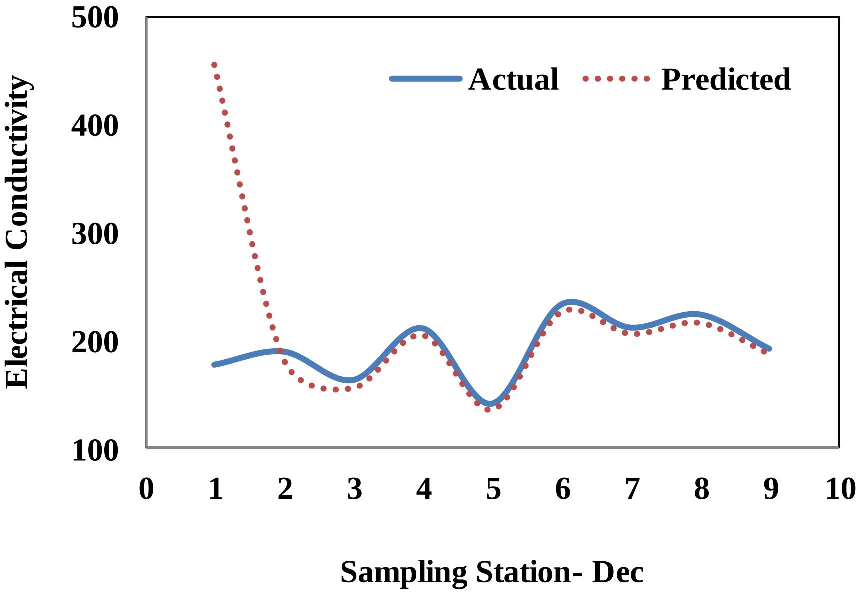


Figure 5.13: Comparison of actual and predicted data of electrical conductivity for December season

5.3.3 Model : February

In this model the approach was to consider all the twelve parameters and all the sampling data for the entire study period. Based on that approach, the multiple linear regression as well as the multiple non-linear regression analysis has been done. The final empirical equations observed from this model are given below:

$$EC = (506.3 + (0 \times pH) - (0.96 \times TDS) + (1.16 \times Hardness) - (19.9 \times DO) + (0 \times BOD_5) - (2.1 \times HCO_3^-) + (0.17 \times Alkalinity) + (3.96 \times Turbidity) + (0 \times PO_4^{3-}) - (3.05 \times Ca^{2+}) + (0 \times Mg^2))$$

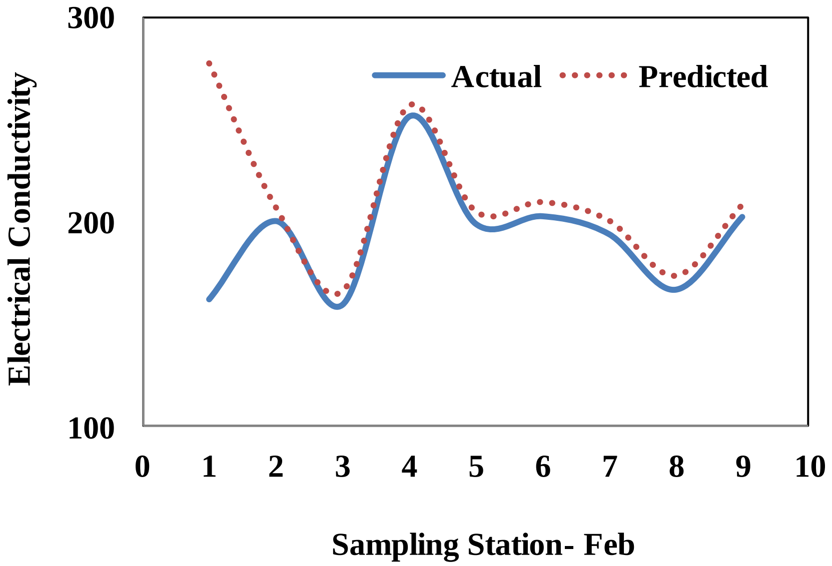


Figure 5.14: Comparison of actual and predicted data of electrical conductivity for February season

5.4Bacteriological water quality status of River Yamuna in Delhi Stretch

5.4.1 Introduction

The natural bacterial communities of freshwaters are largely responsible for the self purification processes which biodegrade organic matter. They are particularly important with respect to the decomposition of sewage effluents. However domestic sewage effluents also add to water bodies large numbers of certain bacterial species which arise from intestine. Presence of these bacteria presents significant health risks.

Coliform bacteria have been used for microbial analysis of drinking water, groundwater, food, pharmaceuticals, freshwater, marine water and other environmental samples. The coliform group refers to Gram –ve, non-spore forming oxidase, rod shaped bacteria capable of growth in the presence of bile salts or other surface-active agents. This group is able to ferment lactose at 35 □□0.5ºC with the production of acid, gas and aldehyde within 24-48 hrs. Faecal coliforms are among the coliform group of bacteria present in the alimentary canal and faeces of warm blooded animals capable of producing gas from lactose in a suitable culture medium at 44.5 □□0.2ºC for 24 hrs.

CPCB has laid down a primary water quality criteria presently under revision) limits of total coliform organisms in various water quality classes defined on basis of their designated best use (Table 3). In the present study, bacteriological water quality status of River Yamuna on both of its banks subjected to diverse anthropogenic activities has been discussed

5.7 Table : -Primary water quality criteria limits of total coliform.

Total coliform organisms MPN/100 ml, Max.	**Water quality class based on designated best use**				
	A (Drinking water source without conventional treatment but after disinfection)	**B** (Outdoor bathing)	**C** (Drinking water source with conventional treatment & disinfection)	**D** (Propagation of wildlife)	**E** (Irrigation, industrial cooling, controlled waste disposal)
	50	500	5000	-	-

Source : CPCB, 2001-2002

Table 5.8 : Average, maximum and minimum bacteriological count of the water quality of river Yamuna in Delhi (2002).

Location	Faecal Coliform (MPN/100ml)			Total Coliform (MPN/100ml)		
	Min	**Max**	**Avg**	**Min**	**Max**	**Avg**
1	900	8000	2795	9000	120000	47000
2	79000	190000000	31786556	380	5000000	2351938
3	21000	2000000	943273	1060000	58000000	13986000
4	24000	16000000	3381000	450000	197000000	177596875
5	10000	7000000	1150500	680000	18700000	9523333
6	40000	1100000	363333	200000	110000000	11882500
7	20000	7800000	1850750	120000	50000000	12622500
8	900	19000	6400	10000	350000	120850
9	20000	890000	312400	400000	22500000	6450000

5.5 Conclusions

The results indicated increase in bacterial total count from upstream to downstream stretch of river Yamuna. However the bacterial count at any location depends on hydrological condition, anthropogenic activities prevalent on that location at the time of sampling as well as on the discharges. Bacteriological assessment for any location cannot be compared as the bacteriological water quality is subjected to

frequent changes. Summer months with reduced water content and flow in the river supported the acterial survival. Contribution of high bacterial counts in the river was beyond to the limits specified in the primary water quality criteria of CPCB. Total and faecal coliform count at upstream reference location at Palla was observed to be less than the downstream locations indicating less anthropogenic influence.

was influenced by the backflow of Najafgarh drain. Pre-monsoon, monsoon and Post-monsoon effect in bacterial water quality was also observed in the study. The bacterial count at all the locations was reduced tremendously in the monsoon months due to flushing effect, while count was high in the Pre-monsoon month due to receiving of surface runoffs. The bacterial count again increases in the post monsoon period with reduced water flow. Minimum bacterial counts were observed in the monsoon months of October and September.

The study infers that the bacterial water quality assessment depends totally on hydrological conditions along with the natural or man-made activities influencing the water body at the time of sampling and does not provide an integrated effect of pollution prevalent in the water body. Bacteriological assessment is time and space specific. Sampling point may not be the actual origin of the bacterial population and hence cannot serve as pollution indicator of water quality at particular location.

