Journal of Scientific & Industrial Research
Vol. 82, April 2023, pp. 466-474
DOI: 10.56042/jsir.v82i04.61646

# Comparative Analysis of Regression Models for Remote Sensing-based Water Quality Assessment

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*Received 21 March 2022; revised 12 March 2023; accepted 13 March 2023*

The 80-kilometer-long Vembanad Lake in Kerala, India, is a Ramsar site. Eutrophication is deteriorating its water quality and threatening its biodiversity. In this study, satellite imageries of Sentinel 2A and Landsat 8 OLI were utilized to determine its water quality. Various data sets of the water quality parameters viz. pH, Electrical conductivity, TSS, TDS, BOD, DO, chloride etc. are analyzed and interpreted. Regression models were developed on the parameters taken up for water quality analysis. The empirical $R^2$ values of the developed models evidenced the accuracy of the developed mdoels. The findings show that remote sensing images are reliable for analyzing surface water quality characteristics. The comparative analysis of the model developed illustrated the effectiveness of using the imaging systems mentioned above for water quality index estimation through remote sensing.

**Keywords:** Landsat 8 OLI, Ramsar site, Remote sensing, Sentinel 2 A, Vembanad lake, Water quality

## Introduction

Reservoirs and lakes may be either naturally occurring or artificially created. There are several kinds of lakes on the Indian peninsula. The rapid expansion of the industrial sector, climate change, and other reasons are all contributing to the increasing contamination of these lakes. Human activities like fishing, boating, and so on have led to pollution in these areas. The Ramsar Agreement protects wetlands throughout the tropics and along the coastlines. Determining water quality in bodies of water like lakes, reservoirs, and rivers is an important part of environmental monitoring. Monitoring surface water quality is crucial to evaluate deterioration of the water bodies. Regular monitoring of water quality will allow local and regional authorities to make timely choices about water treatment[1] and preventive measures. In-situ measurements and laboratory analytical methods are used to examine the physic-chemical & biological characteristics of water samples, but are more time-consuming. The limits of existing water sampling technologies are studied by various researchers.[2,3] The typical sampling approach does not account for large scale temporal and spatial variations. As a result, alternatives to standard sampling methods must be developed.

Remote Sensing (RS) and Geographical Information Systems (GIS) may offer more exact results as they utilize image processing techniques. In contrast to traditional procedures, these new technologies have eliminated the disadvantages of time-consuming and costly sampling, travel, and laboratory analysis. Remote sensing approaches are becoming more critical in assessing water quality because they provide superior geographical and temporal sample frequency distributions. Remote sensing evaluates pollution-caused changes in water's optical quality.[3–5] The RS data is used to investigate the optical properties of these investigations.[4] The distributed contaminants in lake water absorb the solar radiation that enters the body of water. It alters the water's color and clarity. The quality of water may be readily determined by analyzing these characteristics. The alternate approach of optical data analysis is less expensive.[5,6] This system also provides regional surface water quality metrics. Early researchers studied the contamination in water bodies through signal-to-noise ratio and visual properties of the images collected. Water quality analysis through digital means, are becoming increasingly popular because of these reasons. Suspended particles, dissolved solids, turbidity, and chlorophyll are the most prominent and active optical water quality measures in the given parameters. Finding them in any water with a wavelength close to the infrared

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range is possible.[7,8] In situ water samples were used to test water quality using hyperspectral remote sensing with ERDAS Imagine 9.1.[(9,10)] In addition to analyzing WQ, RS methods find very effective in estimating the rainfall, as it is the vital water supply source.[11–13] Comparing cloud brightness to rainfall intensity is the basis for satellite rainfall estimates. Satellite rainfall estimation approaches rely on optical remote sensing to identify precipitating clouds in the visible, infrared, and water vapor bands used to detect precipitating clouds. Optical remote sensing's 30 m spatial resolution and frequent temporal sampling makes it ideal for agriculture. Gibson and Power (2000) mention around 20 strategies such as GPI, FAO, RAINSAT, ADMIT, and CROPCAST to study the rainfall prediction.

Remote sensing in hydrology to evaluate water quality, surface roughness, land use cover, and hydro-meteorological variables such as evapotranspiration, all of which are important factors in water management.[14] RS-based water quality analysis uses optical sensors to obtain images of the water surfaces considered for the study. Sometimes these sensors may experience difficulty in distinguishing water outpouring and the upward circulation of water quality markers in water bodies.[15] In passive remote sensing, hyperspectral methods are used with many continuous spectral bands. A distinctive hyperspectral sensor measures reflectance from 200 EMR channels. Significant expenses of hyperspectral or ethereal information and expensive hardware make remote detecting risky for water quality observing. Inside and beachfront streams' visual intricacy ruins remote detecting. Future water quality models will contain RS and GIS methods, widening their utilization in subjective water asset exploration and examination. Because of the intricacy of logical methodologies in principle and handling, observational and semi-exact calculations are still utilized.[16–18] The advancements in RS-systems, and innovations, viz. improved storage, enhanced investigational analysis, and evaluation, provides promising results. EO-1/Hyperion, ALOS AVNOR-2, IKONOS, HICO, and Landsat-8, and flying stages CASI, AISA, AVIRIS, and HyMap are the RS-based methodologies recommended for water quality exploration.

