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Surface Water Quality Analysis in Thamirabarani River Using Remote Sensing And GIS

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ABSTRACT
A combination of twenty different in-situ measurements and satellite-derived Landsat data has been utilized to deduce the correlation between the observed Water Quality Parameters (WQP) between the two sources mentioned above for the area of study, the Tamirabarani river, Tirunelveli, on the ArcGIS software. The correlation proved to be inconsonant with the corollaries stated above when processed through the linear regression model constructed to serve the purpose. The Landsat data and in-situ observed values of total dissolved solids (TDS), pH, salinity, electrical conductivity, and Dissolved Oxygen (DO) were passed through this model quantify the WQP. The results demonstrated that the band combination and band rationing of Landsat against the ground sampling measurements were almost parallel. The averaged estimated values of the ground measurements for pH, BOD, NH_3, NO_3, TSS, and TDS were 7.13, 2.212, 1.68, 2.634, 95.13, 80.71, respectively. The corresponding concentration values for Landsat data are 7.54, 2.568, 0.33, 2.536, 102.466, and 88.002, respectively. These numerals prove that Landsat data would be a good fit for estimating and monitoring Water Quality Parameters (WQP) in the Tamirabarani river, Tirunelveli, on a regional scale.

Keywords: *WQP, TDS, DO, pH, salinity, electrical conductivity*

I. INTRODUCTION

Water plays a vital role in stabilizing the health factor of all living beings. Under the pretext of industrialization, though job opportunities abound and facilities and utilities become available, water is being polluted to a great extent. In contrast to natural sources, anthropogenic sources contribute heavily to water pollution. This calls for consistent monitoring of water quality. Untreated domestic sewage and industrial effluents being let out into the water bodies affect water utility for drinking, agricultural, recreational, and other purposes. Conversely, discharging toxic components into aquatic bodies cause harm to marine life, which in turn affects humans and the surrounding environment. Since water scarcity is on the rise, to make healthy drinking water available for humankind in the present and future epochs, water quality assessment is indispensable.

To cater to the need, this project explored the effectiveness of remotely sensed data in the Tamirabarani river, Tirunelveli, by comparing with the in-situ measurements to validate the study of existing literature. This region was chosen for the study due to its impact on the environment. The Tamirabarani waters have become polluted mainly due to the increasing population, industrialization, and other anthropological activities, altering the physical, chemical, and biological parameters of the waters. Thus, continuous monitoring has to be enforced to prevent further degradation of the basin.

Fraser R.N. (2013) showed through their study the robust correlation of multispectral reflectance data (from Landsat Thematics Mapper) with turbidity among21 lakes in Nebraska, USA, sampled in June 1994. Mean lake reflectance percentages ranged between 5 ± 12 (TM1), 4 ± 18 (TM2), 2 ± 12 (TM3) and 1 ± 5 (TM4). The turbidity ranged from 2.7 ± 82.3 nephelometric turbidity units, and the correlations were highly significant ($\gamma > 0.68$; $\varrho < 0.001$) between each of the TM bands and turbidity. Here, linear models were useful for measuring lakes, despite potential floor effects or variation in turbidity components due to a range of water quality.

Similarly, Leif G. et al. (2012) proposed to generate the water clarity atlas of the 10,000 lakes of Minnesota in two years, between 2011 and 2012. Based on a strong relationship between Landsat TM 1 and 3 bands, and the Secchi disk transparency, the water clarity atlas was developed. Image processing and procedural classification techniques were employed to the Landsat imageries considered for the study. The product has been utilized to assess the spatial and temporal patterns of the water clarity based on the integration of the surrounding land use and land cover features collected through GIS.

While the literature above concentrated on the overall health of the water bodies, Luoheng et al. (2012) developed an algorithm that estimated chlorophyll-a concentration in the Pensacola Bay using Landsat 7 ETM+ data. Through band rationing and regression modeling, the in-situ and satellite-derived concentrations were compared and contrasted to identify that the procured data served well to monitor chlorophyll-a concentration. Based on this study, the current project derived its inspiration and explored the possibilities of using a similar technique to determine the water quality parameters' concentrations.