Chapter 6

Analysis of Water Quality Data through Aq.QA Software

Chapter 6

ANALYSIS OF WATER QUALITY DATA THROUGH Aq.QA SOFTWARE

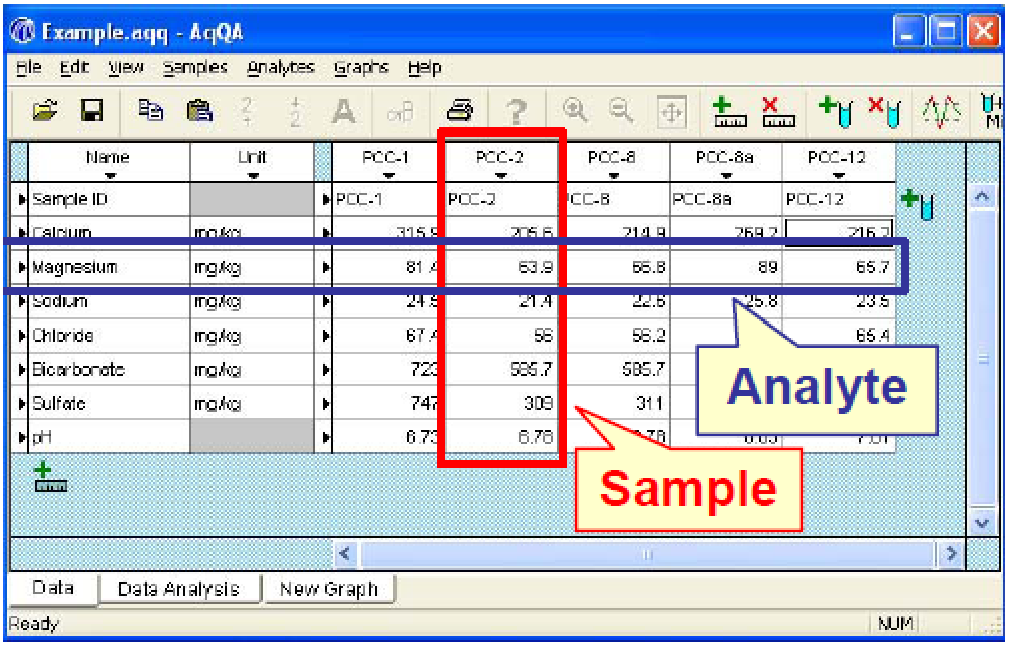
6.1 About Aq•QA

Imagine you could keep the results of your chemical analyses in a spreadsheet developed especially for the purpose. A spreadsheet that knows how to convert units, check your analyses for internal consistency, graph your data in the ways you want it graphed, and so on. A spreadsheet like that exists, and it's called Aq•QA. Aq•QA was written by water chemists, for water chemists. Best of all, it is not only powerful but easy to learn, so you can start using it in minutes. Just copy the data from your existing ordinary spreadsheets, paste it into Aq•QA, and you're ready to go.

6.1.1 Data Sheet

When you start Aq•QA, you see an empty Data Sheet. Click on **File** → **Open…**, move to directory "\Program Files\AqQA\Examples" and open file "Example1.aqq".

The example Data Sheet

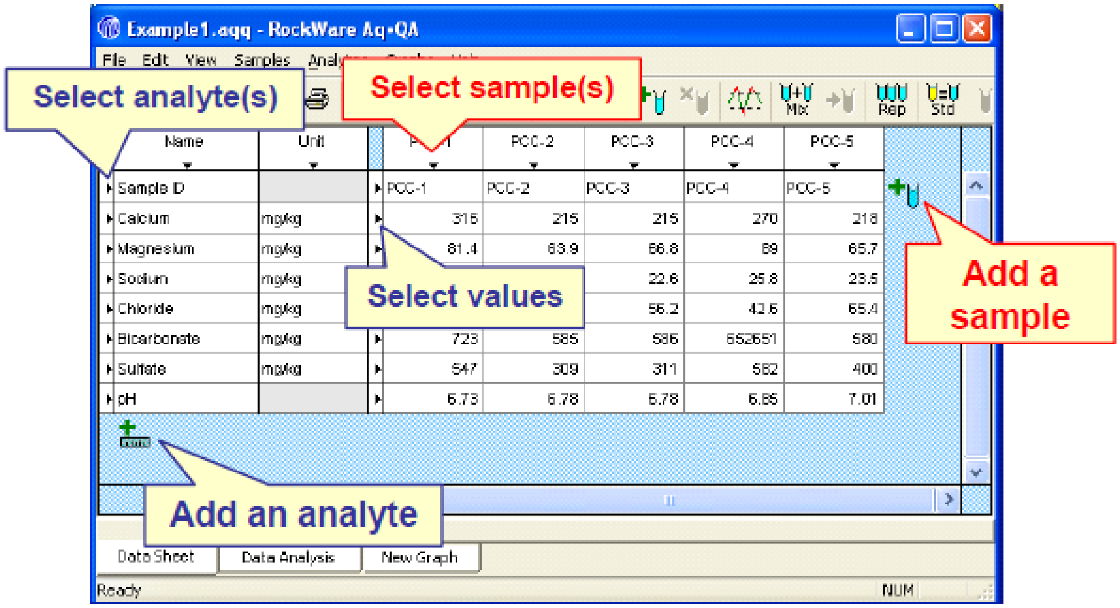


Name	Unit	PCC-1	PCC-2	PCC-8	PCC-8a	PCC-12
Sample ID		PCC-1	PCC-2	CC-8	PCC-8a	PCC-12
Calcium	mg/kg	315.9	205.6	214.9	269.2	216.2
Magnesium	mg/kg	81.4	63.9	66.8	89	65.7
Sodium	mg/kg	24.9	21.4	22.6	25.8	23.5
Chloride	mg/kg	67.4	56	56.2	[illegible]	65.4
Bicarbonate	mg/kg	723	585.7	585.7	[illegible]	[illegible]
Sulfate	mg/kg	747	309	311	[illegible]	[illegible]
pH		6.73	6.78	[illegible]	[illegible]	[illegible]

Fig 6.1 The Data Sheet

is arranged with samples in columns, and analytes – the things you measure – in rows.

You can flip an Aq•QA Data Sheet so the samples are in rows and analytes in columns by selecting **View** → **Transpose Data Sheet**. Click on this tab again to return to the original view. To include more samples or analytes in your Data Sheet, click on the "Add Sample" or "Add Analyte" button:



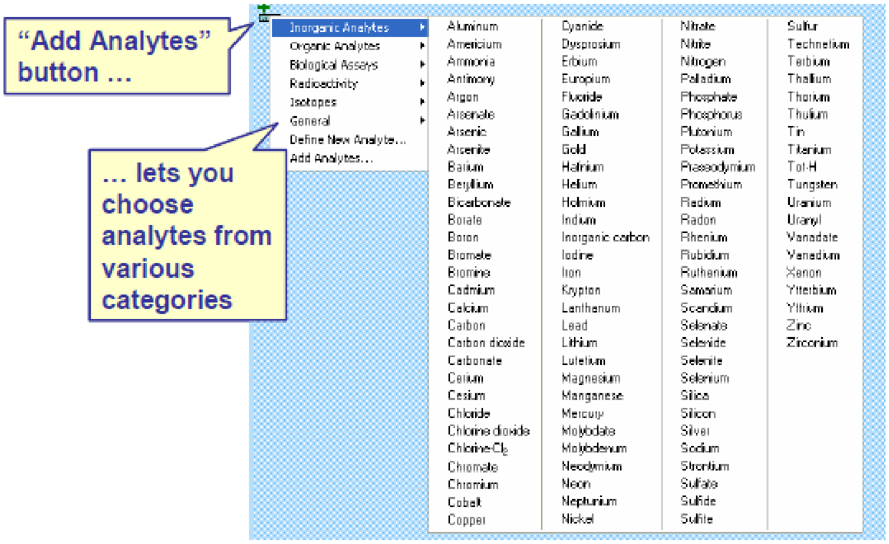
Name	Unit	P 1	PCC-2	PCC-3	PCC-4	PCC-5
Sample ID		PCC-1	PCC-2	PCC-3	PCC-4	PCC-5
Calcium	mg/kg	316	215	215	270	218
Magnesium	mg/kg	81.4	63.9	56.8	89	65.7
Sodium	mg/kg	[illegible]	[illegible]	22.6	25.8	23.5
Chloride	mg/kg	[illegible]	[illegible]	56.2	42.6	65.4
Bicarbonate	mg/kg	723	585	586	652651	580
Sulfate	mg/kg	547	309	311	562	400
pH		6.73	6.78	6.78	6.85	7.01

Fig 6.2 Analyte Analysis

You select analytes or samples by clicking on "handles", marked in the Data Sheet by small triangles. You can select the values associated with an analyte using a separate set of handles, next to the "Unit" column.

6.1.2 Entering Data

To see how to enter your own data into an Aq•QA Data Sheet, begin by selecting **File** → **New**. Add to the Data Sheet whatever analytes you need, and delete any you don't need. When you click on the "Add Analyte" button, you can pick from among a number of predefined choices in various categories, such as "Inorganic Analytes", "Organic Analytes", and so on:



"Add Analytes" button …

… lets you choose analytes from various categories

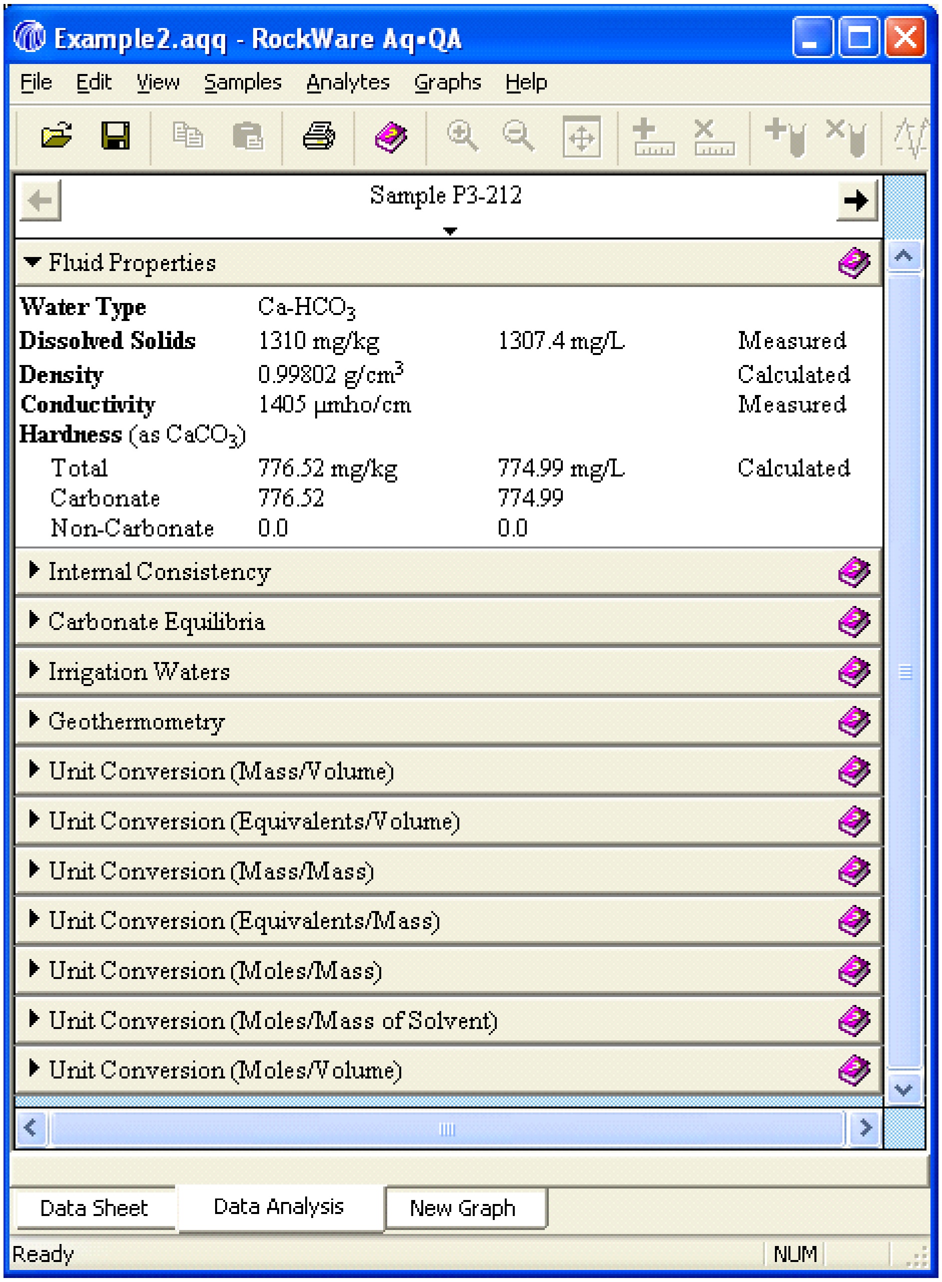
Fig 6.3 Analyte Category

A number of commonly encountered data fields (Date, pH, Temperature, …) can be found in the "General" category.

6.1.3 Working With Data

Once you have entered your chemical analyses in the Data Sheet, Aq•QA can tell you lots of useful information.

Click on **File** → **Open…** and load file "Example2.aqq" from directory "\Program Files\AqQA\Examples". To see Aq•QA's analysis of one of the samples in the Data Sheet, select the sample by clicking on its handle and then click on the Data Analysis tab. This moves you to the Data Analysis pane, which looks like



Water Type	Ca-HCO_3		
Dissolved Solids	1310 mg/kg	1307.4 mg/L	Measured
Density	0.99802 g/cm^3		Calculated
Conductivity	1405 µmho/cm		Measured
Hardness (as $CaCO_3$)			
Total	776.52 mg/kg	774.99 mg/L	Calculated
Carbonate	776.52	774.99	
Non-Carbonate	0.0	0.0	

Fig 6.4 Data Analysis

There are a number of categories in the Data Analysis pane. To open a category, click on the corresponding bar. A second click on the bar closes the category.

The top category, **Fluid Properties**, identifies the water type, dissolved solids content, density, temperature-corrected conductivity, and hardness, as measured or calculated by Aq•QA.

The next category, **Internal Consistency**, reports the results of a number of Quality Assurance tests from the American Water Works Association “Standard Methods” reference. For example, Aq•QA checks that anions and cations balance electrically, that TDS and conductivity measurements are consistent with the reported fluid composition, and so on.

The **Carbonate Equilibria** category tells the speciation of carbonate in solution, carbonate concentration calculated from measured titration alkalinity and vice-versa, the fluid's calculated saturation state with respect to the calcium carbonate minerals calcite and aragonite, and the calculated partial pressure of carbon dioxide.

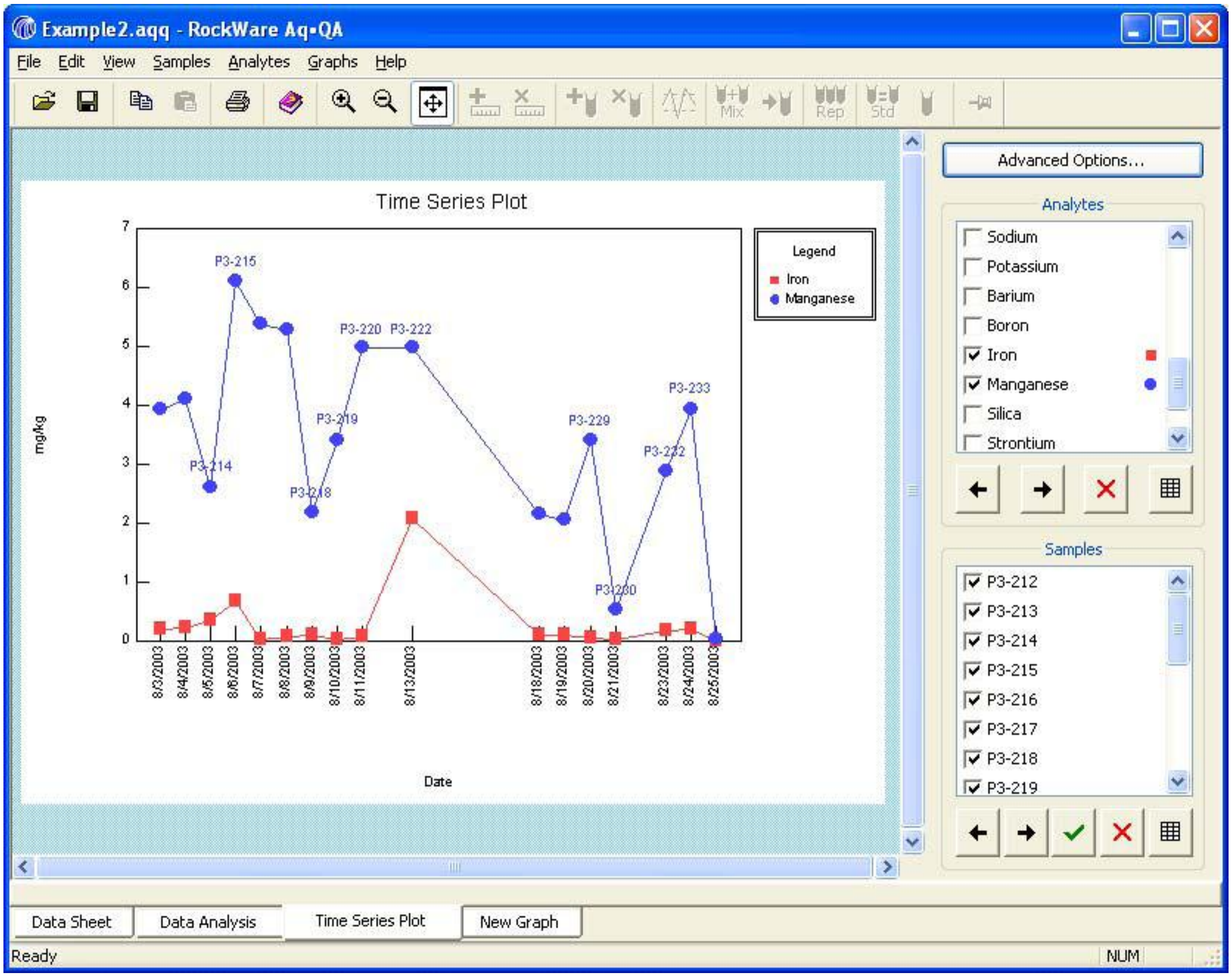
The **Irrigation Waters** category shows the irrigation properties of a sample, and the **Geothermometry** category shows the results of applying chemical geothermometers to the samples, assuming they are geothermal waters. Finally, the sample's analysis is displayed in a broad range of units, from mg/kg to molal and molar

6.1.4 Graphing Data

Aq•QA can display the data in your Data Sheet on a number of the types of plots most commonly used by water chemists. To try your hand at making a graph, make sure that you have file "Example2.aqq" open. If not, click on **File → Open…** and select the file from directory "\Program Files\AqQA\Examples".

On the Data Sheet, select the row for Iron. Hold down the **ctrl** key and select the row for Manganese. Click on New Graph and select **Time Series Plot**. The graph appears in Aq•QA as a new pane.

The result should look like:



Analytes

☐ Sodium
☐ Potassium
☐ Barium
☐ Boron
☑ Iron
☑ Manganese
☐ Silica
☐ Strontium

Samples

☑ P3-212
☑ P3-213
☑ P3-214
☑ P3-215
☑ P3-216
☑ P3-217
☑ P3-218
☑ P3-219

Fig 6.5 Time Series Plot

You can select the analytes and samples to appear in the graph on the control panel to the right of the plot. Right clicking on the pane’s tab, along the bottom of the Aq•QA window, lets you change the plot to a different type, or delete it.

