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Surface Water Quality Assessment Using Remote Sensing, Gis and Artificial Intelligence

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ABSTRACT

The deterioration of surface water quality occurs due to the presence of various types of pollutants from human activities such as agriculture, industry, construction, deforestation, etc. Thus, the presence of various pollutants in water bodies can lead to deterioration of both surface water quality and aquatic life. Conventional surface water quality assessment methods are widely performed using laboratory analysis, which are labour intensive, costly, and time consuming. Moreover, these methods can only provide individual concentration of surface water quality parameters (SWQPs), measured at monitoring stations and shown in a discrete point format, which are difficult for decision-makers to understand without providing the overall patterns of surface water quality. To such problem, Remote Sensing has been a blessing because of its low cost, spatial continuity and temporal consistency. The relationship between SWQPs and satellite data is complex to be modelled accurately by using regression-based methods. Therefore, our study attempts to develop an artificial intelligence modelling method for mapping concentrations of both optical and non-optical SWQPs.

This study aims to develop techniques for estimating the concentration of both optical and non-optical SWQPs from Satellite Imagery (Landsat8) which supports coastal studies and mapping the complex relationship between satellite multi-spectral signature and concentration of SWQPs. It will also focus on classifying the most significant SWQPs that contribute to both spatial and temporal surface water quality. In contrast to traditionally performed surface water quality assessment methods, this research project will be focused on identifying such parameters incorporating the new and evolving machine intelligence that is Artificial Intelligence (AI). Significant number of samples have to be collected along with the GPS data which is used to model the relationship. In this context, a remote-sensing framework based on the back-propagation neural network (BPNN) will be developed to quantify concentrations of different SWQPs from the Landsat8 satellite imagery. The study area chosen for this research is Bijayapur River of distance approximately 10 km flowing above, through and down the Pokhara city. The sole purpose of this research is to examine the water quality before it flows through the city and analysing after it passes through the city.

KEYWORDS: *Artificial Intelligence (AI), GPS, Landsat8, optical and non-optical SWQPs, Remote Sensing, Regression*

1. INTRODUCTION

Surface water quality is the measure of the state of water resources with respect to specific requirements and necessities, such as human needs. Deteriorating surface water quality due to natural (i.e., soil erosion, landslides, GLOF events, and sediment transport) and anthropogenic (i.e., urban development, industrial, mining, and agricultural activities) processes threatens the stability of the biotic integrity and consequently the aquatic life. Thus, providing continuously updated information about surface water quality is indeed essential to help the managers, local administrators, and decision-makers in taking the right action at the right time to protect water bodies. Conventional methods of assessing surface water quality of water bodies are limited to a set of in-situ water sampling points and laboratory analysis. These methods are time consuming and cost intensive, and only provide limited information in terms of spatial and temporal surface water quality aspects (Liu, Chin and Gong).

Remote sensing estimation of surface water quality is based on mapping the relationship between remote sensing multi-spectral 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. SWQPs can be broadly classified into two main classes: optical and non-optical SWQPs. Optical parameters are optically sensitive parameters which can be sensed by remote sensing and hence can be approximated. A significant number of studies have been conducted for assessing optical parameters. A challenge is to approximate both optical and non-optical describing the underlying relationship between optical and non-optical parameters. Optical SWQPs, such as turbidity and total suspended solids (TSS), are most likely to affect the water color, the reflected signals, and consequently can be detected by satellite sensors. On the other hand, non-optical SWQPs, such as chemical oxygen demand (COD), biochemical oxygen demand (BOD), dissolved oxygen (DO), total solids (TS), total dissolved solids (TDS), power of hydrogen (pH), electrical conductivity (EC), and surface water temperature are less likely to affect the reflected radiation (Din).

Mapping the relationship between Satellite Data and 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 multi-spectral data (Din).

2. STUDY AREA

The selected area for the study is Bijayapur River flowing through one of the major cities in Nepal, Pokhara (28.2380° N, 83.9956° E).