So, on a deeper analysis, it was found that Zhou et al. (2012) had developed and applied multi-temporal models to estimate and map the concentrations of total suspended matter (TSM) in Lake Taihu, China. Simultaneously, Zhnag et al. (2013) monitored the surface water quality of the Miyun reservoir using a remote sensing method based on the empirical correlation between the water quality parameters and band combinations of the imageries. The study deduced that bands 3 and 4 showed better results for estimating chlorophyll-a concentration. And, the bands 2, 3, and 4 proved robust outcomes for nitrogen concentrations. Then, the developed empirical model was applied to the whole surface water of the Miyun reservoir.

In much contrast, however, Bilgehan et al. (2013) investigated the spatial patterns in water quality in Lake Beysehir, the largest freshwater reservoir in Turkey, through Landsat 5 TM data and ground surveys. Suspended sediment (SS), turbidity, Secchi disk depth (SDD), and chlorophyll-a data were collected from 40 sampling stations in August 2006. The spatial patterns in these parameters were estimated using Bivariate and multiple regression techniques based on Landsat 5 TM multispectral data and water quality sampling data. Single TM bands, band ratios, and TM bands' combinations were estimated and correlated with the measured water quality parameters. The resultant regression models showed that the measured and estimated water quality parameters' values were in good agreement (0.60 < R2 < 0.71).

Alternatively, Bilge et al. (2013) determined the relationships between water quality parameters and digital data from the Landsat satellite to estimate and map the WQPs in the Porusk Dam reservoir. The suspended solids (SS), chlorophyll-a, NO_3-N, and transmitted light intensity depth (TLID) were the parameters for brightness values (BV) of the TM data, and thus the WQPs were determined. Using the TM data, they developed multiple regression equations to estimate the WQPs, and the validation of these equations was checked using ANOVA. The effects of SS, NO_3-N, chl-a, and TLID were tested not only for ground data but also for TM datasets. Regression equations were developed for two different datasets, and the homogeneity of those equations was tested. Finally, these regression equations from digital TM and ground data were applied to map the acute TLID values. This clearly shows that Landsat data serves well to estimate and map the WQPs in correlation with the ground samples. The algorithms developed for the regression models have proved robust since they could dictate the ideal results.

II. MATERIALS AND METHODS

A. Study Site

The study area lies in the Tamirabarani river basin, Tirunelveli district, Tamil Nadu, geographically bounded by 77°09' 77°54' E and 08°08' 09°23' N (Fig.1). Having been fed by both its tributaries and the monsoons, the Tamirabaranibasin procures its major annual rainfall of around 815 mm, between October and mid-January, with a relative humidity of 55 to 65 percent. The topography is comprehensively characterized as flat with a gentle slope, and it flows roughly east to enter the Gulf of Mannar of the Bay of Bengal, near Palayakayal.

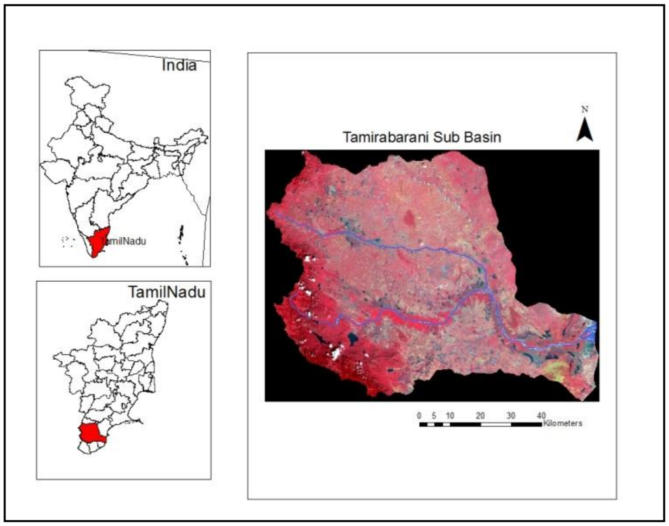

Figure 1: Location of Tamirabarani Basin, Tirunelveli, Tamil Nadu

B. Satellite Spectral Factors

The surface water quality assessment study has been carried out by evaluating Landsat 8 imageries whose spectral factors are depicted in Table 1.