Aq•QA can display your data on a broad variety of graphs and diagrams: simply choose a diagram type from the pulldown. In addition to Time Series plots, Aq•QA can produce the following types of diagrams:

Series Diagrams.

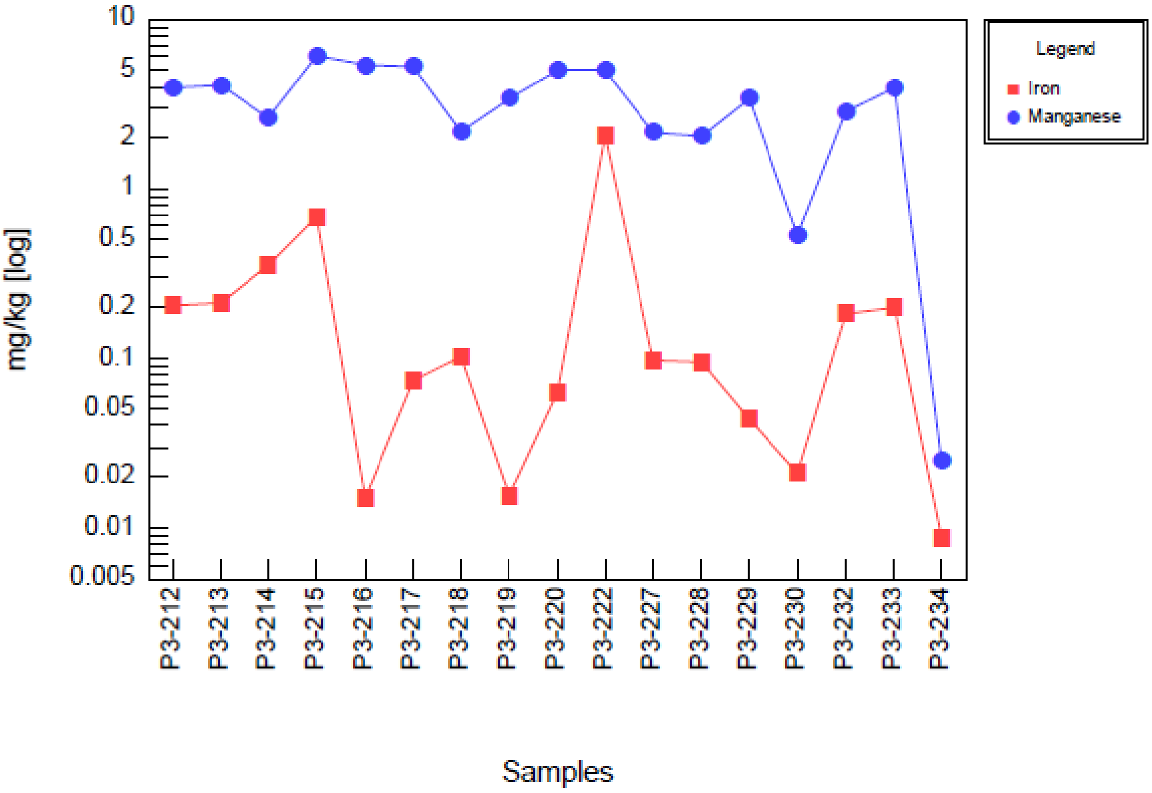
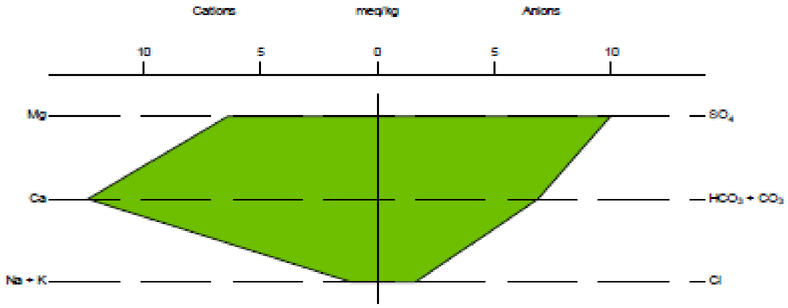


Fig 6.6 Series Diagrams

Stiff diagrams.



Radial diagrams.

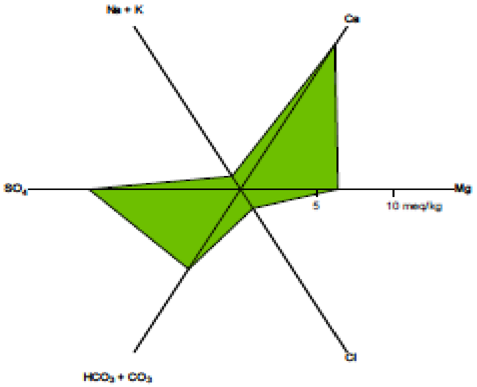
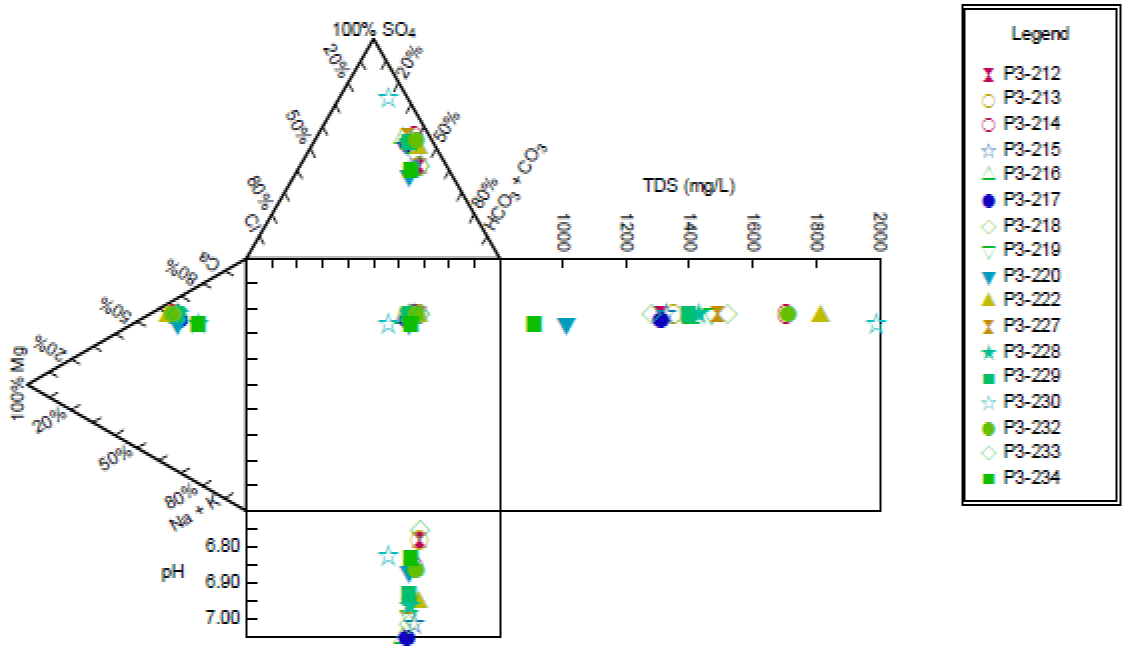
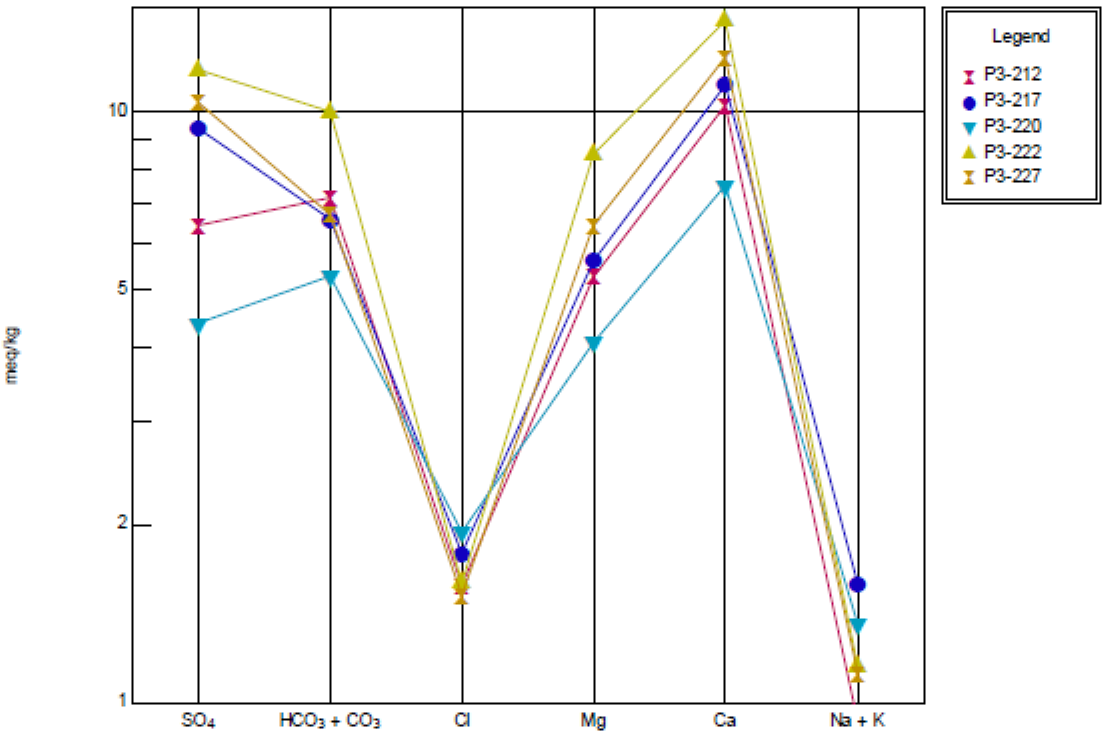