Many researchers have suggested multivariate geometric approaches such as PCA/FA, discriminant analysis, and cluster analysis to interpret detailed water quality data better to understand water bodies' biological condition better.[19–21] These approaches may also detect major pollution sources contaminating water systems, making them useful for accurate water resource management and speedy pollution cleanup. Only a few studies extracted geographical and temporal patterns of surface water quality from surface water. Most studies aimed to identify the major factors that adversely influence water bodies using multivariate statistical methodologies.

The earlier research shows that hydrological modeling is necessary to determine and assess the water's quality. According to the studies mentioned earlier, hundreds of RS papers have put forth strategies in recent years to address the previously mentioned difficulties and precisely measure the biogeochemical parameters of WQ. However, most of these assessments concentrate on creating methodologies rather than using RS to comprehend the dynamics of WQ. The examined literature also revealed a need for more analysis that considers multiple WQ factors instead of concentrating solely on one, as is frequently the case with suspended solids or chlorophyll. Due to the radiation at different wavelengths carried between the atmosphere, water surface, and water body, calculating the water-leaving reflectance is necessary, and difficult to extract various water quality characteristics quantitatively. Different WQ analysis methods through RS are classified as Empirical, physical, semi-empirical, and intelligent modes. Among these, the Artificial Intelligence mode is an empirical mode that uses several statistical techniques.

Here are a few of the most significant drawbacks of traditional techniques:

1. Water quality parameter measurements and in-situ sampling require time, effort, and money.
2. It is nearly impossible to investigate the geographical and temporal fluctuations and trends in water quality in big water bodies.
3. It may be impossible to monitor, forecast, or control an entire body of water because of the topography.
4. Both field-testing mistakes and lab blunders could raise doubt about the exactness and accuracy of in-situ information that has been acquired.

Using remote detection in water quality observation can be a useful way to deal with getting around these limitations. Remote detecting has exhibited the intense ability to follow and evaluate the type of inland waters for over 40 years. The Vembanad Lake in India, a Ramsar Site, was selected as a study area for the water quality analysis. The lake's water quality was assessed using remote sensing methods and GIS. As per the examination, the lake may be utilized for mining, fishing, the travel industry, and lime shell stores. Rice cultivating, estates and get-away retreats will be polished in the encompassing regions. The virtue of the lake is urgent to these cycles. The lake's habitat is undergoing alteration due to human activity and hydrological changes. Local health is impacted. The lake is unusable since activities have altered the habitat and flow.

## Materials and Methods

### Study Area

Vembanad Lake, Kerala's biggest lake, is located between 09°00'-10°40'N and 76°00'-77°30'E. Ramsar Convention on Wetlands named it a Ramsar Site in November 2002 because of its geology, physiography, hydrology, climate, and land use fauna and flora. Lake and its marshlands have backwaters and Kol lands. More than half of the state's marshland surrounds the lake. The lake's northern part is saltwater, whereas the south is fresh. Thanneermukkom bund, which lengths about 4 km, divides them. It prevents saltwater from invading crops and promotes double cropping. This bund protects fifty-five thousand hectares of low-lying crops. Vembanad is 1–12 meters deep. Thottappally[1,2] has a spillway to prevent flooding, and the lake is home to marine fish and shrimp. This lake and its surroundings directly or indirectly feed many people. As a result of these considerations, the Vembanad Lake has been considered as the study area, and the following experiments were carried out.

- Development of regression model using Sentinel 2A and Landsat 8 OLI capabilities.
- Compare two image-sensing approaches to determine the lake's water quality.

During a field survey in December 2020, water sampling was carried out. Thirty samples were taken at random from the study region. Each sample point was noted using a mobile GPS in the lake. The same data was acquired from the USGS website at about the same time. The initial step in the investigation was to analyze the water samples in the lab. The chemical parameters such as BOD, Chloride, Total Hardness, EC, pH, TDS, TSS, and DO (dissolved oxygen) were determined. The water samples collected are tested with standard protocols viz. APHA, IS 3025, etc., and the parameters are found. The study's approach is depicted in Fig. 1. Artificial Neural Network based strategy was introduced to foresee the WQ Index. Brain Organizations Models were produced for the expectation of yearly upsides of the water quality record of Vembanad Lake and its essential inflows. The yearly information of eight water-quality boundaries (pH, electrical conductivity, dissolved oxygen, etc.) for 2007–2019 were chosen for this investigation. For brain network model development, yearly information is haphazardly separated into three subsets:

- Preparing set (70%)
- Approval set (15%)
- Testing sets (15%)

### Remote Sensing Process

RS is an excellent strategy for evaluating regional and progressive changes in the parameters of water quality characteristics. When developing satellite-based models, it is indispensable to relate the results with those acquired from in-situ observations and the data acquired from satellites for the same samples. Furthermore, the correctness of the developed models can be verified using field and laboratory measurements of water quality parameters.[22–24] This research used RS technology through Landsat 8 OLI and Sentinel 2A to monitor Vembanad Lake water quality. 30 Vembanad Lake water samples were taken post-monsoon in December 2020. The locations and digitization of the study area obtained from the

