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Analysis of River Water Quality Using Geo-Spatial and Temporal Data: A Case study

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Abstract

The conventional approach of water quality assessment via sampling followed by laboratory measurement methods comprises the analysis of different properties such as chemical, physical. The main idea behind detection of water quality parameters using imaging is based on the presence of pollutants in water and absorption of the incoming solar radiation. In this study, by considering data of the conventional water quality testing,an attempted is made to identify the association between the laboratory results and the indices and bands values obtained from spatial data, to determine their applicability in water quality estimation and prediction. The study makes use of two types of data, visually, spatial and non-spatial data. The spatial data used was Landsat-8 OLI from which the water index was calculated. While under non-spatial data ancillary information and water parameters were considered. Based on the analysis an approach was made to find the relation between Water Quality Index and spatial parameters. Further, a model was established to estimate WQI from spatial data.

Key words: Water pollutants; Spatial estimation; Regression analysis; Water quality index; Anthropogenic waste.

AMS Subject Classifications: 62K05, 05B05

1. Introduction

Water is an elixir of life. It is a precious natural resource and an important component of human survival and to maintain life cycle on our blue plant. Out of the total water reserves of the world, about 97% is salty water (marine) and only 3% is freshwater. Even this small fraction of freshwater is not available to us as most of it is locked up in polar ice caps and just 0.003% is readily available to us in the form of groundwater and surface water Pawan and Pradeep (2015). Due to its unique properties it is an essential part of all living organisms on the planet. Human beings depend on water for almost every development activities like drinking, irrigation and transportation, washing and waste disposal for industries and used as a coolant for thermal power plants. Water shapes the earth's surface

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and regulates our climate. With increasing human population and rapid development, the world water withdrawal demands have increased many folds and a large proportion of the water withdrawal is polluted due to atmospheric activities. Rivers are the most important water resources. It has long been used for discharging wastes. Unfortunately, the rivers are being polluted by indiscriminate disposal of sewage, industrial wastes and by human activities Pawan and Pradeep (2015).

The conventional approach of water quality assessment *via* sampling followed by laboratory measurement methods comprises the analysis of different properties such as chemical, physical, biological and other indicators Ouma *et al.* (2018). However, water sampling and the subsequent measurements of water quality parameters (WQP) are helpful in representing point-based estimates of the quality of water conditions in terms of time and space both, while, obtaining spatial-temporal variations of water quality indices for large water bodies is very challenging Ritchie *et al.* (2015), ouma *et al.* (2018). Apart from the factors like tedious, work serious and exorbitant, some of the other significant limitations associated with the conventional method for water quality assessment are inability to monitor, forecast and manage the entire water body due to the water surface extent and its topographic characteristics and the lack of spatial-temporal data. To overcome these limitations, there is a need for technology which is fast, inexpensive, simple, automated and non-invasive in operational and productive aquatic environmental monitoring. Measurements and observations taken with such tools should provide essential information with respect to bio-geophysical water quality aspects Garaba *et al.* (2015), which is economically efficient, along with adequate spatial coverage, resolution and most important available on regular time intervals as well.

By utilizing remote detecting, the optically dynamic water constituents can be identified depending on their cooperation with light and the resulting change in the energy of the occurrence radiation as reflected from the water body Ritchie *et al.* (2015). The main idea behind detection of water quality parameters using imaginary data is based on pollutants present in water and absorption of the incoming solar radiation and the water quality can be correlated with the characteristics of the water segments, such as colour and transparency Dor and Ben-Yosef (1996). This implies that optical information can give an elective means to getting generally minimal expense and synchronous data on surface water quality conditions Dor and Ben-Yosef (1996), Dekker *et al.* (1993). Regardless of the capacity of remote detecting to be utilized for the appraisal of water quality with the ideal benefits of being convenient and practical, the procedure may not be adequately exact and should be benchmarked with the conventional testing techniques and field studies. That is, for better understanding, incorporated utilization of remote detecting, in-situ estimations and PC water quality displaying is probably going to bring about a more fiery information on the water quality in each surface water framework Gholizadeh *et al.* (2016).