Pokhara lies in western part of Nepal in Gandaki Province. It is originated from Mauja and gets mixed with Seti River in Bhole Chautara. The selected study site is approximately 1.6 kms towards the upstream and downstream from the Bijayapur Bridge. The site was selected as it was near to the Industrial state and we could determine the effects of industrial and anthropogenic wastages flowing through the city. During late summer and rainy season, the period of flow is high.

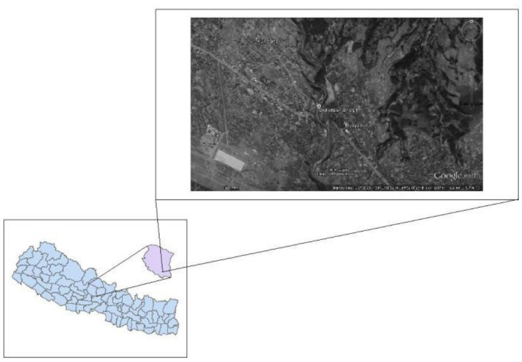

Figure 1: Study Area (Bijayapur Khola)

3. OBJECTIVES

3.1. Primary Objective

- To solve the identified limitations and problems as mentioned in a progressively improving manner mainly in terms of cost, effort, and computational steps.

3.2. Secondary Objectives

- Estimation of the Concentrations of Surface Water Quality Parameter (SWQP) from Satellite Imagery
- Mapping the Relationship between Satellite Data and Concentrations of SWQPs
- Extracting the Accurate Levels of Surface Water Quality within a Water Body
- Identifying the Major SWQPs Contributing to Spatio-temporal Surface Water Quality Variations

4. METHODOLOGY

The satellite data for this research were acquired primarily from Landsat 8 which is freely available in the USGS website and samples of water were collected going into the field along with the GPS location. Laboratory examination of water sample and its modelling for analysis through image were carried out as discussed below.

4.1. Estimation of the Concentrations of Surface Water Quality from Water Sample

Laboratory analysis of the water sample is the first and foremost work of the project. Altogether 16 water samples were taken from the Bijaypur River. The samples were then taken to Laboratory for analysis of water quality parameter. Optical parameter TSS (Total Suspended Solid), TDS (Total Dissolved Solids), Turbidity and Non optical parameter DO (dissolved oxygen) were analyzed in chemistry laboratory.

The descriptive statistics were measured for turbidity, TSS, TDS, and DO. For the used 16 water samples, the following results are obtained:

Table 1: Result of Turbidity, TSS, TDS, DO

meter	Range	Average
idity (in NTU)	6-187	82.68
(in mg/l)	4.80-86.64	29.55
(in mg/l)	360-1000	707.5
(in mg/l)	4.5-11.52	7.10

4.2. Satellite Image Processing Stage:

4.2.1. Correction

After the acquisition of satellite image, corrections (atmospheric and radiometric) were done. The effects of the atmosphere were considered in order to measure the reflectance at the ground (Cambell). Atmospheric correction removes the scattering and absorption effects from the atmosphere to obtain the surface reflectance characterizing (surface properties). Radiometric correction is done to reduce or correct errors in the digital numbers of satellite data. This is due to the sun's azimuth and elevation and atmospheric conditions that can influence the observed energy. Therefore, in order to obtain the real ground irradiance or reflectance, radiometric errors must be corrected. Correction was applied in the image using QGIS software.

4.2.2. The Water Interface

The water interface was masked using the adjusted Normalized Difference Water Index (NDWI) to separate water and non-water features. Equation (3) was used to calculate the adjusted NDWI and the results of the index ranged from [-1.00 to +1.00]. Water feature showed negative values due to their typically higher reflectance of green band than near-infrared band and accordingly water pixels were directly separated from non-water pixels, which showed positive and zero values.

Equation 3 (NDWI) = [(NIR) − (G)] / [(NIR) + (G)]

Where NIR is the near-infrared band; and G is the green band.