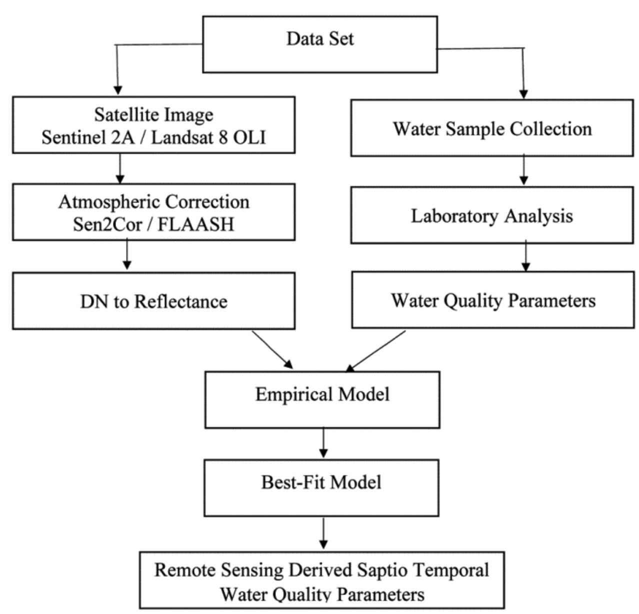


Fig. 1 — Approach flow diagram

satellite image in December 2020, from where the water samples are collected are illustrated in Fig. 2.[(25)] These localities utilize Google Earth Pro satellite and aerial imagery. Topography, ocean bathymetry, and internet geographic data are involved. Google Earth Pro can print high-resolution pictures and handle ESRI shape files. Google Earth shape file parameters are entered. Digitalizing the study's boundaries requires location data, made easy through USGS ArcMap. It makes maps, analyses spatial data, and organizes geographic data. The files obtained from Google Earth Pro are files with the extension .kml. ArcMap only accepts .shp files; therefore, kml must be converted. The sentinel-2 high-resolution images are downloaded from the USGS website. Sentinel-2 pictures have a 10–60 m resolution for overland and coastal water bodies. Once images are obtained from the USGS, the next step is to process them. Then, the effects of the environment have to be taken out of these images, called as atmospheric correction. If this doesn't happen, then it won't be able to use the images to analyse the water quality because they won't be clear enough. By taking into account things in the air, the collected spots suggest possible reasons for reflectance. These points are used to figure out the pollutant reflectance in the image that Snap makes after adjusting for the weather. In the spectral distribution, different wavelengths stand for different physical, chemical, and biological parts of water.

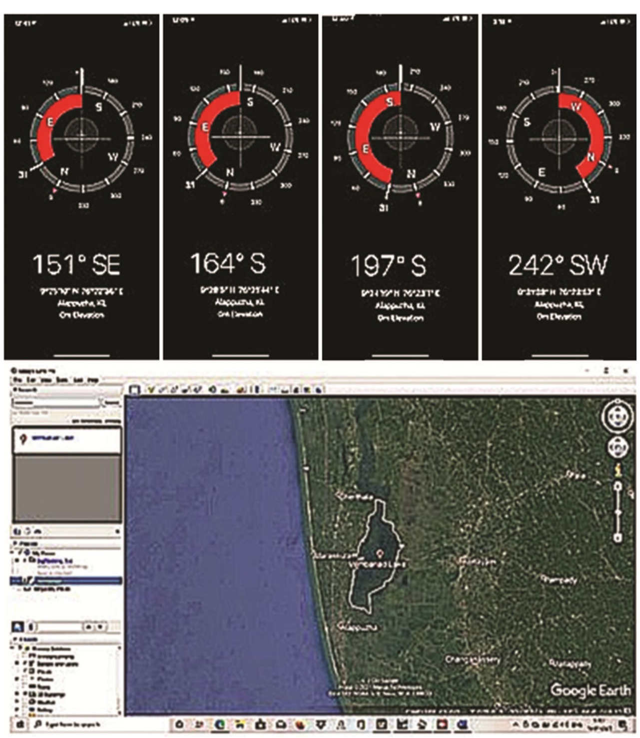


Fig. 2 — Locations of samples collected

***Sentinel 2A***

Two satellites 180 degrees apart from one another in a sun-synchronous orbit make up the Copernicus Sentinel-2 system. These satellites are responsible for monitoring the polar areas. Its huge sweep width of 290 kilometers and extended revisit time (ten days at the equator with one satellite, five days in cloud-free conditions with two satellites, or two to three days in mid-latitudes) may help monitor the atmosphere and climate of the Earth.

***Landsat 8 OLI***

The Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) are the two sensors on board the Landsat 8 satellite, launched in February 2013. According to Global Reference System-2, the satellite takes photographs of Earth on a 16-day repetition cycle and stores them on a hard drive. These photographs can be seen at any time. There is a delay of 8 days between the acquisitions made by the satellite and those made by Landsat 7. The multispectral data may be obtained from the USGS website and were then used for analyzing temporal changes.

***Atmospheric Correction***

Adjustments to the satellite photos were made using the software application that included both atmospheric and radiometric parameters. The Digital Number (DN) was changed in the satellite image to reflectance by applying the atmospheric correction. The effects of environmental scattering and absorption can be eliminated using an atmospheric adjustment to obtain surface reflectance.[25] To obtain a result that accurately represents the irradiance or reflectance of the ground, radiometric errors would need to be addressed. The data were cleaned up with the help of SNAP and ENVI. The FLAASH method was utilized for the Landsat 8 OLI datasets, while the Sen2Cor methodology was utilized for the Sentinel 2A data set. The parameters used for atmospheric correction are tabulated in Table 1.