Band	Spatial Resolution (m)	Spectral Resolution (µm)
Coatal	30	0.43 - 0.45
Blue	30	0.45 - 0.51
Green	30	0.53 - 0.59
Red	30	0.63 - 0.67
NIR	30	0.85 - 0.88
SWIR1	30	1.57 - 1.65
SWIR2	30	2.11 - 2.29
PAN	15	0.50 - 0.68
Cirrus	30	1.36 - 1.38
TIR1	100	10.60 - 11.19
TIR2	100	11.50 - 12.51

We have developed models with the procured data to identify if the 20 different water samples collected from in-situ measurements were similar to that of the satellite-derived data. The overall methodology adopted for this study is depicted in Fig 2.

a) Geometrical Correction

Primarily, the study site's obtained imageries have been geo-registered to the topographic maps of the Tirunelveli district by referencing the ground control points. When the desired root means the square error of less than one had been achieved, the nearest-neighbor resampling technique was used to preserve the imageries' original brightness values.

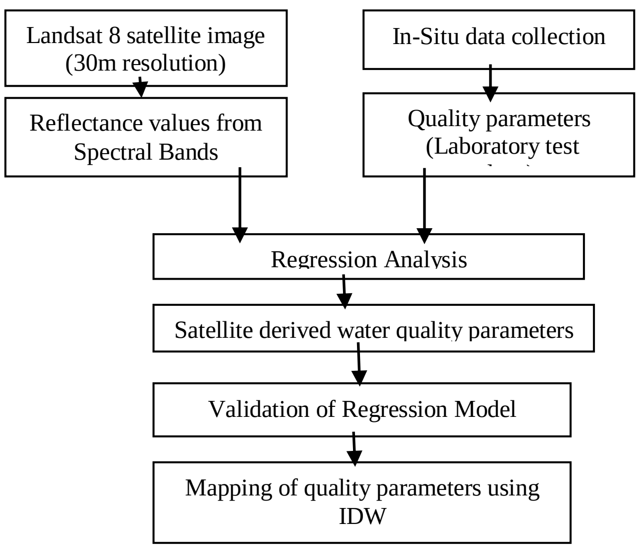

Figure 2: Working Methodology

b) Delineation of Tamirabarani Basin

To delineate the basin, SRTM DEM data of 30m resolution was used. In ArcGIS 10.1, the Terrain Preprocessing sequential process in the Arc Hydro Tool was employed to derive the watershed's shapefile.

Then the contours were digitized to prepare the digital elevation model. All the sinks were filled in the DEM to identify the flow direction. After this, the flow accumulation raster was generated. Then, by determining the pour points, the watershed was delineated.

c) Extracting Reflectance Values from Landsat TM Image

Since water is best assessed in the red, green, NIR, and MIR bands, different band rationing combinations involving the four bands have been adopted, as below:

Band Rationing 1 = Red/Green
Band Rationing 2 = Red/NIR
Band Rationing 3 = NIR/Green
Band Rationing 4 = MIR/Green

Upon band rationing, it was found that latent information regarding the inverse relationship between two spectral responses to the same biophysical phenomenon was expressed clearly.

From the digital numbers, to thus derive the reflectance values, a two-stage process was incorporated after deducing the rapport between the spectral responses.

Here, the ideology was to convert the digital numbers into radiance values, which were then converted into reflectance values to identify the behavior of PH, TDS, BOD, TSS, NO_3, NH_3, EC. Thus, we obtained the distance between the sun and the earth in astronomical units and the solar zenith angle, along with the Julian date, to perform this conversion for each of the scenes.

1) DN to Radiance Conversion

This is also a process that's termed atmosphere correction. Two formulae were used, each in conjunction with the data available for scene calibration in the header files.

(a) Gain and Bias Method

This method of converting digital numbers to radiance required the gain multiplied with the DN values, summed up with the bias factor.

$$\mathbf{L_\lambda = gain * DN * bias}$$

Where,
L_λ is the cell value of the radiance
Gain is the specific band's gain factor
DN is the digital number value
Bias is the specific band's bias factor

(b) Spectral Radiance Sealing Method

In this method of converting digital numbers to radiance, we used the following formula:

$$L_\lambda = ((L_{MAX\lambda} - L_{MAX\lambda})/(QCAL_{MAX} - QCAL_{MIN}))*(QCAL-QCAL_{MIN}) + L_{MIN\lambda}$$