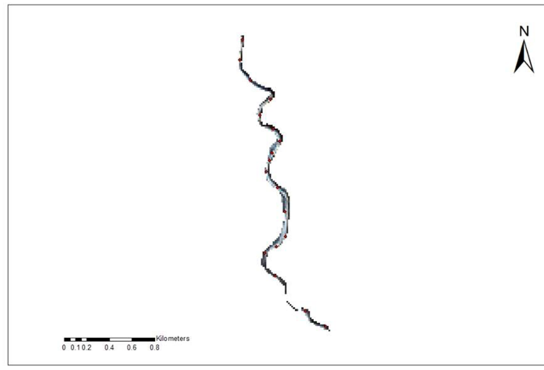

Figure 2: Water Interface

4.3. Estimation of the Concentrations of SWQPs

From Satellite Imagery Monitoring and estimating concentrations of optically and non-optically active surface water quality parameters (SWQPs) on a large scale by exploiting remotely sensed data is essential for providing the targeted treatment to watersheds. Remote sensing provides significant benefits over conventional water quality monitoring methods, mainly due to the synoptic coverage and temporal consistency of the data. Remote sensing of non optical SWQPs is the major challenge of the project. However, concentrations of non-optical SWQPs may be correlated with optical variables, such as TSS, which have the potential to affect water color, the reflected radiation, and consequently can be detected by satellite sensors. Therefore, this research project is based on the use of step wise regression (SWR) technique to develop mathematical model for estimation of concentration of SWQPs.

4.4. Model Development

The SWR method selects a sub-set from a list of explanatory (independent) variables and removes and adds variables to the regression model for the purpose of identifying a useful subset of the predictors (Derksen). The SWR first finds the explanatory variable with the smallest significant value (P-value) to start over. The SWR then tries each of the remaining explanatory variables until it finds the two variables with the smallest P-value. After that, the SWR tries all of them again until it finds the three variables with the smallest P value, and so on. Generally, the process continues until no significant improvement in p-value. Sampling points were subdivided into two datasets; calibration (75% of all samples) and validation (25% of all samples) to establish and validate the developed models (Din).

4.5. Mapping Concentrations of SWQPs Using the BPNN Algorithm

- ANN Input and Output Selection
- ANN Data Division
- ANN Architecture Selection
- ANN Structure Selection
- ANN Training
- ANN Evaluation

4.6. Estimation and Validation of the Landsat 8-Based-BPNN Developed Models

The main steps of developing the Landsat 8-based-BPNN models, as well as the way the data flow through and the outcomes achieved, are given in the following subsections.

- ANN Input and Output Selection
- ANN Data Division
- ANN Architecture Selection
- ANN Structure Selection
- ANN Training
- ANN Evaluation

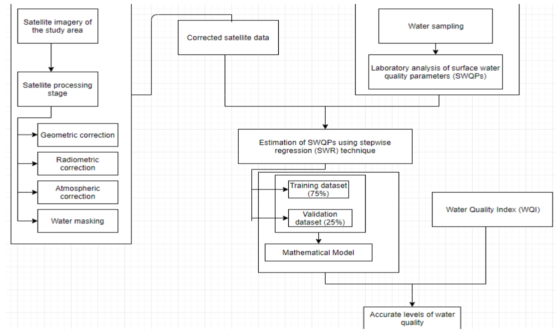

Figure 3: Methodology

5. EXPERIMENTAL

5.1. Problem Identification

Contamination caused by industrial activities around the Bijaypur River creates the vast pollution in stream water. So due to the industrial area and anthropogenic activities problems to degradation of surface water is taken in consideration.

5.2. Field Visit and Data Collection

Water sampling was performed during field trip in April 1st, 2019. All together 16 samples were randomly selected and distributed across the entire study area (Bijaypur Khola) as shown in fig 1. Coordinates of each sample point were recorded in the field using a mobile GPS device (OSM tracker). In order to carry out this study efficiently, water samples were collected just beneath water surface and around the same time the satellite sensor should overpass so that we can acquire the satellite data in-between 4 hours.