***Model Development***

Landsat and Sentinel 2A images covering Vemaband Lake were retrieved from the USGS Earth Explorer website. The Sentinel 2A and Landsat 8 imageries cover the region selected for the research with no cloud cover or just a 10% cloud cover, depending on the time of day. The Sen2Cor technique was used to do atmospheric correction in the SNAP program. At the same time, FLAASH converted digital numbers to reflectance values for Landsat 8 OLI and ENVI data after determining the most significant match between the band ratios and water quality metrics. Multiple linear regression analysis was performed on the surface reflectance of each band in conjunction with another band, as well as the concentrations of water quality measures at each sample location. This study identified independent variables with a high coefficient of determination ($R^2$) and a positive relationship with reflectivity.[26]

The use of regression analysis to forecast water quality has been quite useful.[27,28] Utilizing the acquired data, a linear regression model was developed using the reflectance values of the Vembanad Lake components. By means of regression analysis, we can determine the relationships between independent and dependent variables. It leads to an equation where the variable coefficients indicate correlation. The water quality metrics' reflectance values are generated from Sentinel-2A and Landsat 8 OLI data. The wavelength functions of the WQ parameters of all the site locations (SL) are painted in Fig. 3.[(29,30)] The qualitative difference between Sentnel-2A and Landsat 8 OLI images is evidenced through the previous studies.[31,32]

Analyzing water's spectral reflectance reveals that wavelengths are dependent on quality. Optical water quality factors, including suspended particles, pH, EC, BoD, Do, and chlorophyll, etc., may be inferred from the spectral reflectance curve. Peak reflectance values between 440 and 490 nm show the presence of chlorophyll, peak reflectance values between 550 and 590 nm indicate the presence of total suspended solids, and peak reflectance values between 690 and 740 nm indicate the presence of turbidity.[31] Reflectance modifies water's consistency as the wavelength is stretched or compressed.

Table 1 — Parameters used for FLAASH atmospheric correction

| | |
|---|---|
| Ground elevation (m) | 0 |
| Pixel size (m) | 30 |
| Flight date | 24 Dec 2022 |
| Flight time | 11:10:28 |
| Atmospheric model | Tropical |
| Water retrieval | Yes |
| Aerosol model | Rural |
| Aerosol retrieval | None |
| No. of bands | 9 |
| MODTRAN resolution ($cm^{-1}$) | 15 |
| Output reflectance scale factor | 10,000 |

## Results and Discussion

Two regression models with correlation values for water quality parameters with reflectance instances were created by applying the DOS and Sent2Cor to a set of Landsat 8 OLI and Sentinel 2A data. The regression models developed from the spectral data are tabulated in Table 2, and samples are portrayed for various parameters, as depicted in Fig. 4. The best-fit model for both the satellite images can be predicted from the $R^2$ values tabulated in Table 2. The relation between the band spectral reflectance ratio and the parameter can be used to predict the values of WQI, from the satellite image, through Table 2 parameters. These expressions are in line with the previous study results.[32,33] Landsat 8 OLI and Sentinel 2A data were used to develop regression models for water quality measurements in settings with optical water properties and spectral fingerprints. With the use

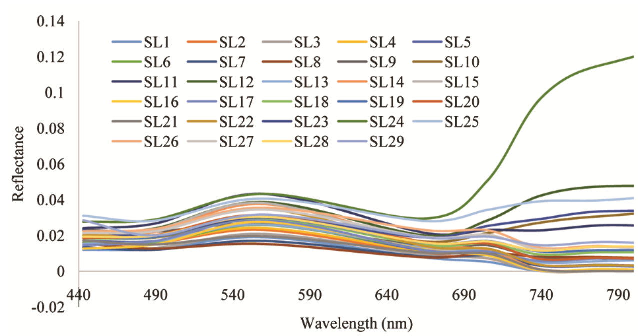


Fig. 3 — Spectral reflectance

Table 2 — Regression model

| Parameters | Sentinel 2A | | Landsat 8 OLI | |
|---|---|---|---|---|
| | Best fit model | $R^2$ | Best fit model | $R^2$ |
| pH | 5.0159 × (B2/B4) | 0.9798 | 5.6782 × (B1/B2) | 0.9972 |
| EC (μS/cm) | 142.35 × (B3/B5) | 0.9111 | 224.94 × (B3/B4) | 0.9464 |
| TDS (mg/L) | 171.0 × (B4/B5) | 0.8223 | 125.9 × (B3/B4) | 0.8722 |
| TSS (mg/L) | 19.984 × (B2/B3) | 0.8202 | 8.4827 × (B1/B3) | 0.8246 |
| TH (mg/L) | 18.656 × (B2/B5) | 0.8117 | 26.489 × (B4/B5) | 0.8136 |
| DO (mg/L) | 4.7068 × (B1/B4) | 0.9697 | 5.3111 × (B1/B2) | 0.9871 |
| BOD (mg/L) | 3.8759 × (B1/B2) | 0.7902 | 3.2052 × (B1/B2) | 0.8037 |
| Cl (mg/L) | 45.685 × (B2/B5) | 0.8080 | 29.468 × (B1/B4) | 0.8122 |