Sampling and field measurements, have been the standard techniques that are been practiced since long in the determination of water quality with help of certain variables, at the same time various tests and approaches have been carried out for the estimation of different water parameters, in different case studies using novel methods and procedures. Despite being the traditional approach for water quality testing, the laboratory methods are unable to present the real-time spatial overview which is necessary for the monitoring of water quality at certain regular interval and make decisions Brivio *et al.* (2001). In this study, by considering data of the conventional water quality testing, an attempted is made to identify the association between the laboratory results and the indices and bands values obtained from spatial data, to determine their applicability in water quality estimation and prediction. For further analysis, a correlation of the distribution of the measured WQP using laboratory measurements and the remote sensing models are spatially analysed. Retrieval of water quality characteristics from remote sensing was made possible using Landsat sensors, namely, operational land imager (OLI). This was used to establish relationship between water quality parameters, such as power of hydrogen (pH), temperature, dissolved oxygen (DO), biochemical oxygen demand (BOD) and chemical oxygen demand (COD). Nonetheless, dispect of many advantage that is possesd by Landsat the use of Landsat data has the few limitations: (1) the repeat cycle of sensor is of 16 days and that imposes major limitations on intra-seasonal monitoring more accurately, especially in areas characterized by frequent cloud cover and (2) the water quality parameter characteristics must be related to the inherent optical property (IOP) that can be measured by the satellite sensor Brezonik *et al.* (2005).

Remote detecting based models have broader uses in vast sea waters. While, investigations on inland freshwater bodies by that of remote detecting estimations are bit complex. Making it hard to foster functional freshwater remote detecting calculations. Besides, it is unimaginable to expect to utilize existing algorithmic models for exact water quality assessment. Not withstanding the calculations having been approved in explicit contextual investigations, the confined attribute of every space makes it important to rethink and revalidate the current calculations for their potential applications in other WQP forecast contextual analyses Ouma *et al.* (2018).

Remote sensing estimation of surface water quality is based on mapping the relationship between remote sensing multispectral signatures and measurements of ground truth data (*i.e.*, concentrations of SWQPs). Additionally, a remote sensing study of surface water quality requires multispectral data for the surface features, as they would be measured at ground level. Surface Water Quality Parameters (SWQPs) can be broadly classified into two main classes: optical and non-optical SWQPs. Optical parameters are optically sensitive parameters that can be sensed by remote sensing and hence can be approximated. A significant number of studies have been conducted for assessing optical parameters KC *et al.* (2019). A challenge is to approximate underlying relationship between both optical and non-optical parameters. Optical SWQPs, such as turbidity and total suspended solid (TSS) are most likely to affect the watercolour, the reflected signals and consequently can be detected by satellite sensors. On the other hand, non-optical SWQPs, such as COD, BOD, DO, total dissolved solid (TDS), pH and surface water temperature are less likely to affect the reflected radiation (Din). Mapping the relationship between Satellite Data and the Concentrations of SWQPs is achievable via regression techniques. Theoretically, the relationship between satellite multi-spectral signatures and the concentrations of SWQPs is too complex, especially in the presence of various pollutants at the same time. Moreover, it is very challenging for regression techniques to model such a complex relationship. The proposed solution aims at developing a novel artificial intelligence *i.e.*, learning-based) modelling method for mapping concentrations of both optical and non-optical SWQPs by using remotely sensed multispectral data Ouma *et al.* (2018).

The organization of the paper is as follows: The details about the methodology and study area are presented in Section 2. The data capture methods along with their specifications are discussed in Section 3. Section 4 presents the detailed analysis and interpretations. Some recommendations on the quality index are also studied in this section. The paper ends with a conclusion in the last section.

2. Materials and methods

2.1. Methodology

In this study two different types of data, visually, spatial and non-spatial data were used. The spatial data used was Landsat-8 OLI from which water index was calculated and water body area was extracted from the raw data using shapefile. While under non-spatial data ancillary information and water parameters were considered. Based on the analysis an approach was made to find the relation between Water Quality Index and spatial parameters. Further, a model was established to estimate WQI from spatial data.