Where,

L_λ is cell value as radiance

$L_{MIN\lambda}$ is the spectral radiance scales to $QCAL_{MIN}$

QCAL is the digital number

$L_{MAX\lambda}$ is the spectral radiance scales to $QCAL_{MAX}$

$QCAL_{MIN}$ is the minimum quantized calibrated pixel value, typically 1

$QCAL_{MAX}$ is the maximum quantized calibrated pixel value, typically 25

2) Radiance to Reflectance Conversion

The next step, after determining the radiance value, is to calculate the reflectance value. For this, the Landsat 8 Users Handbook was used to derive the formula below:

$$\boldsymbol{\rho_\lambda = \pi * L_\lambda * d2/ ESUN_\lambda * COS\ \theta_s}$$

Where,
ρ_λ is the unitless planetary reflectance
L_λ is the spectral radiance
d is the distance between the earth and the sun in

astronomical units
ESUN$_\lambda$ is the mean solar exo-atmospheric irradiance
θ_s is the solar zenith angle
Upon subjecting the radiance values through this conversion step, the obtained reflectance values ranged between zero and one.

C. Development of Regression Model

From the literature studies, it was gathered that the most common approach to derive a correlation between the spectral data and the water quality parameters was through statistical techniques, which is why a regression model is being developed for this study, to determine which brand of the Landsat data coheres well with the in-situ measurements. Therefore, a series of statistical models were developed and examined for determining the best relation between measurements of WQPs and the derived parameters through TM/ETM data. Multiple regression models were selected to represent the best relation between the WQPs and their corresponding brightness values of the Landsat TM/ETM data.

So, this step consists of developing the algorithm that predicts clear values from the satellite imagery's spectral features. Since a continuous dependent variable is required, regression analysis is recommended to be carried out, and in this case, a multiple linear regression (spectral values vs. WQP).

The major parameters adopted for the analysis of surface water were PH, TDS, BOD, TSS, NO3, NH3, and EC. The correlation between the LANDSAT data and WQPs shows the relationship of band values with the measured data. The band that indicated a good correlation with each measured parameter was selected to construct multiple linear regression models, and the linear regression model with a best significant relationship with WQPs through LANDSAT data with in-situ measured data was obtained. The highest significant values were obtained through the LANDSAT bands' contribution (band 4 and band 5). Their reflectance values displayed the strongest relationship with the ground-based measurements of the WQPs. The in-situ water sample measurements are recorded in Table 2.

Table 2: In-situ WQPs Concentrations

Sample NO	PH	EC Mg/l	TDS Mg/l	TSS Mg/l	NH3 Mg/l	NO3 Mg/l	BOD Mg/l
1	7.20	60	34.67	30.00	0.49	2.00	2.21
2	7.07	85	43.00	208.00	0.36	2.00	2.25
3	7.23	100	50.00	114.33	0.64	1.67	2.30
4	7.20	105	52.33	131.33	0.45	2.33	4.20
5	7.37	105	62.33	145.33	0.47	2.33	2.49
6	7.6	195	101.00	70.00	0.59	2.00	2.56
7	7.47	145	74.33	66.67	0.51	2.00	2.47
8	7.43	150	77.67	96.33	0.74	2.67	2.65
9	7.70	140	75.33	97.33	1.63	2.33	2.59
10	7.63	150	76.67	60.00	0.66	2.67	1.99
11	7.63	155	77.56	105.33	0.44	2.60	4.11
12	7.30	160	83.67	83.33	0.19	3.60	3.38
13	7.57	180	90.67	81.33	0.19	3.00	2.63
14	7.55	200	113.33	62.33	0.21	2.67	3.05
15	7.58	210	104.67	100.33	0.28	2.50	2.66
16	7.56	225	118.33	182.67	0.18	2.67	2.50
17	7.80	225	115.00	46.67	0.14	2.33	2.19
18	7.87	265	127.00	61.33	0.05	1.67	2.91
19	8.10	260	132.00	60.00	0.16	1.67	2.56
20	8.13	390	160.00	47.67	0.17	1.00	2.53

D. Validation of The Regression Model

When the values as obtained in Table 2 were correlated with the satellite-derived data, the band 4 and band 5, that is, the red and near-infrared wavelengths, proved optimal to record the right values of the WQPs concentration levels. The following graphs demonstrate the difference between the estimated and the ground concentration values of the WQPs.