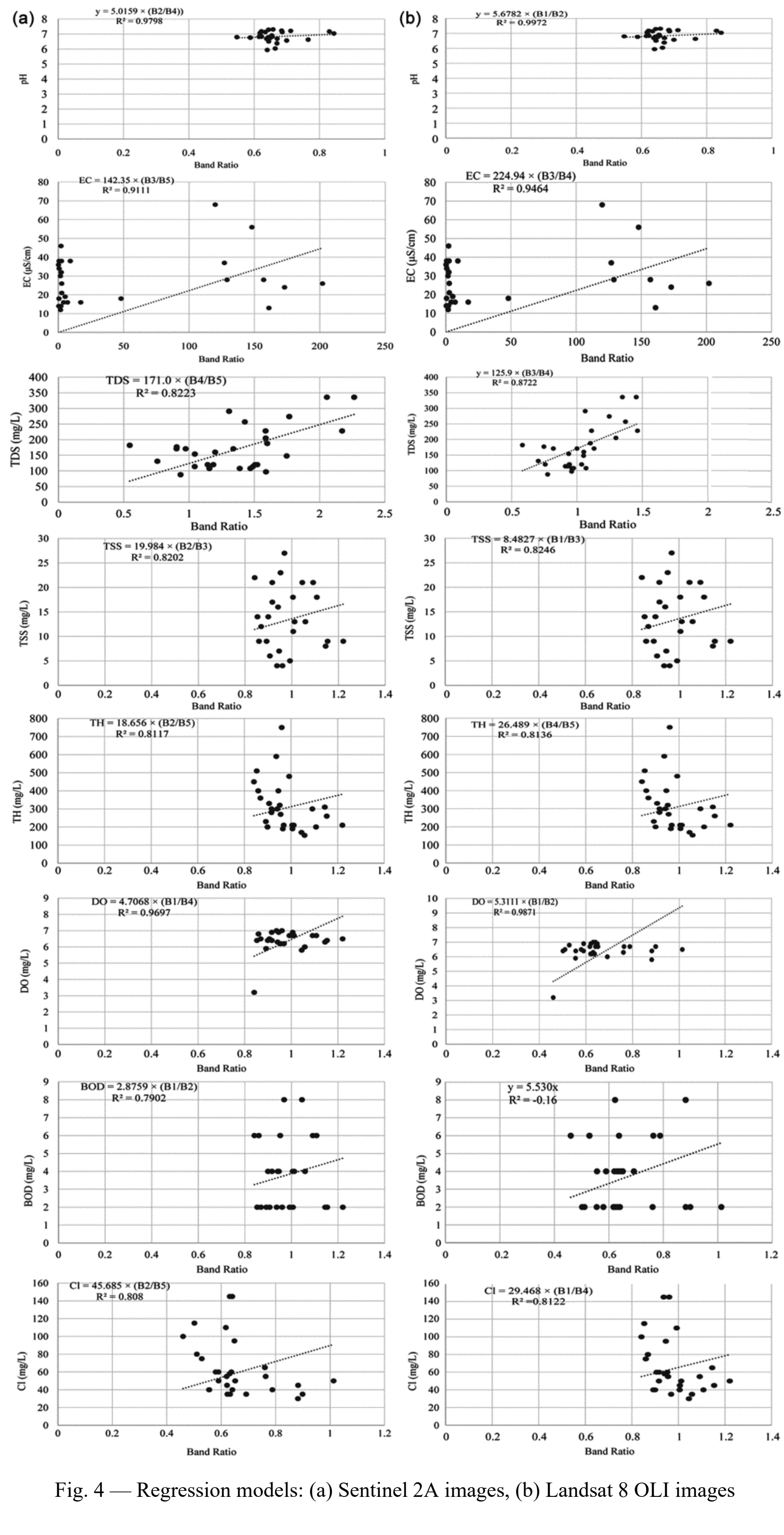


Fig. 4 — Regression models: (a) Sentinel 2A images, (b) Landsat 8 OLI images

of satellite data, the researchers were able to show that the visible band algorithms may be used to approximate parameters of water quality levels. However, there are still limitations in applying the models to forecast absolute concentrations of water quality indices in practical practice. Incorporating the effects of temporal variations in optically active component concentrations into the visible band models may increase the accuracy of the visible band facsimiles. Since Sentinel 2A and Landsat 8 OLI are experiencing several issues; these are multispectral data with degraded radiometric accuracy and a short life expectancy; In the remote sensing industry, the appropriateness and obtainability of such data are still important considerations.

Despite the relatively poor spectral and radiometric resolution of Landsat 8 OLI data, the return capability and low cost per area allow for producing multispectral satellite pictures that are useful for water quality monitoring. As a result of the substantial correlation between the water quality metrics, a quantitative analysis was conducted to enhance the relations among chemical properties and their sources of origin. Wastes from agriculture, sewage from households, tourist wastes, artificial bunds, and shells formed from lime and sand mining, and wastes from industries are contributing to the deterioration of water quality in Vembanad Lake. It leads to water quality deterioration in terms of total hardness, total dissolved solids, and chlorides. According to a comparison of remote sensing data collected before and during the monsoon season, the quality of water improved significantly in vast areas of Vembanad, as shown by decreases in optical water quality metrics. It affected all acute and quasi-contaminated water within and around the Vembanad Lake system.[25,34]

Eight water quality measures pH, Electrical Conductivity (EC) in µS/cm, Total dissolved solids(TDS) in mg/L, Total Suspended Solids (TSS) in mg/L, Dissolved Oxygen (DO) in mg/L, Total Hardness (TH) as $CaCO_3$ in mg/L, Biological Oxgen Demand (BOD) at 27°C for 3 days in mg/L, and chloride (Cl) in mg/L were used for this analysis, including annual data from 2007–2019. When building neural network models, we used a 70%-strong training set, a 15%-strong validation set, and a 15%-strong testing set derived from annual data. Using the yearly values of the other existing water quality metrics as inputs into the improved Neural Network models, the findings (for both the training and test data sets) demonstrate the models' ability to predict annual values of the water quality index at the monitoring station. Due to their low cost and high spatial and temporal resolution, satellite remote sensing methods have been increasingly popular in recent decades for environmental monitoring and evaluating many types of water bodies.