Fig 6.7 Stiff & Radial Diagrams

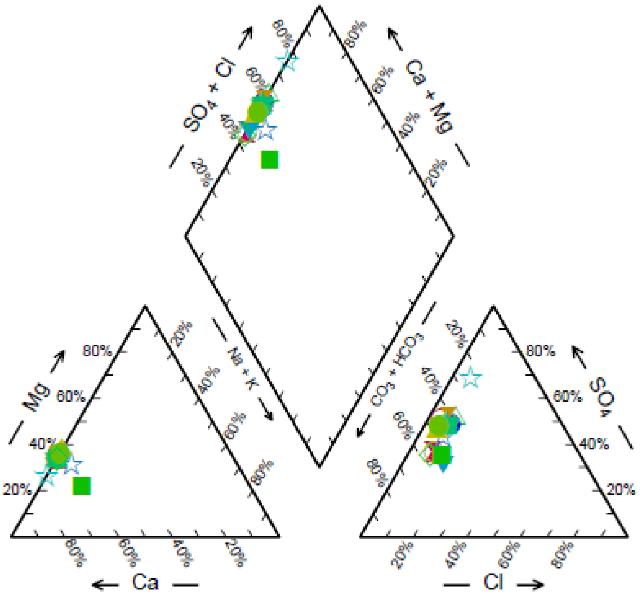
Durov diagrams.



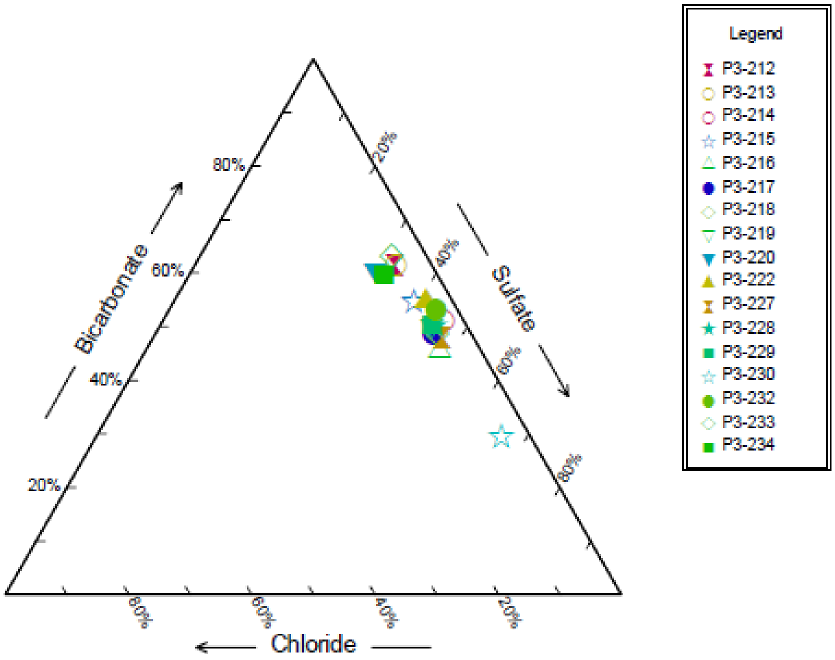
Schoeller diagrams.



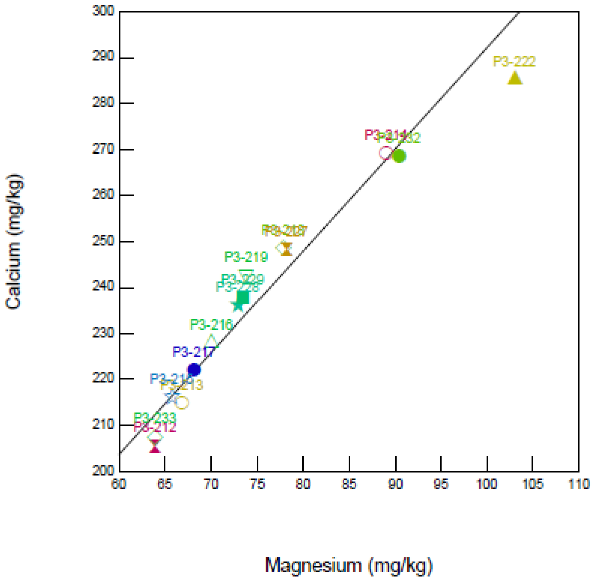
Piper diagrams.



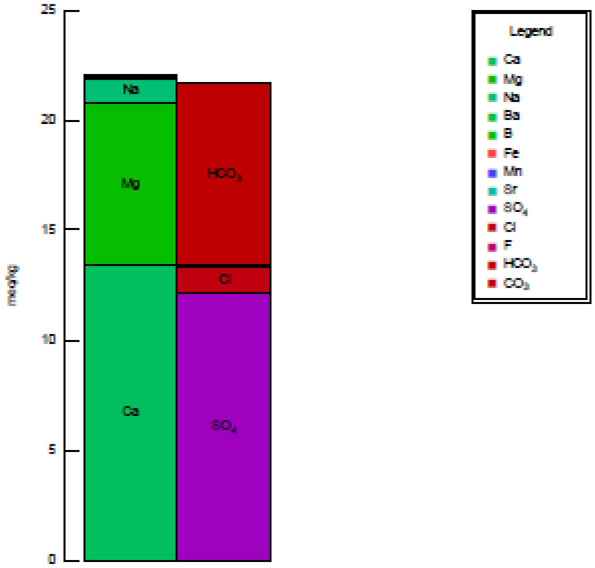
Ternary diagrams.



Cross Plots, in linear and logarithmic coordinates.



Ion balance diagrams.



Pie charts.

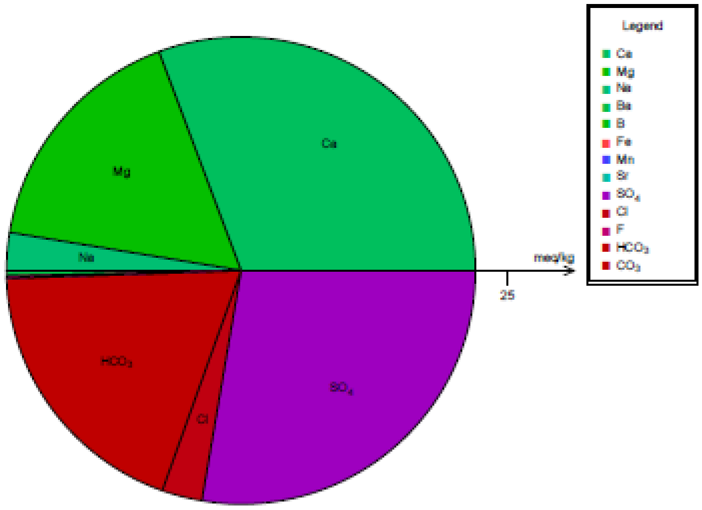


Fig 6.8 Ternary Diagrams , Cross Plots , Ion balance diagrams & Pie Charts

6.2 The Data Sheet

6.2.1 About the Data Sheet

The Aq•QA® Data Sheet is a special spreadsheet that holds your chemical data. The data is typically composed of the values measured for various analytes, for a number of samples. You can enter data into a Data Sheet and manipulate it, as described below.

6.2.2 Creating a New Data Sheet

To create a new Aq•QA Data Sheet, select **File → New**, or touch **ctrl+N**. An empty Data Sheet, containing a number of analytes, but no data, appears. The appearance of new Data Sheets is specified by a template. You can create your own template so new Data Sheets contain the analytes you need, in your choice of units, and ordered as you desire. For more information, see **Template for New Data Sheets** in the **Tapping AqQA's Power** chapter of this guide.

6.2.3 Opening an Existing Data Sheet

Aq•QA files end with the extension ".aqq". These files contain the data entered in the Data Sheet, as well as any graphs produced and the program's current configuration.

You can open an existing Data Sheet by clicking on **File → Open…** and selecting a ".aqq" file, either one that you have previously saved or an example file installed with the Aq•QA package. A number of example files are installed in the "Examples" directory within the Aq•QA installation directory (commonly "\Program Files\AqQA").

6.2.4 Layout of the Data Sheet

An Aq•QA Data Sheet contains the values measured for various analytes (Na+, Ca2+, HCO3
−, and so on) for any number of samples that have been analyzed. Each piece of information about a sample is considered an analyte, even sample ID, location, sampling date, and so on.

By default, each analyte occupies a row in the Data Sheet, and the samples fall in columns. You can reverse this arrangement, so analytes fall in columns and the samples occupy rows, by clicking on **Edit →Transpose Data Sheet**. To flip the Data Sheet back to its original arrangement, click on this tab a second time.You can rearrange the order of analytes or symbols on the Data Sheet, as described below under **Reordering Rows and Columns**.