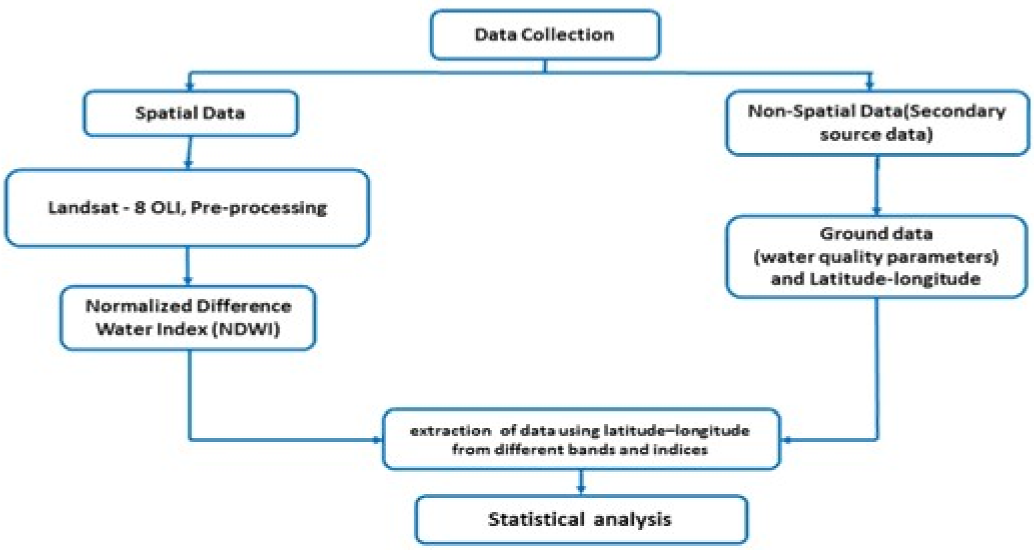

Figure 1: Methodology of the study

2.2. Study area

This study was carried out with respect to the location Dhuvaran situated in the Mahi basin. Dhuvaran (22.539188° N latitude and 72.412128° E longitude) is a remote village that comes under Khambhat taluka of Anand district, located at the point where Mahi river ends and the gulf of Khambhat starts. This village has a population size of 8043 of which 4168 are male and 3875 are female as per the population census 2011. The climate is semiarid with a temperature range of 15°C in winter and 34°C in summer. Significant rainfall occurs during the Southwest monsoon winds, from June to September and receive annual rainfall ranging from 20 inches to 30 inches. The location is very close to a nuclear power plant which is infamous for industrial pollution and anthropogenic waste accumulation. This effect the quality and consumption of water for everyday usages. The site is also famous for unusual climatic and temporal variations towards water scarcity and quality problems, which attracts environmentalists and statisticians to carry out studies to help policymakers to have interventions and strategies. The study area is shown in Figure 2.

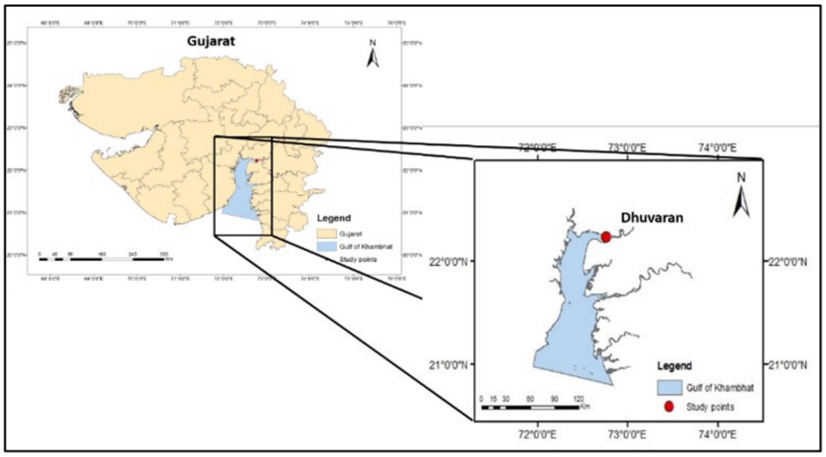

Figure 2: Study area map

3. Data presentation

3.1. Remote sensing data acquisition

Remote sensing data used for this context was based on the Landsat 8 optical land imager (OLI) level-2 imaginary (path:148 and row:45), acquired for free through united states geological survey (USGS) earth resources observation and science center (EROS) from January 2015 to March 2021. For this study bi-monthly data was considered with no or less cloud coverage. Overall, we had 51 spatiotemporal data scenes. The acquired data of the study area was already geometrically corrected and further, radiometric correction of multispectral imagery was done of acquired data by converting digital numbers (DNs) to the spectral radiance. Landsat 8 OLI level-2 processed data consists of 10 bands ranging from 435 nm-11190nm, which comprises of visible bands, NIR, SWIR and TRIS bands with a resolution of 30 meters for visible, NIR and SWIR; and 100 meters for TRIS. Data for the same can be acquired after every 15 days. Table 1 presents the specifications of these bands.

Table 1: L-8 OLI level-2 band description

Band Number	Band Description	Band Range (nm)
B1	Costal Aerosol	435 - 451
B2	Blue	452 -512
B3	Green	533 -590
B4	Red	636 -673
B5	Near Infrared (NIR)	851 -879
B6	Short Wave Infrared (SWIR-1)	1566 -1651
B7	SWIR-2	2107 -2294
B10	Thermal Infrared Sensor	10600 - 11190

3.2. Ground data

A sampling of surface water was collected from January 2010 to December 2020 from a predefined site. Parameters like pH and temperature were taken on the ground while, parameters like TDS, BOD, DO samples were brought to the lab for physicochemical experiments. Standard methods were carried out for capturing data related to these parameters Singh and Jayakumar (2016), APHA (2005). They are further considered for calculating the water quality index and were compared with the standards of WQI, as shown in Table 2.