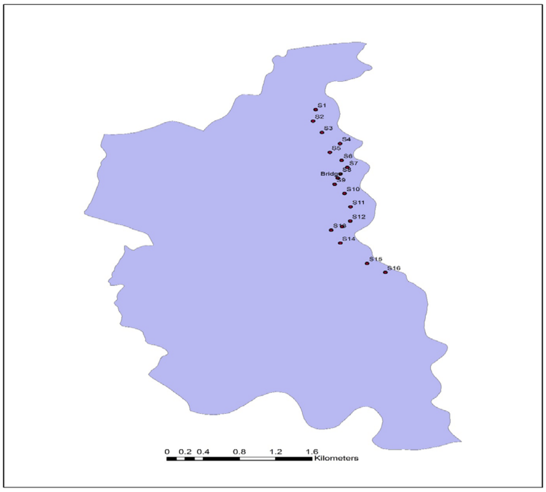

Figure 4: Location of sampling area

5.3. Lab Examination of Water:

Concentration of turbidity, Total Suspended Solids (TSS), Total Dissolved Solids (TDS) and Dissolved Oxygen (DO) were measured according to the standard methods for lab examination of water.

5.3.1. Turbidity:

Turbidity measures the cloudiness/haziness of a fluid. It is a key test for water quality, turbidity is caused by particles of varying size scattering/absorbing the light and creating a cloudy appearance. The turbidity of a sample will increase with the amount of undissolved solids present. Turbidity of all samples were measured using turbidity tube. Turbidity tube is a tube with a black cross at the bottom and the measurement is done by pouring water into the tube until they can no longer make out the black cross at which point we can read off the scale on the outside of the tube in NTU. The result shows that upper part of study area has higher concentration of turbidity. Turbidity of samples is tabulated below:

Table 2: Turbidity Value

S/N	SAMPLING STATION	EASTING(DEGREE)	NORTHING(DEGREE)	TURBIDITY(NTU)
1	S1	28.203252	84.025175	187
2	S2	28.201670	84.024911	139
3	S3	28.200021	84.025636	97
4	S4	28.198306	84.027549	108
5	S5	28.197185	84.026493	89
6	S6	28.196064	84.027746	93
7	S7	28.195075	84.028538	108
8	S8	28.194218	84.027549	101
9	S9	28.192569	84.026955	86
10	S10	28.191382	84.028010	89
11	S11	28.189470	84.028736	91
12	S12	28.187359	84.028472	71
13	S13	28.186040	84.026691	6
14	S14	28.184194	84.027549	6
15	S15	28.181292	84.030186	32
16	S16	28.179973	84.032033	20

5.3.2. Total Suspended Solids (TSS)

It is the dry weight of suspended particles that are not dissolved, in a sample of water that can be trapped by a filter that is analysed using a filtration apparatus. Test of TSS have been done by pouring a carefully measured volume of sample water (25ml) through the pre-weight filter paper then weighing the filter paper with residue again after drying process that removes all water on the filter. TSS of the samples are tabulated below:

Table 3: TSS Value

S/N	SAMPLING STATION	EASTING(DEGREE)	NORTHING(DEGREE)	TSS(mg/ltr)
1	S1	28.203252	84.025175	400
2	S2	28.201670	84.024911	400
3	S3	28.200021	84.025636	200
4	S4	28.198306	84.027549	100
5	S5	28.197185	84.026493	400
6	S6	28.196064	84.027746	100
7	S7	28.195075	84.028538	800
8	S8	28.194218	84.027549	400
9	S9	28.192569	84.026955	300
10	S10	28.191382	84.028010	1200
11	S11	28.189470	84.028736	100
12	S12	28.187359	84.028472	100
13	S13	28.186040	84.026691	100
14	S14	28.184194	84.027549	100
15	S15	28.181292	84.030186	100
16	S16	28.179973	84.032033	33