6.2.5 Selecting Rows and Columns

To select a row or column, click on the marker to the left of a row, or the top of a column. The marker for a row or column appears as a small triangle. Analytes have two markers, one for selecting the entire analyte, and one for selecting only the analyte's data values. You can select a range of rows or columns by holding down the left mouse button on the marker at the beginning of the range, then dragging the mouse to the marker at the end of the range. Alternatively, select the beginning of the range, then hold down the **shift** button and click on the marker for the end of the range.

To select a series of rows or columns that are not necessarily contiguous on the Data Sheet, select the first row or column, then hold down the **ctrl** key and select subsequent rows or columns. By clicking on one of the small blue squares at the top or left of the Data Sheet, you can select either the entire sheet, or all of the data values on the sheet.

6.2.6 Reordering Rows and Columns

You can easily rearrange the rows and columns of samples and analytes in your Data Sheet. To do so, first select a row or column, or a range of rows and columns, as described under **Selecting Rows and Columns**. Then, holding down the **alt** key, press the left mouse button, drag the selection to its new position, and release the mouse button.

6.2.7 Adding Samples and Analytes

To include more samples or analytes in your Data Sheet, select on **Samples → Add Sample**, or **Analytes → Add Analyte**, or simply click on the or buttons on the toolbar. To add several analytes at once, select **Analytes → Add Analytes…**, which opens a dialog box for this purpose. When you add an analyte, you choose from among the large number that Aq•QA knows about. These are arranged in categories: inorganics, organics, biological assays, radioactivity, isotopes, and a general category that includes things like pH, temperature, date, and sample location.

If you don't find the analyte you need, you can quickly define your own.

Select **Analytes → New Analyte…**, or **New Analyte…** from the dropdown menu. For more information about defining analytes, see the **Analytes** chapter of the guide.

6.2.8 Deleting Samples and Analytes

To delete analytes or samples, select one or more and click on **Analytes → Delete**, or **Samples → Delete**. Alternatively, select an analyte and click on the button, or a sample and click on .

Using Analyte Symbols Analytes are labeled with names such as Sodium, Calcium, and Bicarbonate. If you prefer, you can view them labeled with the corresponding chemical symbols, such as Na+, Ca2+, HCO3
click on **View → Show Analyte Symbols**. A second click on this tab returns to labeling analytes by name.

6.2.9 Data Cells

Each cell in the data sheet contains one of several types of information:

1. A numerical value, such as the concentration of a species.
2. A character string.
3. A date or a time.

Numerical values are, most commonly, simply a number. You can, however, indicate a lack of data with a character string, such as “n/d” or “Not analyzed”, or just leaving the cell empty.

If an analysis falls below the detection limit for a species, enter the detection limit preceded by a “<”. For example, “<0.01”.

Character strings, such as you might enter for the “Sample ID”, contain any combination of characters, and can be of any length. You can enter dates in a variety of formats: “Sep 21, 2003”, 9/21/03”, “September 23”, and so on. Aq•QA will interpret your input and cast it in your local format (e.g., mm/dd/yy in the U.S.). Similarly, enter time as “2:20 PM” or “14:20”. Append seconds, if you wish: 2:20:30 PM”. To change the width of the data cells (i.e., the column width), drag the dividing line between columns to the left or right. This changes the width of all the data columns in the Data Sheet.

6.2.10 Entering Data

To enter data into an Aq•QA Data Sheet, you can of course type it in from the keyboard, or paste it into the cells in the Data Sheet, one by one. It is generally more expedient, however, to copy all of the values as a block from a source file, such as a table in a word processing document, or a spreadsheet. To do so, set up your Aq•QA Data Sheet so that it contains the same analytes as the source file, in the same order (see **Adding Samples and Analytes** above, and **Reordering Rows and Columns**). You don't necessarily need to add samples: Aq•QA will add columns (or rows) to accommodate the data you paste. Now, select the data block from the source document and copy it to the clipboard. Move to Aq•QA, click on the top, leftmost data cell, and select **Edit → Paste**. If the source data is arranged in the opposite sense as your Data Sheet (the samples are in rows instead of columns, or vice-versa), transpose the Data Sheet (**View → Transpose Data Sheet**), or select **Edit → Paste Special → Paste Transposed**.

Changing Units You can change the units of analytes on the Data Sheet at any time. To do so, select one or more analytes, then click on **Analytes → Change Units**. Alternatively, right click and choose a new unit from the options under **Change Units**. If you have entered numerical data for the analyte (or analytes), you will be given the option of converting the values to the new unit.

Some unit conversions require that the program be able to estimate values for the fluid's density, dissolved solids content, or both. If you have entered values for the Density or Dissolved Solids analytes, Aq•QA will use these values directly when converting units. If you have not specified this data for a sample, Aq•QA will calculate working values for density and dissolved solids from the chemical analysis provided. It is best, therefore, to enter the complete analysis for a sample before converting units, so the Aq•QA can estimate density and dissolved solids as accurately as possible. Aq•QA estimates density and dissolved solids using the methods described in the **Data Analysis** section of the User's Guide, assuming a temperature of 20°C, if none is specified. Aq•QA can estimate density over only the temperature range 0°C –100°C; outside this range, it assumes a value of 1.0 g/cm3, which can be quite inaccurate and lead to erroneous unit conversions. **Using Elemental** You may find that some of your analytical results are reported as elemental equivalents. For example, sulfate might be reported as "SO4 (as S)”, bicarbonate as “HCO3 (as C)”, and so on. In this case, select the analyte or analytes in question and click on **Analytes → Convert to Elemental Equivalents**. Alternatively, select the analyte(s), then right click on your selection and choose **Convert to Elemental Equivalents**. To return to the default setting, select **Analytes → Convert to Species**, or select the **Convert to Species** option when you right-click.

6.3 Notes and Comments

When you construct a Data Sheet, you may want to save certain notes and comments, such as a site’s location, who conducted the sampling, what laboratory analyzed the samples, and so on.
To do so, select **File → Notes and Comments…** and type the information into the box that appears. This information will be saved with your Aq•QA document; you may access it and alter it at any time.

6.4 Flagging Data Outside Regulatory Limits

You can highlight on the Data Sheet concentrations in excess of an analyte’s regulatory limit. Select **Samples → Check Regulatory Limits**. Concentrations above the limit now appear highlighted in a red font. Select the tab a second time to disable the option. Touching **ctrl+L** also toggles the option. Aq•QA can maintain a regulatory limit for each analyte. The analyte library contains default limits based on U.S. water quality standards at the time of compilation, but you should of course verify these against standards as implemented locally. You can easily change the limit carried for an analyte, as described in the **Analytes** chapter of this guide.

6.5 Saving Data

Before you exit Aq•QA, you will probably want to save your workspace, which includes the data in your Data Sheet, any graphs you have created, and so on, in a .aqq file. To save your workspace, select **File → Save**, or click on the button on the Aq•QA toolbar. To save your workspace as a .aqq file under a different name, select **File → Save As…** and specify the file’s new name.

You may also want to save the data in the Data Sheet as a file that can be read by other applications, such as Microsoft® Excel®. For information on saving data in this way, see the next section, **Exporting Data to Other Software**.

6.6 Exporting Data to Other Software

When Aq•QA saves a .aqq file, it does so in a special format that includes all of the information about your Aq•QA session, such as the current option settings and the plots you have created. In this way, you can resume working where you left off. You may wish, however, to save the data in your Data Sheet in a format that you can read from programs such as Excel, or with a text editor. To do so, you create a text file in which the data cells are delimited with a special character, such as a comma or tab.

Select **File → Export Data…** and on the resulting dialog box choose a character (e.g., comma or tab) to serve as the column separator. On this box, you can also set details of how you want the data saved and what data you want included in the file.

6.7 Printing the Data Sheet

You can print the contents of the Data Sheet by selecting **File → Print…**. To control the appearance of the printed page, such how to scale the Data Sheet to the page, select **File → Print Setup…**.

You can check what the printed Data Sheet will look like before you print it be selecting **File → Print Preview**. If you wish to continue, select the **Print…** button. To return to the Data Sheet, select the **Close** button.

6.8 Analytes

6.8.1 About Analytes

Analytes are the various measurements or properties of a sample that Aq•QA® can store, use, and display. Analytes include sodium, TCE, temperature, and so on.

Analytes in Aq•QA fall into six categories.

1. Inorganic Analytes – calcium, sulfate, and so on.
2. Organic Analytes – tricholorethylene, vinyl chloride, etc.
3. Biological Assays – coliform bacteria, viruses, etc.
4. Radioactivity – α particles, β particles, etc.

5. Isotopes – 18O, 13C, and so on.
6. General – temperature, pH, etc.

Aq•QA comes with a set or "library" of predefined analytes, each of which has a set of properties that you can alter, if you wish. You can also readily define your own analytes to meet your needs.