Table 2: Water quality index scale

WQI	Rating
0-25	Excellent
26-50	Good
51-75	Poor
76-100	Very poor
Above 100	Unsuitable

4. Analysis and findings

4.1. Modified normalized difference water index (MNDWI)

MNDWI was proposed by Xu *et al.* (2006) who noticed a limitation about NDWI of not being able to suppress the signal reflected from the land and the build-up efficiently Yun Du *et al.* (2016), Xu. *et al.* (2006). Based on the finding, the proposed formula of MNDWI is shown as:

$$MNDWI = \frac{\rho_{\mathrm{Green}} - \rho_{\mathrm{SWIR}}}{\rho_{\mathrm{Green}} + \rho_{\mathrm{SWIR}}} \tag{1}$$

where ρ_{Green} is the top of atmosphere (TOA) reflectance of the green band and ρ_{SWIR} is the TOA reflectance of the SWIR band. In Landsat-8 OLI band 3 is mapped as a green band that has a spatial resolution of 30 m while band 6 is SWIR-1 and has the same spatial resolution of 30 m. So, with respect to resolution for Landsat 8 OLI formula can be rewritten as:

$$MNDWI_{30\ \mathrm{m}} = \frac{\rho_3 - \rho_6}{\rho_3 + \rho_6} \tag{2}$$

The normalized values were obtained by subtracting and adding the same bands in numerator and denominator and the values will range between -1 to +1.

4.2. Water parameters

The visualisation of ground and spatial data was done in the exploratory data analysis to understand the trend and distribution of the data. As illustrated in Figure 3, a line chart was created using the lower and higher limits set by the water pollution control board (WPCB/PCB) for each parameter. From 2013 to 2017, there was a notable shift in all Water parameters for the area, as shown in Figure 3. To capture the information's regarding the water quality, it was decided to have continuous monitoring and assessment of all variables as described below.

Dissolve oxygen (DO)

This parameter measures the amount of oxygen present in the water in dissolved formed. which is an important factor for the survival of the biotic components present under the water bodies. It depends on several factors like temperature, water agitation, type and number of aquatic plants and light penetration amount of dissolved suspended solids Sudarshan *et al.* (2018). The optimum range for good water quality ranges from 4-6 mg/l, which ensures healthy aquatic life in a water body Sawyer *et al.* (1994), Leo and Dekkar (2000), Burden *et al.* (2002), De (2003). Figure 3(a) indicates that the DO level dropped dramatically between 2013 and 2014, eventually reaching its lowest point in 2015. As a result, the survival rate of all biotic components presents in the waterbody in that area may have reduced leading to unsuitable for everyone's survival. The overall average of the DO data is 6.5 which falls under the range of good water quality which reflects a good aquatic life.

Biological oxygen demand (BOD)

BOD determines the strength in terms of oxygen required to stabilise the domestic and industrial wastes Shah *et al.* (2016). From 2012 to 2016 the demand for oxygen was high in the study area which resulted in a fall in the level of DO. On basis of which our assumption is, wastes released in the water body was not treated as per the standards and hence to stabilise more oxygen was required. The data on BOD showed a declining trend after 2016 with a severe fall till 2018 and after that, the value remained below constantly as observed in Figure 3(b).

pH

pH is one of the most common parameters affecting quality and hence is given due consideration in this study. Data related to this variable is directly captured from the field and no laboratory testing is performed on this. This parameter reflects the acidic or basic property of water (Figure 3(c)). The value of pH below 6.5 causes discontinuation in the making of vitamins in the human body. When pH becomes more than 8.5, the taste becomes saltier and causes eye irritation and skin disorders Gupta *et al.* (2017). The average pH value in our study is for the defined time frame was 7.9 which is close to 8 means salt contamination is more.

Temperature

Temperature is the easiest and common parameter but has a significant role to play for other parameters. Many parameters have a direct relationship to temperature. the temperature data chart showed an increasing trend, crossing the upper specification may limit during the 2017-2018 period (Figure 3(d)).

4.3. Measuring unit of variables

The source and nature of data considered in this study are different as a result the measuring units are also varying. Water parameters like DO, BOD, TDS have measuring unit milligram per liter, pH has an ordinal scale ranging from 0 to 14, temp. is measured in degree celsius and bands of geospatial data has unit nanometer (nm) while WQI and MNDWI are unit free.