This study determined the optimum Landsat and sentinel bands in the visible wavelength region: for BOD, Sentinel 2A B1/B2 (443/490 nm) with $R^2$ value of 0.7902, Landsat 8 OLI B1/B3 (450/590 nm) with $R^2$ value of 0.8037, for Chlorides Sentinel 2A B3/B5 (500/705 nm) with $R^2$ value of 0.808, Landsat 8 OLI B2/B4 (510/670 nm) with $R^2$ value of 0.8122, for DO Sentinel 2A B2/B3 (490/560 nm) with $R^2$ value of 0.9697, Landsat 8 OLI B1/B2 (430/510 nm) with $R^2$ value of 0.9871, total hardness Sentinel 2A B2/B5 (490/705 nm) with $R^2$ value of 0.8117, Landsat 8 OLI B4/B5 (670/880 nm) with $R^2$ value of 0.8136, for pH Sentinel 2A B2/B4 (490/665 nm) with $R^2$ value of 0.9798, Landsat 8 OLI B1/B2 (450/510 nm) with $R^2$ value of 0.9972, for TDS Sentinel 2A B4/B5 (665/705 nm) with $R^2$ value of 0.8223, Landsat 8 OLI B3/B4 (590/670 nm) with $R^2$ value of 0.8722, for EC Sentinel 2A B3/B5 (500/705 nm) with $R^2$ value of 0.9111, Landsat 8 OLI B3/B4 (590/670 nm) with $R^2$ value of 0.9464, and, for TSS Sentinel 2A B2/B3 (490/560 nm) with $R^2$ value of 0.8202, Landsat 8 OLI B1/B3 (450/590 nm) with $R^2$ value of 0.8246.

The comparison between the developed regression models from Landsat 8 OLI and Sentinel 2 data infers that model based on Landsat 8 posses more accuracy, with superior $R^2$ value. The analysis of the regression model developed made through SPSS software and tabulated in Table 3, evidence the same. It was determined that the surface temperature was consistent with a simple regression between thermal band 10 on Landsat and the actual temperature obtained on the ground. Furthermore, it has been claimed that the Sentinel 2 sensor has calibration issues, making it difficult to convert radiation to temperature completely. However, this needs to account for the extremely low $R^2$ value. From the best

Table 3 — Model summary from SPSS software

| | |
|---|---|
| R | 1.000 |
| $R^2$ | 1.000 |
| Adjusted $R^2$ | 0.999 |
| Standard Error of the Estimate | 0.873 |
| $R^2$ Change | 1.000 |
| F Change | 1132.127 |

Table 4 — WQ parameters deduced from best-fit LandSat 8 OLI model

| Location No., Reference | pH at 25°C | EC (µs/cm) | TDS (mg/L) | TH (mg/L) | TSS (mg/L) | BOD (mg/L) | DO (mg/L) | Cl (mg/L) |
|---|---|---|---|---|---|---|---|---|
| L1, ALT/JAN/21/W-26307 | 7.31 | 750 | 428 | 68 | 9 | 4 | 6.1 | 165 |
| L2, ALT/JAN/21/W-26308 | 7.23 | 590 | 336 | 56 | 4 | 2 | 7 | 145 |
| L3, ALT/JAN/21/W-26309 | 7.18 | 480 | 274 | 28 | 5 | 2 | 6.7 | 110 |
| L4, ALT/JAN/21/W-26310 | 7.14 | 400 | 228 | 28 | 7 | 4 | 6.9 | 95 |
| L5, ALT/JAN/21/W-26311 | 7.29 | 210 | 120 | 16 | 13 | 4 | 6.7 | 50 |
| L6, ALT/JAN/21/W-26312 | 7.07 | 190 | 108 | 13 | 11 | 2 | 6.9 | 45 |
| L7, ALT/JAN/21/W-26313 | 7.21 | 200 | 114 | 16 | 18 | 6 | 6.7 | 40 |
| L8, ALT/JAN/21/W-26314 | 7.17 | 210 | 120 | 21 | 9 | 2 | 6.5 | 50 |
| L9, ALT/JAN/21/W-26315 | 7.04 | 170 | 97 | 19 | 21 | 8 | 5.8 | 30 |
| L10, ALT/JAN/21/W-26316 | 6.91 | 154 | 88 | 18 | 13 | 4 | 6 | 35 |
| L11, ALT/JAN/21/W-26317 | 6.93 | 200 | 114 | 14 | 14 | 4 | 6.4 | 40 |
| L12, ALT/JAN/21/W-26318 | 6.83 | 230 | 131 | 14 | 9 | 2 | 5.9 | 40 |
| L13, ALT/JAN/21/W-26319 | 6.74 | 300 | 171 | 32 | 17 | 4 | 6.4 | 60 |
| L14, ALT/JAN/21/W-26320 | 6.77 | 360 | 205 | 18 | 12 | 2 | 6.5 | 80 |
| L15, ALT/JAN/21/W-26321 | 6.82 | 400 | 228 | 26 | 19 | 6 | 6.8 | 75 |
| L16, ALT/JAN/21/W-26322 | 6.8 | 450 | 257 | 37 | 22 | 6 | 6.2 | 100 |
| L17, ALT/JAN/21/W-26323 | 6.76 | 510 | 291 | 26 | 14 | 2 | 6.4 | 115 |
| L18, ALT/JAN/21/W-26324 | 6.79 | 210 | 120 | 14 | 27 | 8 | 6.2 | 35 |
| L19, ALT/JAN/21/W-26325 | 6.69 | 210 | 120 | 12 | 18 | 4 | 6.7 | 40 |
| L20, ALT/JAN/21/W-26326 | 6.51 | 280 | 160 | 16 | 21 | 4 | 6.9 | 50 |
| L21, ALT/JAN/21/W-26327 | 6.63 | 260 | 148 | 24 | 9 | 2 | 6.4 | 45 |
| L22, ALT/JAN/21/W-26328 | 5.94 | 330 | 188 | 38 | 6 | 2 | 6.5 | 60 |
| L23, ALT/JAN/21/W-26329 | 6.04 | 310 | 177 | 34 | 8 | 2 | 6.3 | 65 |
| L24, ALT/JAN/21/W-26330 | 6.38 | 320 | 182 | 36 | 23 | 6 | 6.2 | 60 |
| L25, ALT/JAN/21/W-26331 | 6.57 | 300 | 171 | 38 | 27 | 6 | 6.7 | 55 |
| L26, ALT/JAN/21/W-26332 | 6.69 | 300 | 171 | 38 | 16 | 4 | 6.3 | 55 |
| L27, ALT/JAN/21/W-26333 | 6.75 | 270 | 154 | 46 | 14 | 4 | 6.2 | 55 |
| L28, ALT/JAN/21/W-26334 | 6.83 | 190 | 108 | 30 | 9 | 4 | 6.2 | 35 |
| L29, ALT/JAN/21/W-26335 | 7.14 | 190 | 108 | 14 | 8 | 2 | 6.7 | 35 |
| L30, ALT/JAN/21/W-26336 | 6.32 | 290 | 165 | 36 | 28 | 6 | 6.1 | 55 |