6.8.2 Analyte Properties

Each analyte has associated with it a set of properties that define how Aq•QA treats it. Depending on category, the analyte properties may include:

- Name. A label, such as "Sodium" or "Dissolved Solids", for referring to the analyte.
- Symbol. An optional symbol, such as "Na" or "TDS", for referring to the analyte.
- Dimension. The type of unit, such as "concentration", "density", or "distance", used to measure the analyte.
- Display Unit. The unit, such as "mg/kg", "g/cm3", or "cm", used by default to represent the analyte.
- Mole Weight. The molecular weight of the analyte, if it is a chemical species.
- Equivalent Element. An element sometimes used to represent an analyte. The concentration of carbonate, for example, is sometimes represented in terms of elemental carbon as "mg/kg as C"; sulfate in terms of sulfur as "mg/kg as S".
- Elemental Atoms Per Molecule. If the analyte is a species that has an equivalent element, this is the number of times the element appears in the species' formula.
- Ionic Charge. The electrical charge on the species, if the analyte is a species.
- Conductivity Factor µmho/cm per meq/L. The numerical factor used with the analyte's concentration to calculate electrical conductivity, according to Standard Method 2510-A.
- Minimum Acceptable Limit Value. A regulatory or other limit on the least acceptable value for the analyte.
- Minimum Acceptable Limit Units. The unit corresponding to this value.
- Maximum Acceptable Limit Value. A regulatory or other limit on the greatest acceptable value for the analyte.
- Maximum Acceptable Limit Units. The unit corresponding to this value.

- Regulation. The regulatory source, such as a USEPA MCL, or Maximum Contaminant Level, for above.
- Description. An optional note describing the analyte.
- Source. An optional note giving the data source.
- Aq•QA Uses As. If the program recognizes the analyte as having a special role in its calculations, that role is noted here.
- Significant Digits. The number of digits used to display a value for the analyte.
- Conserved. A flag indicating whether the analyte is conserved during mixing, used in Aq•QA's "mix" feature.

6.8.3 Changing the Properties of an Analyte

You can change the properties of any analyte on your Data Sheet. You might, for example, want to change the acceptable limit for lead to a new value.

To change an analyte's properties, click on **Analytes → Analyte Properties** and select the analyte category corresponding to the analyte in question. Alter any or all of the properties for the analyte, then click on the **Data Sheet** pane to return to your data. When you change properties in this way, you alter them only within the current Aq•QA document. To alter properties in future documents, see

6.8.4 Editing the Analyte Library.

Creating a New Analyte

You can create your own analyte to reflect, for example, a species not included in the analyte library. Click on **Analytes → New Analyte…** and in the dialog box that appears select the appropriate category ("Inorganic Analytes", "Organic Analytes", etc.). If no other category seems applicable, choose "General". Fill in the properties requested on the dialog box and click "OK". The new analyte appears in your Data Sheet, along with Aq•QA's pre-defined analytes. You can change the analyte's properties, as well as define those not included in the dialog box, at any time by clicking on **Analytes → Analyte Properties**.

6.9 Analyte Libraries

Aq•QA comes with a library of analytes known to it, and analytes' properties. The analyte library, named "library.aqq", is installed in the Aq•QA installation directory (e.g., "\Program Files\AqQA").

You can easily define your own library, generally by modifying or adding to the analytes in library.aqq, as discussed in the next section, **Editing the Analyte Library**. You can save your custom library under any name, in any directory.

To tell Aq•QA to use a custom library instead of the default, select on **File → Preferences** and click on the **Browse** button next to the **Import Standard Analytes From** field. From now on, when you add analytes to your Data Sheet, or create a new Aq•QA file, Aq•QA will take analytes and their properties from your custom library.

6.9.1 Editing the Analyte Library

To create a custom analyte library, open the library as you would any Aq•QA file, by clicking on **File → Open…**. It's a good idea to save a copy of the default library that comes with Aq•QA under a different name, and modify the copy. As described in the previous section,

Analyte Libraries, use the **File → Preferences** dialog to tell Aq•QA to use the custom instead of default library. Once you have opened the custom library, select the category (inorganics, organics, and so on) you would like to edit from **Analytes → Analyte Properties**. Edit the analytes as you would any Aq•QA Data Sheet. You can add analytes, delete them, and alter analyte properties. Continue by editing the analytes in the other categories, as desired.When

you are done editing the library, save it as you would any other Aq•QA file, by clicking on **File → Save** or **File → Save As…**. **Updating Aq•QA Files**

Once you have changed analyte properties in the analyte library, or added analytes to the library, your changes will appear in the new Aq•QA documents you create, provided you have set Aq•QA to use the new library (on the **File → Preferences** dialog).

Your exisiting .aqq files, however, will be unaffected by changes to the library, unless you update them. For example, if you change the regulatory limit for an analyte in the standard library, the new limit will be reflected in new .aqq files you create, but not exisiting files, unless you update them. If you have modified any of the analyte definitions in the default template (“default.aqq”) or any templates you have created (see **Template for New Data Sheets**), furthermore, you will need to update these files.

To update an Aq•QA document, open it (**File → Open…**) and click on **Analytes → Update Analytes…**. The resulting dialog box allows you to reconcile analyte properties in the current document with an analyte library, or with the analyte properties in any other Aq•QA document.

The dialog box will list the analyte properties that differ between your document and the library.

To accept the updates, click on **Select All**¸or select only those you wish to apply, and then **Apply Selected**. Click on **Done** to return to working with the revised Aq•QA document.

6.10 Data Analysis

6.10.1 About Data Analysis

The Data Analysis pane displays useful information about a water sample from the Data Sheet. The sheet contains a number of categories of information, with horizontal bars for each category labeled “Fluid Properties”, “Internal Consistency”, and so on. To see the information under a given category, click on the bar. Clicking on the bar a second time closes the category, and clicking on the button displays helpful information about the category. The label for the sample in question is shown at the top of the pane. Also there are two arrow buttons that allow you to scan forward and backward through the samples on the Data Sheet. In performing the calculations on this pane, Aq•QA® assumes conditions of 20°C, unless a temperature has been entered for the sample on the Data Sheet. In no density is reported, Aq•QA will estimate an appropriate value, as described below. Aq•QA can estimate density over only the temperature range 0°C –100°C; outside this range, it assumes a value of 1.0 g/cm3, which can be quite erroneous. Finally, if no value is reported for dissolved solids, Aq•QA calculates one from the sample’s chemical analysis, as described below.

In this chapter, an “AWWA Standard Method” refers to a method described in the cited section of the AWWA “Standard Methods” volume. The complete reference to this volume is:

Clesceri, L.S., A.E. Grrenberg, and A.D. Eaton, 1998, Standard Methods for the Examination of Water and Wastewater, 20th ed., American Public Health Association (Washington), American Water Works Association (Denver), and Water Environment Federation (Alexandria, VA).

6.10.2 Fluid Properties

The Fluid Properties category of the Data Analysis pane reports various properties of the water sample.

6.10.3 Water Type

The water type – e.g., Ca-HCO3 or Na-SO4 – is determined by finding the predominant inorganic cation and anion, figured on the basis of electrical equivalents.

In determining water type, Aq•QA accounts whenever possible for the carbonate speciation in solution, using the sum in electrical equivalents of the CO32− and HCO3 − concentrations to represent carbonate. If carbonate is the dominant anion by this criterion, Aq•QA states the water type in terms of whichever of the two species is present in larger equivalent concentration (e.g., Ca-HCO3 or Na-CO3). Aq•QA also calculates, where pH is given, the free ion concentrations of H+ and OH−, and accounts for these species when assigning a water type. An acidic solution might be typed H-SO4, for example, or an alkaline water, Ca-OH .

6.10.4 Dissolved Solids

The program displays the water's calculated dissolved solids content, along with the measured value, if supplied on the Data Sheet. Aq•QA calculates dissolved solids by summing the inorganic analytes, following by Standard Method 1030-E, except that it accounts for all of the inorganic analytes on the Data Sheet, and it accounts for carbonate specied as described in the next paragraph. The contribution of carbonate to dissolved solids is taken as the sum of the masses of analytes bicarbonate, carbonate, and carbon dioxide (HCO3, CO3, and CO2). If none of these analytes is specified, Aq•QA accounts for carbonate in one of the following ways:

(1) from an analyses of total carbon,

(2) from the carbonate concentration calculating from a specified alkalinity and pH, as described below under **Carbonate Speciation**, or

(3) from a specified alkalinity in the absence of pH, according to 0.6 × alkalinity. **Density**

The program displays the water's calculated density, in g/cm3, along with the measured value, if supplied on the Data Sheet. Density is calculated from salinity (dissolved solids expressed as permil salts) according to Standard Method 2520-C. Aq•QA calculates density only over the temperature range of 0°C–100°C.

6.10.5 Electrical Conductivity

The water's calculated electrical conductivity, in μmhos/cm, is displayed along with the measured value, if supplied on the Data Sheet. The temperature-corrected conductivity is calculated according to Standard Method 2510-A, accounting for ionic strength effects.

Wherever possible, Aq•QA figures when calculating conductivity the speciation of carbonate to produce HCO_3^- and CO_3^{2-}. Aq•QA also

specified.

6.10.6 Hardness

The program reports three values calculated for hardness: total hardness, carbonate hardness, and non-carbonate hardness. Each value is given in mg/L as an equivalent amont of $CaCO_3$.

Total hardness is calculated from the $Ca^{2+}$and Mg^{2+} content of the water from the equation Hardness [mg/L as $CaCO_3$] = 2.497 [Ca^{2+}, mg/L] + 4.118 [Mg^{2+}, mg/L] as prescribed by Standard Method 2340-B.