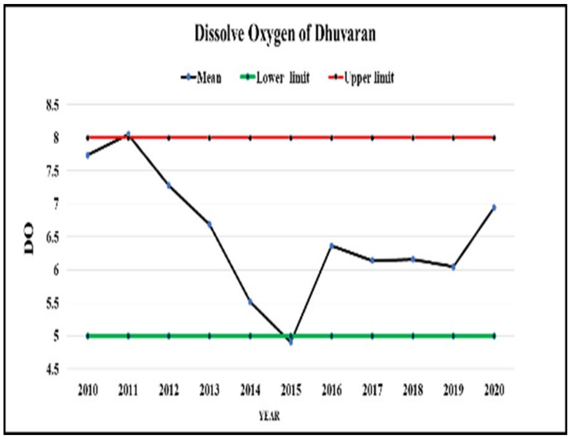

Figure 3(a): Control chart of DO

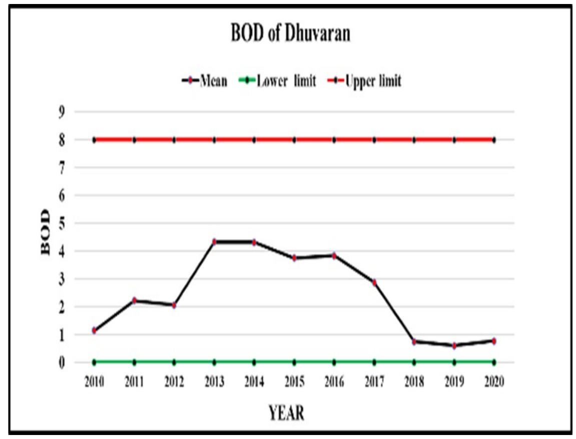

Figure 3(b): Control chart of BOD

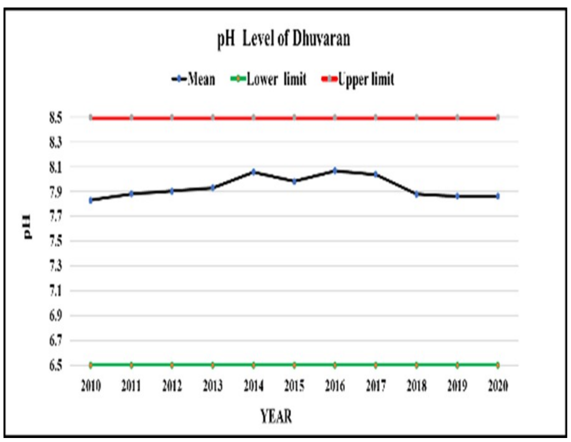

Figure 3(c): Control chart of pH

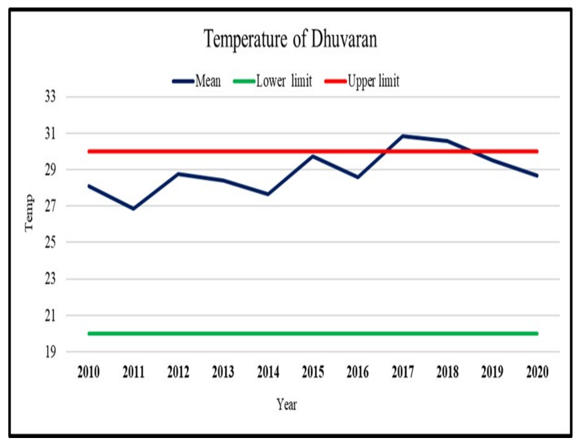

Figure 3(d): Control chart of temp.

4.4. Water quality index (WQI)

Despite monitoring individual water parameters, it is a bit difficult to assure the quality of water at a given point of time and location by looking at these parameters. Water quality plays an important role in such cases while making decisions with respect to water management and interventions for improving the quality. It defines the whole status of the water body by a single number and informs the public about its state APHA (2005), Sudarshan *et al.* (2018), Ashok *et al.* (2011). This single value gives information about the quality state of water at a given point of time for any space Alobaidy *et al.* (2010). In this study, weighted arithmetic mean WQI (WAWQI) is used to calculate the quality index Horton (1965), Sudarshan *et al.* (2018). Four parameters namely pH, DO, BOD, temperature were considered for calculating the WQI. Standards for drinking water was recommended by BSI (Indian standard specification for drinking water, 2012). The WAWQI is calculated as:

$$WAWQI = \frac{\sum_{i=0}^{i=n} W_i Q_i}{\sum_{i=0}^{i=n} W_i} \tag{3}$$

where unit weights (W_{i}) were calculated for each parameter by following the formula as given in Tiwari and Mishra (1985)

$$W_i = K_j \in \left(\frac{1}{s_n}\right), \tag{4}$$

where $K_j = \frac{1}{\frac{1}{S_1}+\frac{1}{S_2}+...+\frac{1}{S_n}}$.

Now Quality rating scale (Q_{i}) was calculated using the formula for all parameters except two variables DO and pH of pure water.

$$Q_i = \frac{Q_{(act)} - Q_{(ideal)}}{S_{(std)} - Q_{(ideal)}} \times 100 \tag{5}$$

where, W_i = unit weight of each water quality parameter, K = Proportionality constant, Q_{i} = Quality rating scale for each parameter, Q_{act}= Estimated concentration of i^{th} parameter in the analyzed water, Q_{ideal} = Value of the parameter in pure water, S_{std} = Standard value of ith parameter and n = No of water quality parameters.