fit regression model developed through Landsat 8 OLI image, the water quality parameters are determined as tabulated in Table 4. Form the estimated parameters, it is verified that shifts in water quality indices were most pronounced in the lake's middle and southern parts. The empirical values of water quality parameters align with the study's results.[35] In May 2020, in-situ inspections confirmed distant reports of declining water quality in southern Lake Vembanad. While longer-term trends could suggest an annual rise in both water quality measures in Lake Vembanad's southern sections, we observed a decrease in TSS and TDS during 2020.

## Conclusions

Evaluation of water quality employing remote sensing techniques has proven fruitful. Analysis of both the Sentinel 2 A and Landsat 8 OLI images evidenced that the quality of water in the lake has deteriorated. The comparative analysis of the Regression models developed through these images illustrated the effectiveness of using the aforementioned imaging systems for water quality analysis. The developed models predicted the relation between the band reflectance and the parameter taken up for study. Simulated results of these models concluded using SPSS, indicate that Landsat 8 OLI image data provides better accuracy than the Sentinel 2 A data. Furthermore the research can be extended by considering many other influential parameters that affects the quality of water.

## References


1 Carpenter S R, Caraco N F, Correll D L, Howarth R W, Sharpley A N & Smith V H, Non-point pollution of surface waters with phosphorus and nitrogen, *Ecol Appl*, **83** (1998) 559–568.

2 Purandara B K, Environmental issues of wetland ecosystem management: a case study, *Ecol Environ Conserv*, **14** (2008) 439–448.

3 Purandara B K & Dora Y L, Studies on texture and Organic matter in the sediments of Vembanad Lake and near shore sediments, *Proc National Seminar Estuarine Manag* (New Delhi) 1997, 449–452.

4 Purandara B K, Jamadar B S, Chandramohan T, Jose M K & Venkatesh B, Water quality assessment of a lentic water body using remote sensing: A case study, *Environ Pollut*, 2018, 371–380.

5 Ritchie J C & Cooper C M, Remote sensing techniques for determining water quality: applications to TMLDs, *TMDL*

*Sci Issues Conf Water Environ Federation* (Alexandria, VA) 2001, 367–374

6 Naithani R, Physicochemical assessment of water quality with respect to Remote sensing and GIS techniques, *Adv Pure Appl Chem*, **1** (2012) 1–6.

7 Akbar T A, Hassan Q & Acharia G, A remote sensing based framework for predicting water quality of different source waters. Satellite based remote sensing approach for acquiring water quality data, *Int Arch Photogramm Remote Sens Spat Inf Sci - ISPRS Arch*, **34** (2010) 1–4

8 Lathrop R, Landsat thematic mapper monitoring of turbid inland water quality, *Photog Eng Remote Sens*, **58** (1992) 465–470.

9 Choubey V K, Monitoring water quality in reservoirs with IRS- 1A-LISS-I, *Water Resour Manag*, **8** (1994) 121–136.

10 Sugumaran R, Clayton M, Ecker M, Stigliani B, Gimond M & Green N, Hyperspectral remote sensing and geographical information systems tools to assess water quality areas and shallow inland lake, University of Northern Iowa and NASA Kennedy Space Center, Iowa Space Grant (Cooperative), *Final Technical Report*, 2005, 1–35.