5.3.3. Total Dissolved Solids (TDS)

Total dissolved solids is a measure of the dissolved combined content of all inorganic and organic substances present in a liquid in molecular, ionized or micro-granular suspended form. Gravimetric method has been done to find TDS. It involves evaporating the liquid solvent and measuring the mass of residues left. Result are tabulated below:

Table 4: TDS Value

S/N	SAMPLING STATION	LATITUDE(DEGREE)	LONGITUDE(DEGREE)	TDS(mg/ltr)
1	S1	28.203252	84.025175	560
2	S2	28.201670	84.024911	800
3	S3	28.200021	84.025636	920
4	S4	28.198306	84.027549	1000
5	S5	28.197185	84.026493	800
6	S6	28.196064	84.027746	880
7	S7	28.195075	84.028538	920
8	S8	28.194218	84.027549	880
9	S9	28.192569	84.026955	760
10	S10	28.191382	84.028010	800
11	S11	28.189470	84.028736	840
12	S12	28.187359	84.028472	440
13	S13	28.186040	84.026691	400
14	S14	28.184194	84.027549	360
15	S15	28.181292	84.030186	400
16	S16	28.179973	84.032033	560

5.3.4. Dissolved Oxygen (DO)

Dissolved oxygen refers to the level of free, non-compound oxygen present in water. It is one of the important parameters when assessing water quality because of its influence on the organisms living within a body of water. A dissolved oxygen that is too high or too low can harm aquatic life and affect water quality. Dissolved oxygen is measured in lab and results are tabulated below:

Table 5: Dissolved Oxygen

S/N	SAMPLING STATION	LATITUDE(DEGREE)	LONGITUDE(DEGREE)	DO(ppm)
1	S1	28.203252	84.025175	11.52
2	S2	28.201670	84.024911	6.4
3	S3	28.200021	84.025636	8
4	S4	28.198306	84.027549	7.2
5	S5	28.197185	84.026493	7.2
6	S6	28.196064	84.027746	8.64
7	S7	28.195075	84.028538	6.4
8	S8	28.194218	84.027549	5.6
9	S9	28.192569	84.026955	5.6
10	S10	28.191382	84.028010	8.96
11	S11	28.189470	84.028736	4.5
12	S12	28.187359	84.028472	6.4
13	S13	28.186040	84.026691	7.2
14	S14	28.184194	84.027549	8.48
15	S15	28.181292	84.030186	4.64
16	S16	28.179973	84.032033	6.88

5.4. Calculation of Correlation between SWQPs

The correlation between concentrations of optical and non-optical SWQPs was calculated as shown in Table given below. The relationship between turbidity and all SWQPs except DO must be positively correlated and correlation values must lie between 0.8 to 1 while, correlation values between DO levels and turbidity, TSS, COD, and BOD should between -0.8 to -1. The non-optical SWQPs are less likely to affect the light signals measured by satellite detectors, and thus they cannot be measured directly by satellite sensors. The only way they can be measured is indirectly by the fact that their concentrations are correlated in some way with optical SWQPs like TSS or turbidity that do affect the signals measured by satellite sensors. Such indirect effects may be site-specific (Derksen).

Table 6: Correlation matrix of both optical and non-optical SWQPS

❖ Parameters	TDS	TSS	Turbidity	DO
TDS	1	0.3495	0.5840	-0.0719
TSS	0.3495	1	0.38518	0.2478
Turbidity	0.5840	0.38518	1	0.3351
DO	-0.0719	0.2478	0.3351	1

5.5. Satellite Image Processing Stage:

5.5.1. The Water Interface

To estimate the concentrations of different SWQPs over a specific water body, the water surface was delineated accurately from Landsat8>>>>Landsat OLI/TIRS C1 Level 1. Instead of using the whole image pixel in the process of mapping the concentrations of SWQPs, only water pixels were included in this process to accelerate the processing/ computational speed of the developed models. The full Landsat 8 scenes are available free of charge at Level 1T (terrain corrected) at Landsat websites maintained by the US Geological Survey (USGS). The Landsat 8 satellite sub-scenes used in our study were acquired on 1 May 2019. Basically, the Level 1T product is a geometrically corrected image and rectified to the Universal Transverse Mercator (UTM) projection, World Geodetic System 1984 (WGS 84) datum. Digital numbers (DNs) of the Landsat 8 satellite images are stored in 16 bits unsigned integer format, and were subsequently corrected to obtain the top of atmospheric (TOA) reflectance using radiometric rescaling coefficients.