For pH, value of Q_{i} is 7.0 and for DO, it is 14.0. The water quality index finally obtained is visualized in Figure 4. After calculating the weight of the parameter and quality rating scale, values were substituted in the final formula of WAWQI and then the index value were compared.

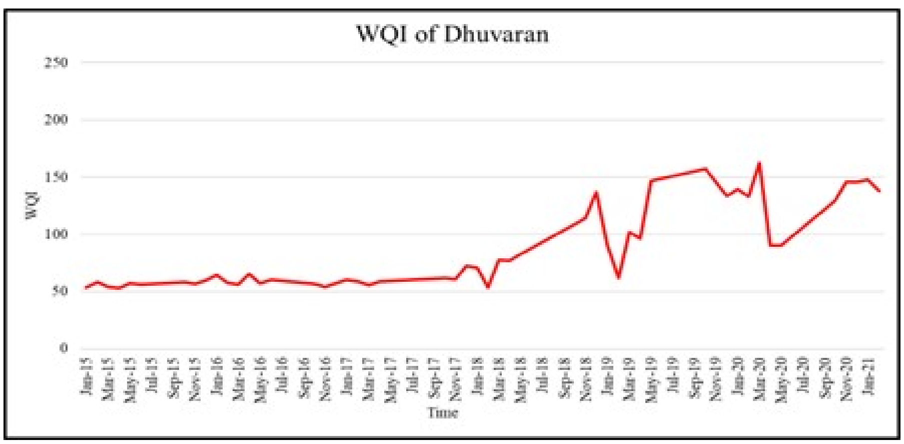

Figure 4: Control chart of Water Quality Index calculated using defined formula

However, looking at the WQI chart (Figure 4), it is seen that the variation was not suitable for an initial period, but with the passage of time, further, fluctuated significantly. This is attributed to an unknown lag effect and hence, the quality of water may not be suitable for consumption and domestic usages. As per our understating some of the factors that affect the quality can either be due to industrial disposal, human activities in the nearby areas, or can be underwater disturbances in aquatic life. To predict WQI and water quality parameters from non-conventional data, it's crucial to see if there's a relationship between the two types of data. To do so, a correlation matrix and a heatmap were created, as shown in Figure 5. It was discovered that DO and WQI had a very high correlation, whereas there was a moderate correlation between spatial and non-spatial data source variables.

Figure 5: Correlation matrix and heatmap chart

4.5. Multiple linear regression analysis

To understand the influence of reflectance data on the WQI and its parameters, a multiple linear regression was carried out to understand the significance of each variable. Regression analysis is the Statistical technique that is used for predicting dependent variables with the help of a single exploratory variable or multiple exploratory variables after expressing the linear relationships between them. This relationship can be written as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \epsilon \tag{6}$$

where,

Y: Dependent variable,

β_0: Intercept,

β_p: Slope,

X_p: Exploratory variables; p: $1,2,3,\ldots,8$,

ϵ: Residual term.

Table 3: Regression models and R^2 values of respective models

Dependent variable	**Equation**	R^2
DO	13.504 + 0.0032***B1** - 0.0043***B2** + 0.0005***B3** + 0.0003***B4** -0.0001***B5** - 0.0005***B6** + 0.0012* **B7** - 0.0002* **B10**	0.12
BOD	37.4192 + 0.0094***B1** - 0.0145***B2** + 0.0032***B3** + 0.0006***B4** + 0.0001***B5** + 0.0061***B6** - 0.0076***B7** - 0.0003***B10**	0.18
pH	8.0053 - 0.0017***B1** + 0.0025***B2** - 0.001***B3** + 0.0002***B4** - 0.0001***B5** + 0.0003***B6** - 0.0003***B7**	0.11
Temp.	- 49.7692 - 0.0072***B1** + 0.0127***B2** + 0.0031***B3** - 0.0072***B4** + 0.0008***B5** - 0.0125***B6** + 0.0138***B7** + 0.0013***B10**	0.35
WQI	1033.5988 + 0.1408***B1** - 0.2361***B2** + 0.213***B3** + 0.0105***B4** + 0.0014***B5** - 0.1124***B6** - 0.0985***B7** - 0.0054***B10** - 3318.431***MNDWI**	0.21

***Note: The location considered for the study is geographically located at a point where the dispersion of soil in water is observed more often due to low and high tides. In geospatial data, the same is reflected and this makes it a bit difficult to establish the accurate relationship between DN values and laboratory data.**

Many studies are conducted where linear models Frenanda *et al.* (2020) and nonlinear KC *et al.* (2019) models are developed to predict WQI. In this study, we constructed various linear models for WQI and its associated parameters. See Table 3 for details along with the values of R^2. It is evident from the Table, that the regression coefficients are positively and inversely related in many cases. These coefficients helps us to understand the influence of the unit percentage change of independent variables on the dependent variable. Since all the abiotic factors are not included in the model, it is difficult to explain the amount of variation present in each model. However, the value of R^2 can explain the amount of variation to a useful extent. As per the analysis, the temperature model yields a high R^2 value as compared to any other model. This can be due to less time difference between spatio-temporal and ground data. The WQI model is also capable to explain around 21% of the total variation present in the data.