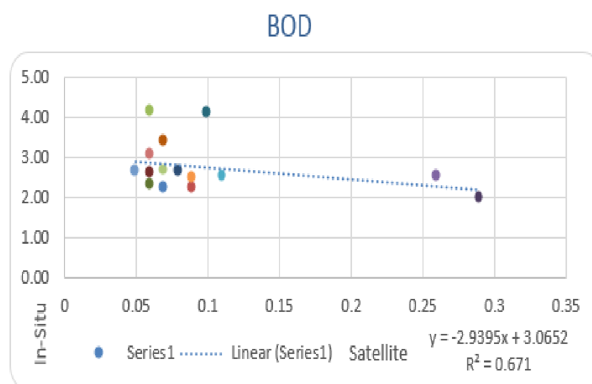

Figure 3: Regression Model of BOD

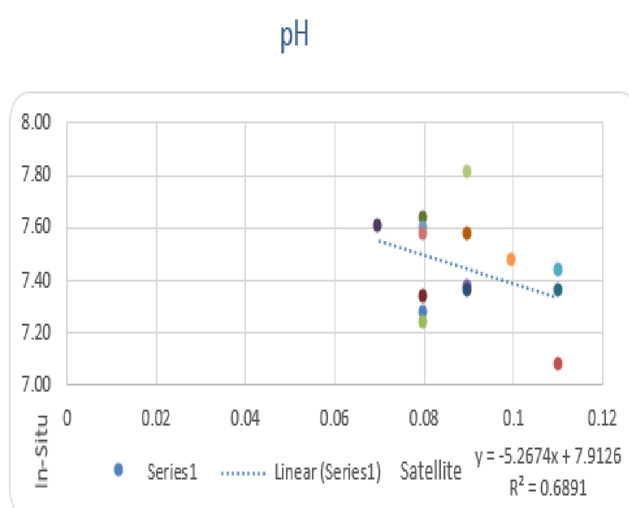

Figure 4: Regression Model of pH

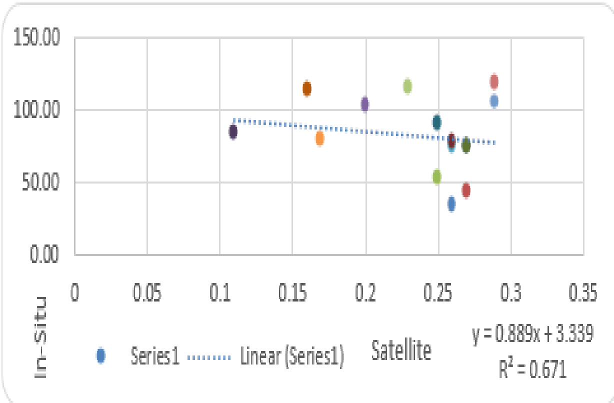

Figure 5: Regression Model of TSS

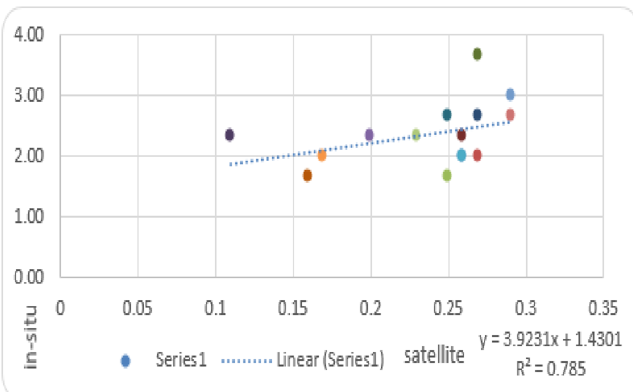

Figure 6: Regression Model of NO_3

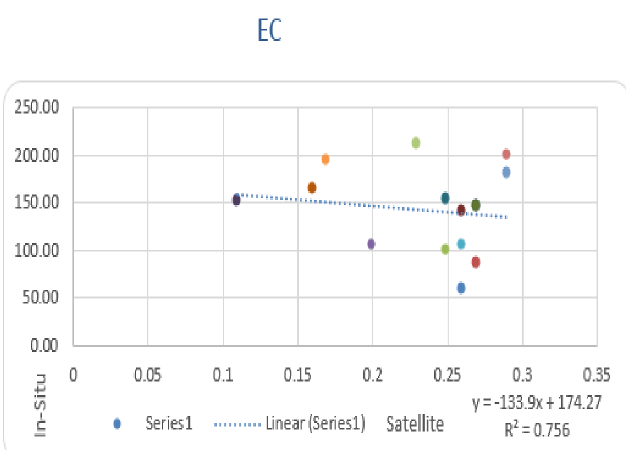

Figure 7: Regression Model of EC

III. RESULT AND DISCUSSION

A. Ph

pH is one of the important parameters of water that determines its acidic and alkaline nature. The pH of good quality water ranges between 7 and 8.3. The pH of the samples was well within the prescribed standards for drinking water. The spatial variation map for pH was prepared and has been presented in Fig 8.