5.5.2. NDWI

Normalize Difference Water Index (NDWI) was used for the water bodies analysis. The index uses Green and Near infra-red bands of remote sensing images. The NDWI enhanced water information efficiently in most cases. It is sensitive to build-up land and result in overestimated water bodies. The NDWI products was used in conjunction with NDVI change products to assess context of apparent change areas. The water interface was masked using the adjusted Normalized Difference Water Index (NDWI) to separate water and non-water features. The adjusted NDWI is derived by using principles similar to those used to derive the normalized difference vegetation index (NDVI). Equation (a) was used to calculate the adjusted NDWI and the results of the index ranged from [-1.00 to +1.00]. Water features showed negative values due to their typically higher reflectance of green band than near-infrared band and accordingly water pixels were directly separated from non-water pixels, which showed positive and zero values.

Equation 4 $(NDWI) = [(NIR) - (G)] / [(NIR) + (G)]$

Where NIR is the near-infrared band; and G is the green band.

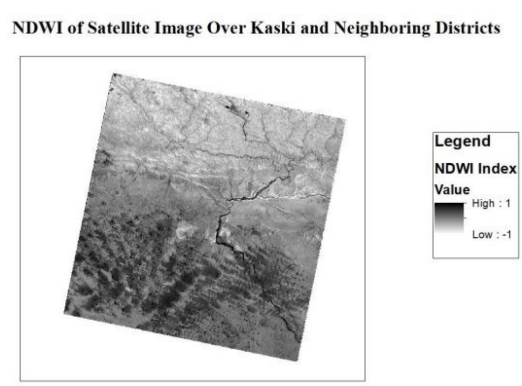

Figure 5: NDWI of Satellite Image over Kaski and Neighbouring Districts

6. RESULT AND CONCLUSION

The optical parameters: turbidity, total suspended solids, total dissolved solids and non-optical parameters: dissolved oxygen were measured through chemical tests. The Landsat 8 composite band image, sample area map were prepared. The correlation techniques were used to find the relation between optical and non-optical parameters and regression techniques process was used to find the appropriate relation between band image and surface water quality parameters. An effective model to determine Surface water quality can be developed by deriving relation between parameters and band image which can be effectively achieved by using NDWI calculated image. The results of this study provide a powerful tool for decision making procedures in surface water quality measurement, as it allows a coherent and efficient use of spatial and non-spatial data. The results maps are shown below:

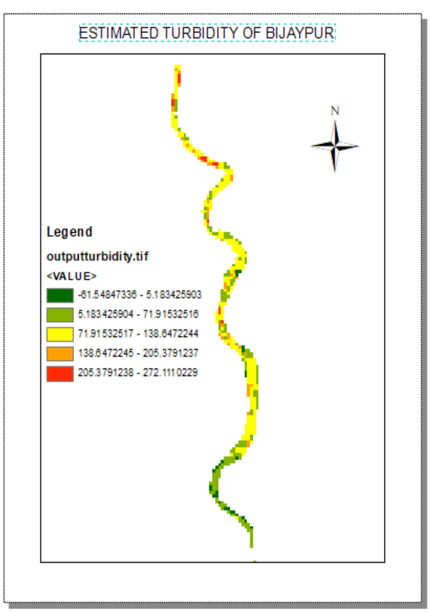

Figure 6: Estimated turbidity of Bijaypur River

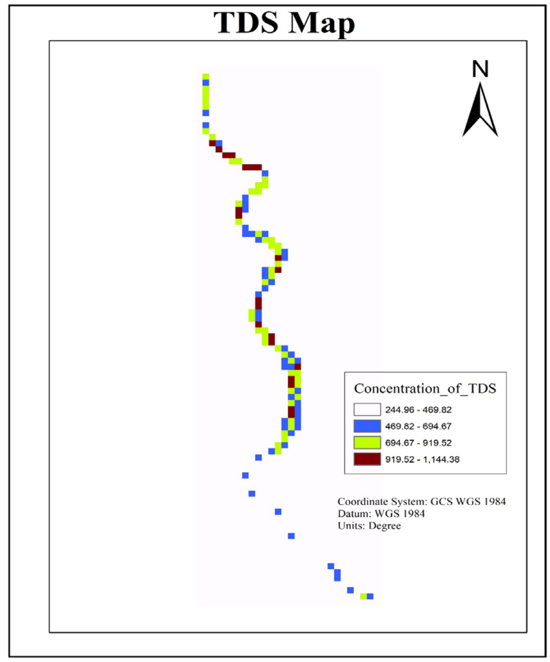

Figure 7: Concentration of TDS of Bijaypur River

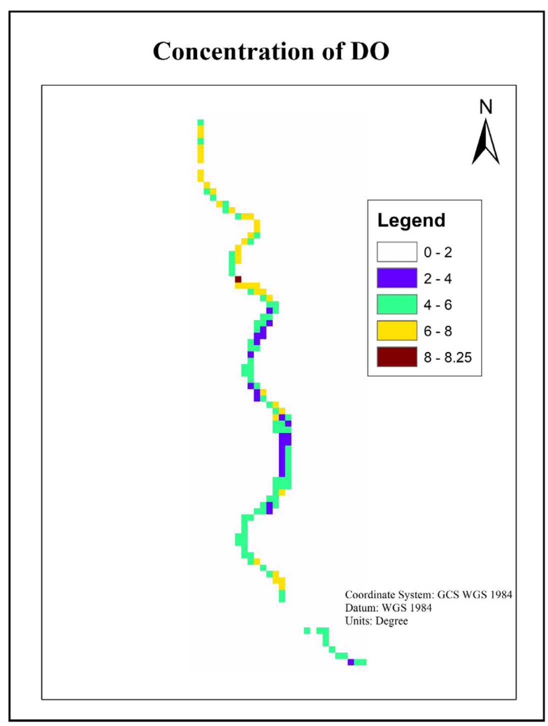

Figure 8: Concentration of Dissolved Oxygen of Bijaypur River

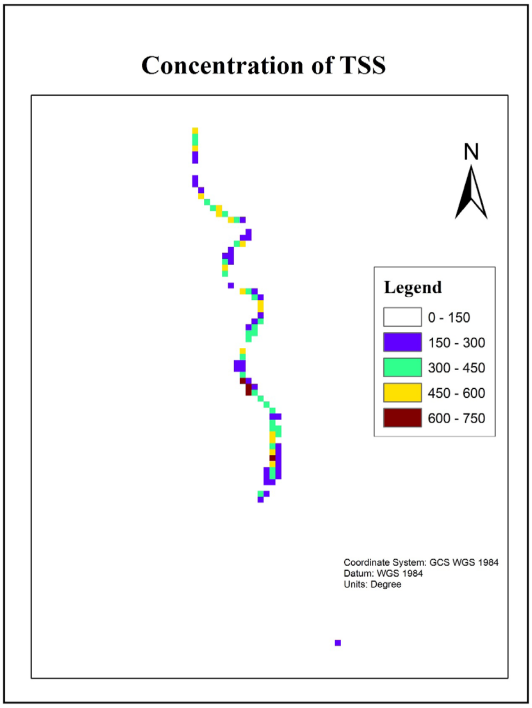

Figure 9: Concentration of TSS of Bijaypur River

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