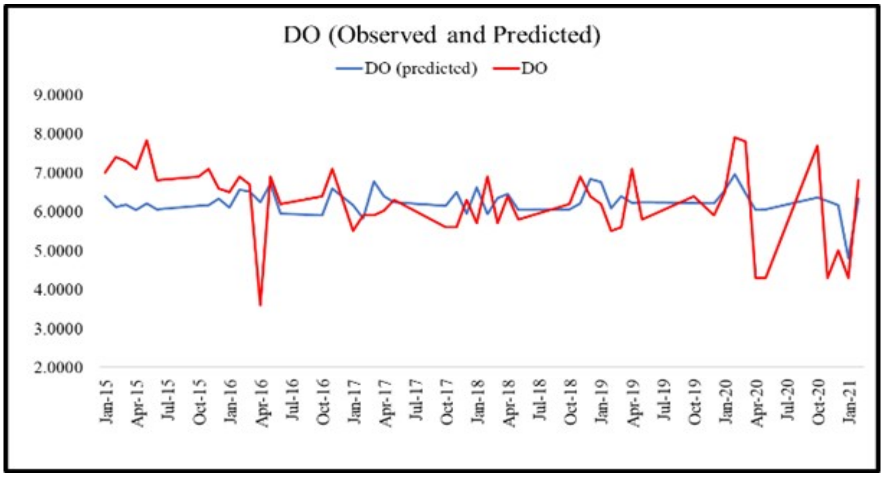

Figure 6(a): Chart of actual values and predicted values of DO

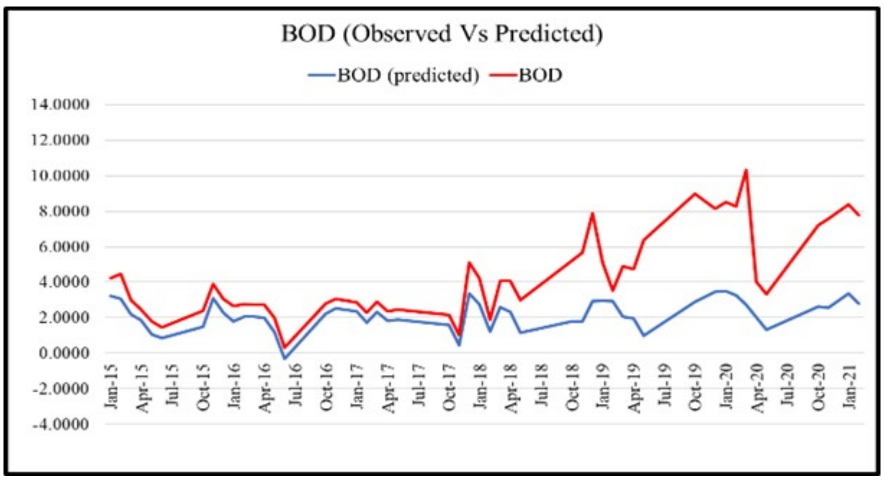

Figure 6(b): Chart of actual values and predicted values of BOD

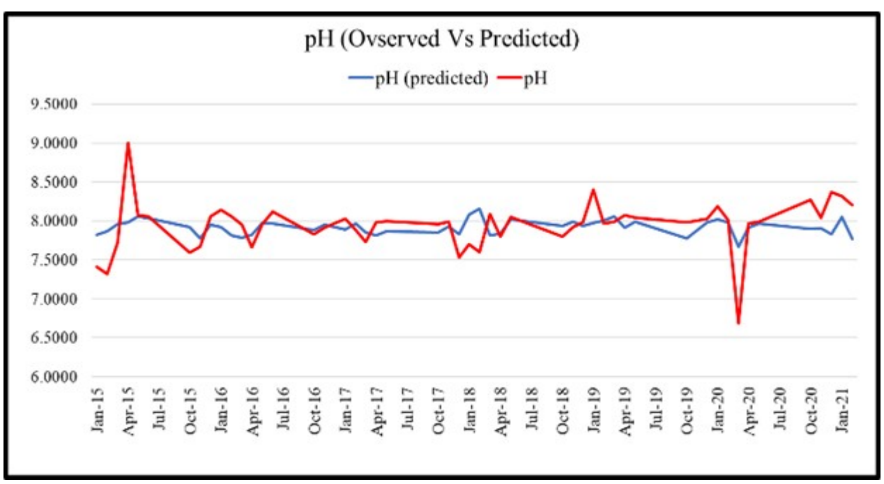

Figure 6(c): Chart of actual values and predicted values of pH

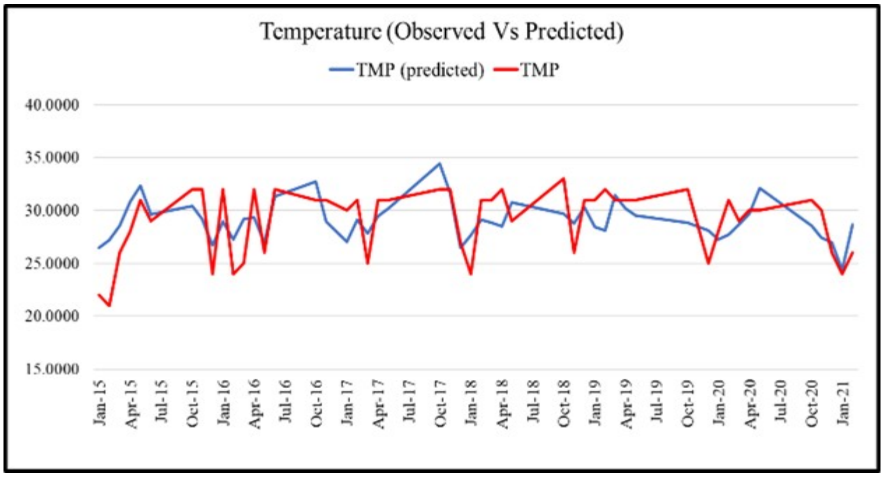

Figure 6(d): Chart of actual values and predicted values of temperature

To understand the prediction capability of each model, we present in Figures 6(a-d), the comparison of actual and predicted values of each variable. It appears that the line charts of projected values appeared to be in the same range as those of real values, however, the model was unable to suit the actual line chart partially or completely due to some elements not included in the model. Figure 6(a-d) shows how a model failed to anticipate a significant spike or dip in the data at some time. It's possible that this phenomenon is related to some climatic changes and fluctuations. The model for BOD was able to follow the trend of real values, but other climatic, physical and supporting variables were not included as factors, thus