Carbonate hardness is the Ca^{2+} + Mg^{2+} that can be balanced by the amount of carbonate (i.e., HCO_3^- + CO_3^{2-} + CO_2) in solution. Ca^{2+} and Mg^{2+} precipitate as a carbonate mineral such as calcite, $CaCO_3$ (i.e., $Ca^{2+} + HCO_3^- \rightarrow CaCO_3 + H^+$), so one mole of carbonate balances one mole of Ca^{2+} + Mg^{2+}. The carbonate hardness cannot exceed the total hardness, even if there's more carbonate than Ca^{2+} + Mg^{2+} in solution. The non-carbonate hardness is total hardness less carbonate hardness.

6.10.7 Internal Consistency

The Internal Consistency category of the Data Analysis pane shows the results of seven quality assurance/quality control tests applied to the analysis of the water sample. A green "OK" identifies each test that was completed successfully. A red message such as "Not within ± 5%" is applied to unsuccessful results. In other cases, as noted, there is not enough information for the sample on the Data Sheet.

The first six of the seven tests are described in 1030-E of the AWWA "Standard Methods" volume. Of the AWWA tests, the first three are considered of primary importance; the latter three may not be reliable for all water types. The final test checks for mass balance among organic analytes. The tests are:

6.10.8 Anion-Cation Balance

This test checks that the analysis honors the requirement that a water maintain electroneutrality. To make this test, the program figures the sum of the concentrations of the cations, expressed in meq/L, and the same value for the anions.

Wherever possible, Aq•QA figures when calculating the anion sum the speciation of carbonate to produce $HCO3^{-}$ and $CO3^{2-}$. Aq•QA also accounts for the contributions of the species H^+ and OH^- to the ion sums, whenever pH is specified.

6.10.9 Measured TDS Matches Calculated TDS

The ratio of the measured dissolved solids to the value calculated by Standard Method 1030-E, accounting for all inorganic analytes on the Data Sheet, should fall in the range 1.0 to 1.2.

6.10.10 Measured Conductivity Matches Calculated Value

The ratio of the measured electrical conductivity to the temperature-corrected value calculated by Standard Method 2510-A should fall in the range 0.9 to 1.1.

6.10.11 Measured Conductivity and Ion Sums

The ion sums for cations and anions multiplied by 100 should both fall within ±10% of the measured electrical conductivity. This test is considered by many to be less reliable and significant than the first three tests in this section.

6.11 Calculated TDS to Conductivity Ratio

The ratio of calculated dissolved solids (mg/L) to measured electrical conductivity (µmhos/cm) should normally fall in the range 0.55 to 0.7. In the presence of poorly dissociated calcium or sulfate ions, the ratio may be as high as 0.8. This test is considered by many to be less reliable and significant than the first three tests in this section.

6.12 Measured TDS to Conductivity Ratio

The ratio of measured dissolved solids (mg/L) to measured electrical conductivity (μmhos/cm) should fall in the range 0.55 to 0.7. This test is considered by many to be less reliable and significant than the first three tests in this section.

6.13 Organic Carbon Cannot Exceed Sum of Organics

This test compares a measured DOC (dissolved organic carbon, mg/L) value to the sum of the concentrations (mg/L, as C) of specific organic analytes. The DOC should not be more than 5% less than the sum. It may, however be greater, since all the organic species in solution have not necessarily been analyzed.

6.14 Carbonate Equilibria

The Carbonate Equilibria category show the speciation among carbonate ions in solution, and various factors that depend on the speciation. Dissolved carbonate is distributed among the carbonate and bicarbonate ions (CO3 2− and HCO3−) and aqueous carbon dioxide (CO2(aq)). In orderfor Aq•QA to figure the species distribution, the following conditions must be met for the sample:

1. The pH must be specified.
2. At least one measure of carbonate concentration must be specified. This may be (A) the concentration of one of the inorganic analytes bicarbonate, carbonate, or carbon dioxide, (B) the carbon concentration [C], or (C) the titration alkalinity.
3. Temperature, which is set to 25°C if not specified, must fall in the range 0°C –300°C. (Note that in the range 100°C–300°C, it is necessary to specify fluid density directly, to avoid possibly significant calculation errors when converting units.)

If these conditions are met, the following information will appear:

6.15 Speciation

The program reports the predicted distribution of carbonate among the three carbonate species: HCO_3^-, CO_3^{2-}, and CO_2.

6.16 Total Carbonate From Titration Alkalinity

If the titration alkalinity is given on the Data Sheet, the program reports the calculated total carbonate concentration.

6.16.1 Titration Alkalinity From Total Carbonate

If the carbonate concentration is given on the Data Sheet, the program reports the calculated titration alkalinity, in mg/kg as $CaCO_3$.

6.16.2 Mineral Saturation

If the calcium concentration is given on the Data Sheet, the program reports the saturation indices calculated for the $CaCO_3$ minerals calcite and aragonite. The saturation indices tell whether the minerals are supersaturated ($SI > 0$), saturated ($SI = 0$), or undersaturated ($SI < 0$).

6.17 Partial Pressure of CO2

The program shows the partial pressure of CO_2 in the water, in atm.

6.18 Irrigation Waters

The following parameters are used to judge the suitability of a water for irrigating crops. Unless noted, concentrations (e.g., [Na]) are in units of meq/L. The program reports a value only in cases in which all of the necessary concentrations are given.

6.19 Graphing Data

6.19.1 About Graphing Data

To make a graph in Aq•QA, you follow these steps:

- On the Data Sheet, select the data you want to appear on the plot. (Don't worry, you can change your choices later.) For example, you might select the row of data for an analyte, or just the data in that row for certain samples.
- Click on the tab, along the bottom of the Aq•QA window and select a plot type.
- Alter the content and appearance of the plot by changing the settings in the control panel along the right side of the Aq•QA plot pane, or by clicking on the **Advanced Settings…** button.

You can delete the current plot by selecting **Graphs → Delete Graph**, or by right clicking on the plot pane's tab, along the bottom of the Aq•QA window. To change the plot to another type, select **Graphs → Change Graph Type**, or right-click on the pane's tab. Many of the graphs Aq•QA produces account for the calculated speciation of carbonate among carbon dioxide, bicarbonate ion, and carbonate ion. If you, for example, report alkalinity and pH, the program will figure the concentrations of the various ions and produce a graph reflecting them. The Piper, Durov, Schoeller, Bar Chart, Radial, and Stiff diagrams work this way. For each of these diagrams except the Piper and Durov plots, you can choose instead to plot the carbonate concentrations as they are entered on the Data Sheet. To do so, click on the **Advanced Settings…** button, then on the tab corresponding to the diagram type, and de-select the "Show carbonate speciation" option.

6.19.2 Time Series Plots

Time Series plots are much like Series plots, except that the horizontal axis shows the sampling date or time.

Chapter 7

Conclusions and Recommendation

Chapter 7
CONCLUSION AND RECOMMENDATIONS

7.1 Conclusions

In the present work, we made a comprehensive effort of water quality investigation in a Delhi stretch of Yamuna river front receiving urban drainage. Starting from sample collection from nine predetermined sites over six months, the work involved the laboratory analysis of seven sets of samples, studying their spatial and temporal variation, determination of Water Quality Indices and finally multiple regression analysis of the data for testing predictive model. Based on the findings, following conclusions can be drawn:

1] The Yamuna River water adjoining the Delhi city is alkaline in nature with pH level reaching the value of 8.5 during the dry season.

2] Electrical Conductivity changes with season indicating seasonal variation in dissolved ion chemistry. Cl^-, HCO_3^- and SO_4^{-2} make up the major anions and Ca^{+2}, Mg^{+2}, Na^+ and K^+ the major cations.

3] Impact of waste water inflow from city drainage is indicated but found to be minimum during the monsoon peak flow, due to dilution by high volume of surface water, accompanied by other natural attenuation processes, whereas the effect were more pronounced in the winter season.

4] The application of a water quality indices approach to the study area allows a water quality classification both spatially and temporally that is reproducible within the watershed by means of uniform, objective criteria.

5] The average quality of the Yamuna River in the vicinity of the city was found to be medium to good for most of the zone. At location 9, it was in a lower quality range (fair to medium) because of the effect of mixing of city sewage discharge coming via a major drainage channel Nizamuddin.

6] From the regression analysis it has been observed that, there are three significant variables (Na^+, K^+ and hardness) which are all strongly correlated with the EC values of the Yamuna River.

7] The variation of different parameters has occurred mainly due to four causes: seasonal variations in flow conditions, upstream contribution of algae and other constituents, the geometry of the study area and the effluent from Delhi city.

8] The water quality of River Yamuna is also not suitable for irrigation purposes and ion balance of water is also not suitable.

8.2 Recommendations

1. Pollution control methods should be applied

2. Minimum flow should be maintained so that dilution is available

3. Waste water which is being discharged through drains should be treated before disposal

8.3 Scope of Future Work

The results of the multivariate regression analysis conducted in this study clearly show that there are a number of variables that influence the EC and consequently dissolved ion concentrations, partially as well as strongly, in the study area. How these variables interrelate and which are the secondary variables that contribute to the primary variables, are not yet completely understood. This work provides a framework to begin understanding the correlation of those parameters as well as their change of trend with respect to time, in the urbanization-impacted stretch of the Brahmaputra River. Concentration of dissolved trace metals and other toxic parameters can also be included in further studies. A more intensified sampling programme, much closer to the river bank, will yield a clearer understanding for formulating suitable water quality management plan for this potentially threatened part of the otherwise pristine river.

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