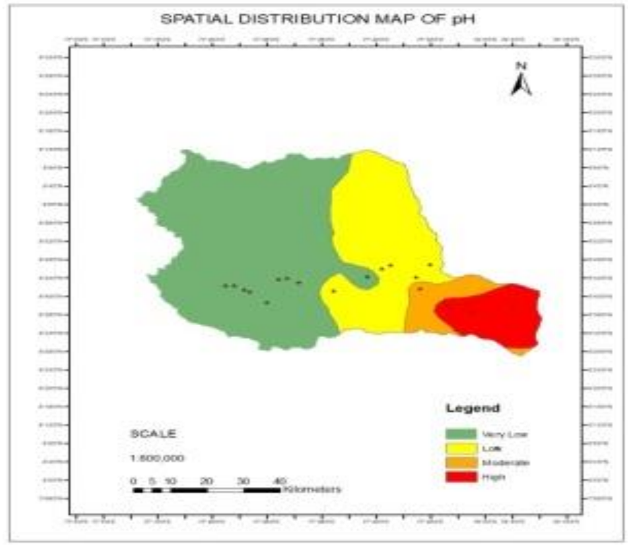

Figure 8: Spatial Distribution Map of pH

B. Electrical Conductivity (EC)

Electrical Conductivity (EC) depends upon temperature, ionic concentration, and types of ions present in the water. Thus, the EC gives a qualitative picture of the quality of groundwater. The Electrical Conductivity (EC) was classified in to three ranges (0-2250 mhos/cm, 2250-3000 mhos/cm and >3000 mhos/cm). The spatial variation map for Electrical Conductivity (EC) was prepared and presented in Fig 9. From the map, it is evident that the river basin's major area has a good range of EC except at the discharge area of the river into the sea.

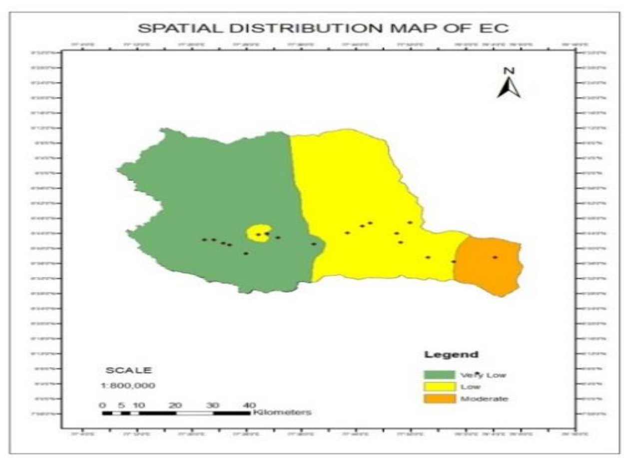

Figure 9: Spatial Distribution Map of EC

C. Total Suspended Solids (TSS)

The Total SuspendedSolids were classified into three ranges (0-50 mg/l, 50-150 mg/l, and >150 mg/l), and based on these ranges, the spatial variation map for total hardness has been obtained and presented in Fig 10. It is clear from the map that except in the central part of the basin has a good range of Total Suspended Solids.

D. Total Dissolved Solids (TDS)

All the mineral constituents dissolved in water constitute the dissolved solids. The concentration of dissolved solids in water decides its usability for drinking, irrigation, and industrial purposes. The Total Dissolved Solids (TDS) were classified into three ranges as that of the TSS (0-500 mg/l, 500-1000 mg/l, and >1000 mg/l). The spatial variation map for TDS was prepared based on these ranges and presented in Fig 11. From the map, it is evident that except for the central and southeastern part of the basin, all the other portions have a good TDS quality range.