the projected values did not go together with the actual values. On other hand, the model was not able to predict random spike, which is evident from the decreasing trend as seen in Figure 6(c) of pH. The same thing happened with the temperature chart as well.

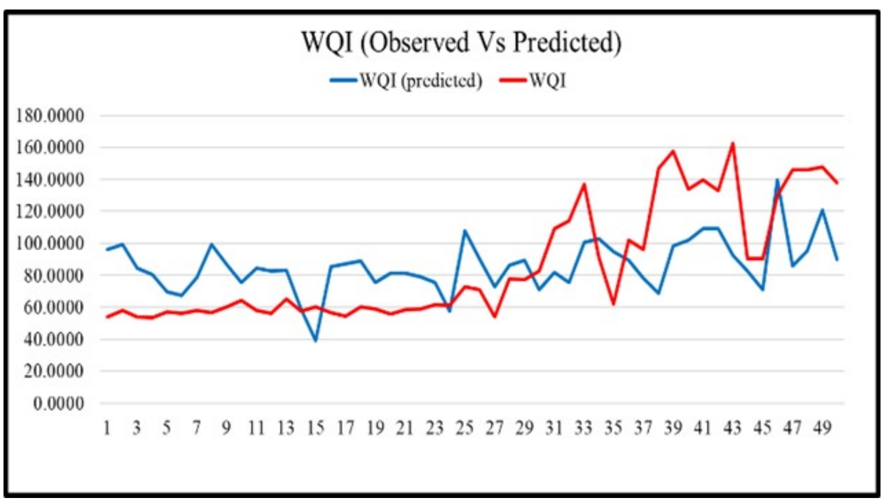

Figure 7: Chart of actual values and predicted values of WQI

It is observed that about 21% of the variation was explained by the WIQ model as per Table 3. However, on plotting the actual and predicted values it can be observed that the model was able to capture the trend in a satisfactory way as shown in Figure 7.

5. Discussion and limitations

The goal of this research is to model parameters using spatial data. In which it was discovered that if we have a region where two separate water bodies are linked, such as our research area, spatial data alone is insufficient to predict water quality properties. Other environmental factors, as well as the lunar cycle, will play a key influence here. We believe that more abiotic elements can be added to every model to make it more useful and trustworthy.

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