11 Sudheer K P, Chaubey I & Garg V, Lake water quality assessment from LANDSAT thematic mapper data using neural network: An approach to optimal band combination selection, *J Am Water Resource Assoc*, 2006, 1683–1695.

12 Weiss M, Jacob F & Duveiller G, Remote sensing for agricultural applications: A meta-review, *Remote Sens Environ*, **236** (2020) 111402.

13 Orimoloye I R & Ololade O, Spatial evaluation of land-use dynamics in gold mining area using remote sensing and GIS technology, *Int J Env Sci Tech*, **17** (2020) 4465–4480.

14 Mohandas K A & Brema J, Remote Sensing based water quality analysis of Vembanad lake using Landsat 8 OLI images and inverse distance weighted (IDW) method, *Des Eng*, 7 (2021) 10295–10310.

15 Kirk J T O, *Light and Photosynthesis in Aquatic Ecosystems* (Cambridge University Press, Cambridge, United Kingdom) 1983.

16 Liu D, Chin C, Gong J & Fu D, Remote sensing of chlorophyll-a concentrations of the Pearl river estuary from MODIS land bands, *Int J Remote Sens*, **31** (2010) 4625–4633.

17 Gibson P J & Power C H, *Introductory remote sensing—digital image processing and applications* (Routledge Pub, London) 2000.

18 Arkin P A & Meisner B N, The relationship between large-scale convective rainfall and cold cloud over the western hemisphere during 1982–84, *Mon Weather Rev*, **115** (1987) 51–74.

19 Schmugge T J, Kustas W P, Ritchie J C, Jackson T J & Rango A, Remote sensing in hydrology, *Adv Water Resour*, **25** (2002) 1367–1385.

20 Shrestha S, & Kazama F, Assessment of surface water quality using multivariate statistical techniques: A case study of the Fuji river basin, Japan, *Environ Model Softw*, **22** (2007) 464–475.

21 Akbar A T, Hassan K Q & Achari G, A methodology for clustering lakes in Alberta on the basis of water quality parameters, *Clean Soil Air Water*, **39(10)** (2011) 916–924.

22 Sharaf El Din E, Zhang Y & Suliman A, Mapping concentrations of surface water quality parameters using a novel remote sensing and artificial intelligence framework, *Int J Remote Sens*, **38(4)** (2017) 1023–1042.

23 Mohandas K A & J Brema, Remote sensing based water quality analysis of Vembanad lake, *J Green Eng*, **11(1)** (2021) 1011–1020.

24 Brando V E & Dekker A G, Satellite hyper spectral remote sensing for estimating estuarine and coastal water quality, *IEEE Trans Geosci Remote Sens*, **41(6)** (2003) 1378–1387.

25 Mohandas K A & Brema J, Linear regression based water quality analysis through spatial distribution of parameters for Vembanad lake, *Int J Aquatic Sci*, **12(3)** (2021).

26 Alparslan E, Aydöner C, Tufekci V & Tüfekci H, Water quality assessment at Ömerli dam using remote sensing techniques, *Environ Monit Assess*, **135** (2007) 391–398.

27 Courault D, Seguin B & Olioso A, Review on estimation of evapotranspiration from remote sensing data: From empirical to numerical modeling approaches, *Irrig Drain Syst*, **19** (2005) 223–249.

28 Govender M, Chetty K & Bulcock H, A review of hyperspectral remote sensing and its application in vegetation and water resource studies, http://www.wrc.org.za/Pages /KnowledgeHub.aspx, (2013).

29 Sri Dhivya K K & Bhuvaneswari P T V, Multiple linear regression based water quality parameter modeling to detect hexavalent chromium in drinking water, in *Int Conf Wirel Commun, Signal Process Netw (WiSPNET)* (2017) (Chennai, India) 22–24 March 2017, 2434–2439.

30 Shafique N A, Fulk F, Autrey B C & Flotemersch J, Hyperspectral remote sensing of water quality parameters for large rivers in the Ohio River basin, *First Interagency Conf Res Watershed* (Benson, AZ) 2003, 216–221.

31 Warren M A, Simis S G, Martinez-Vicente V, Poser K, Bresciani M & Alikas K, Assessment of atmospheric correction algorithms for the Sentinel-2A multi spectral imager over coastal and inland waters, *Remote Sens Environ*, **225** (2019) 267–289.

32 Toming K, Kutser T, Laas A, Sepp M, Paavel B & Nõges T, First experiences in mapping lake water quality parameters with Sentinel-2 MSI imagery, *Remote Sens*, **8(8)** (2016) 640.

33 Elhag M, Gitas I, Othman A, Bahrawi J & Gikas P, Assessment of water quality parameters using temporal remote sensing spectral reflectance in arid environments, Saudi Arabia, *Water*, **11(3)** (2019) 556.

34 Hassan G, Shaheen M E & Taie S A, Prediction framework for water quality parameters monitoring via remote sensing, in *First Int Conf Smart Syst Emerg Technol* (IEEE) (Riyadh, Saudi Arabia) 03-05 November 2020, 59–64.

35 López-Puigdollers D, Mateo-García G & Gómez-Chova L, Benchmarking deep learning models for cloud detection in Landsat-8 and Sentinel-2 images, *Remote Sens*, **13(5)** (2021) 992.