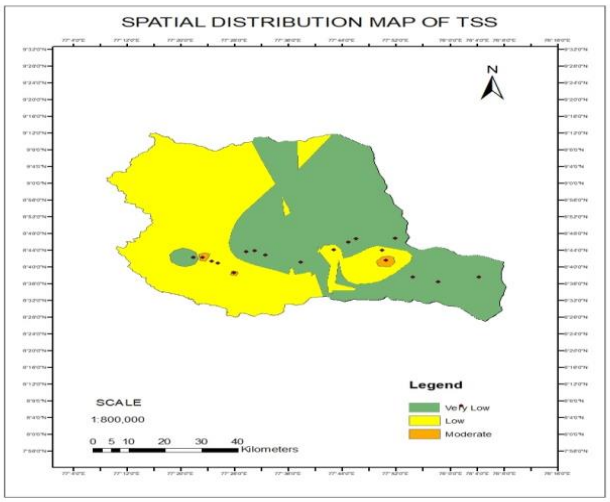

Figure 10: Spatial Distribution Map of TSS

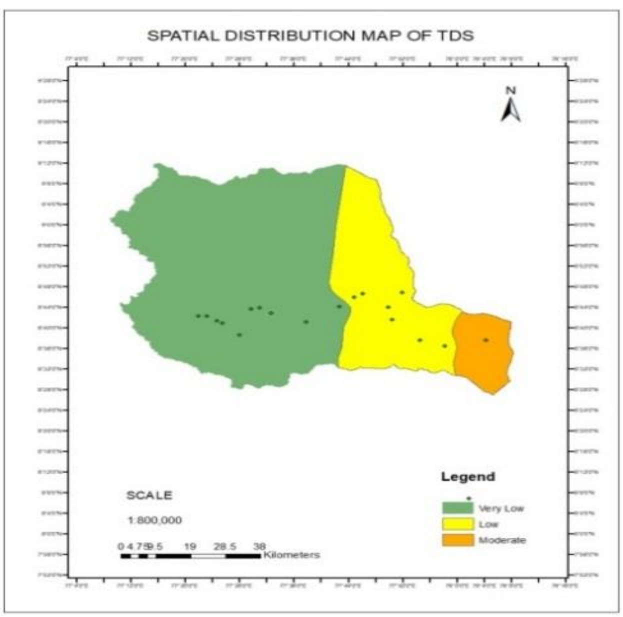

Figure 11: Spatial Distribution Map of TDS

E. Ammonia (NH3)

Ammonia is estimated in water using red litmus paper. When the red litmus paper changes to blue, the presence of ammonia is detected. At a level that is higher than 100 ppm, ammonia is identified to be polluting the basin. Water that is fit for drinking must hold ammonia concentrations between 0.25 – 32.5 mg/l. With these criteria, the spatial variation map for ammonia was prepared and presented in Fig.12.

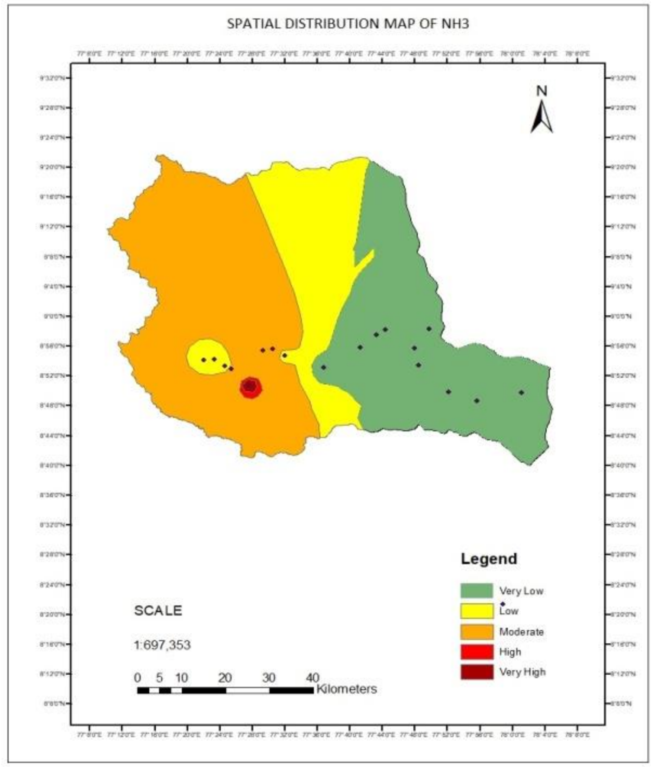

Figure 12: Spatial Distribution Map of NH_3

F. Nitrate and BOD

Nitrate owes its presence in the basin as the end waste product from industrial and agricultural chemicals. While nitrate is an essential mineral that helps build protein in humans and other living beings, a higher concentration, above 45 mg/l, can result in serious disorders such as the blue baby syndrome in infants. Therefore, for water that's fit for drinking, the nitrate must be lesser than or equal to 20 mg/l. As for the BOD, its concentration mustn't exceed 0 mg/l. Fig.13 shows that the variation of nitrate and BOD in the river basin is uniform. Thus, it can be observed that the basin has a very poor BOD concentration, which is liable to elicit serious health disorders if not attended to immediately.

The procured attribute database was integrated with the respective water quality parameters such as the pH, EC, TDS, TSS, NH3, NO3, and BOD with the generated spatial variation maps. This integrated study relates to the existing condition of the Tamirabarani basin.

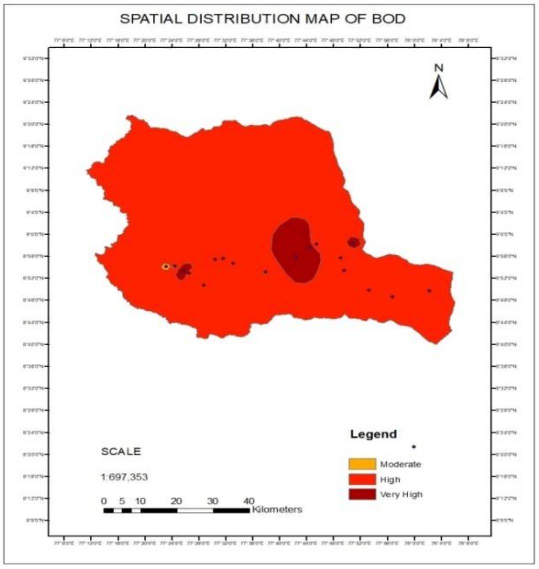

Figure 13: Spatial Distribution Map of BOD

In Table 3, the difference between the tested and estimated WQPs concentration levels is demonstrated.

Table 3: Difference between tested and estimated WQPs concentration levels

SAMPLE	VALUE	PH	BOD	NH_3	NO3	TSS	TDS
1	Tested	7.63	1.99	0.66	2.67	60	76.67
	Estimated	7.20	2.24	0.63	3.20	67	70.05
2	Tested	7.07	2.24	0.36	2.00	208.67	43
	Estimated	6.80	2.22	0.30	2.80	197.65	53.50
3	Tested	7.3	3.38	0.19	3.67	83.33	83.67
	Estimated	6.90	2.50	0.27	3.00	65	65
4	Tested	7.57	2.66	0.28	2.67	100.33	104.67
	Estimated	7.10	2.20	0.38	2.30	83	72
5	Tested	8.13	2.56	0.16	1.67	60	132
	Estimated	7.65	1.90	0.10	1.87	63	123

VI. CONCLUSIONS

In the present study, Band 4 and Band 5 reflectance values rendered the strongest relationship with WQP, although there was a little difference between satellite values and in-situ measured values. This little discrepancy could have arisen from the fact that the regression model completely depended on the satellite reflectance values at 30 m resolution compared to the highly precise in-situ data.

Nevertheless, this study deems a great help to monitor the surface water quality in the Tamirabarani basin, which acts as one of the major water sources. Since it is now facing threats from the rapid growth of population, urbanization, industrial effluents and wastes from urban infrastructure, agriculture, horticulture, transport and discharges from abandoned mines, and deliberate or accidental pollution, monitoring its fitness is vital.

Thus, the present study has been undertaken to analyze whether the spatial variation of major water quality parameters such as pH, Electrical Conductivity (EC), Total Dissolved Solids, Total Suspended Solids, Ammonia, Nitrate, and BOD could be monitored continuously through remote sensing& GIS techniques. The study has shown that GIS is a powerful tool for developing water resource problems by assessing its quality, determining water availability, preventing flooding, understanding the natural environment, and managing water resources on a local and regional scale.

Thus, for all future management activities, the fourth and fifth bands of the Landsat 8 could check the water quality parameters and prevent further water pollution in the Tamirabarani river basin.

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