Evaluation of surface water quality of Ukkadam lake in Coimbatore using UAV and Sentinel-2 multispectral data

Article *in* International journal of Environmental Science and Technology · March 2022

DOI: 10.1007/s13762-022-04029-7

International Journal of Environmental Science and Technology
https://doi.org/10.1007/s13762-022-04029-7

ORIGINAL PAPER

Evaluation of surface water quality of Ukkadam lake in Coimbatore using UAV and Sentinel-2 multispectral data

T. S. Rahul[1] · J. Brema[1] · G. Jims John Wessley[2]

Received: 14 September 2021 / Revised: 5 January 2022 / Accepted: 10 February 2022

Abstract

Remote sensing was used as a potential solution for monitoring the surface water quality parameters as an alternative to the traditional in situ measurements which are time consuming and labour-intensive. While most of the studies are restricted in just analysing the optical water quality parameters, only few studies have attempted the estimation of non-optical water quality parameters. In this paper, a correlation was developed between various optical and non-optical water quality parameters, thereby establishing an indirect relationship between non-optical parameters and reflectance data based on which the predictive models were developed. The water body chosen for this present study is the Ukkadam Lake situated in Coimbatore, Tamilnadu, India (10.9917° North, 76.9722° East). The correlation between reflectance data obtained from Sentinel-2 and Unmanned aerial vehicle images along with in situ measured data were analysed using stepwise regression method. Algorithms were developed for assessing the water quality parameters like turbidity, Total suspended solids, Total organic carbon, Chemical oxygen demand, Biological oxygen demand and Dissolved oxygen that were based on Sentinel-2 with high coefficient of determination (R^2). Unmanned aerial vehicle-based Stepwise regression models were employed for assessing Total suspended solids, Total organic carbon and Chemical oxygen demand. The developed models were validated with 25% of sample data acquired, and the algorithms showed that multispectral data from Sentinel-2 and RGB data from Unmanned aerial vehicles can be effectively used to estimate the concentration of various water quality parameters with reasonable accuracy in case of large water bodies, including the one chosen for this study.

Keywords Accuracy · Stepwise regression · Surface water quality parameters · Total organic carbon · Total suspended solids · Unmanned aerial vehicle · Water bodies

Introduction

Among the earth's renewable resources, freshwater systems are the most endangered habitats in recent years. More than half of the world's wetlands have disappeared from the earth's surface in the past decade with steep decline in water quality due to rapid urbanization and industrialization. Moreover, the climatic changes due to global warming cause drought, flood and noticeable increase in infectious diseases leading to further degradation in the water quality. Hence, from the start of the twentieth century, surface water quality analysis in water bodies was observed as a crucial measure with stringent and precise control of industrial discharges and chemicals through sewage (Bourouhou and Salmoun 2021), (Khaki 2020). Even though the traditional in situ measurements and laboratory testing offer higher accuracy in water quality assessment, its feasibility is typically low in providing constant water quality monitoring database based on regional scale due to enormous time consumption and labour intensiveness (Vercruysse et al. 2020). Remote sensing, with the integration of remotely sensed data, together with technologies like Geographic information system (GIS) and Global positioning system (GPS) was employed as an alternative solution for monitoring the surface water quality parameters (SWQPs) and to enhance different management

Editorial responsibility: J Aravind.

✉ T. S. Rahul
rahul.rce@gmail.com

[1] Department of Civil Engineering, Karunya Institute of Technology and Sciences, Karunya Nagar, Coimbatore, Tamil Nadu, India

[2] Department of Aerospace Engineering, Karunya Institute of Technology and Sciences, Karunya Nagar, Coimbatore, Tamil Nadu, India

Published online: 05 March 2022

plans for various natural resources (El Mountassir et al. 2020).

However, the application of remote sensing for monitoring small water bodies incurs some serious challenges. Due to inappropriate satellite sensors, satellite monitoring was hampered to a greater extent (Tóth et al. 2021). The ocean sensors such as medium resolution imaging spectrometer (MERIS) and moderate resolution imaging spectroradiometer (MODIS) with frequent re-visit time of 1–3 days, and radiometric resolution of 12 bits were not suitable in remote monitoring in small water bodies due to their lower spatial resolution (300–1000 m) (Verpoorter et al. 2014). This inadequacy was made to overcome till some extent with the advent of Sentinel-2 Multispectral instrument (MSI) and Landsat 8 Operational land imager (OLI) sensors. The availability of Unmanned aerial vehicles (UAVs) or drones which can be loaded with multispectral and hyperspectral sensors is another competitive method of remote sensing in small water bodies with high-resolution images captured at very low altitudes over the water bodies (Cillero Castro et al. 2020). Recent studies showed that, UAVs could be utilized in acquiring periodically monitored environmental data by capturing high temporal and spatial resolution images allowing decision-making in hours rather than weeks with major reduction in manpower and operational cost (Tsouros et al. 2019). A considerable amount of studies were reported on the measurement of water quality using indicators like turbidity, Secchi depth, Coloured dissolved organic matter (CDOM) and chlorophyll measured using remote sensing techniques (Papenfus et al. 2020), (Minu et al. 2020), (Alvado et al. 2021), (Mishra et al. 2019), (Gitelson et al. 1993), (Vertucci et al. 1989). There are few findings reported where researchers have attempted to estimate the concentration of non-optical water quality parameters such as total nitrogen (Kapalanga et al. 2021), total phosphorus (Xiong et al. 2019), chemical oxygen demand (Yang et al. 2011), etc.

However, the concentration of non-optical surface water quality parameters could be correlated with optical parameters such as total suspended solids that have the potential in affecting water colour, therefore will be able to be detected by the satellite sensors. Some of the recent case studies and models developed by utilizing these correlations were discussed below. A study carried out by Yu et al. (2016) at Bohai Sea, China correlated the dissolved inorganic nitrogen (DIN), which is considered as a non-optically active compound in water with optical parameters such as Chlorophyll-a (Chl-a) concentration and Total suspended solids (TSS) values to generate a DIN estimation model. Here, the MODIS hyperspectral satellite images were used for the estimation process. Correlation and regression analysis showed a highly significant positive relationship between DIN concentration and various band combinations.

Another research conducted by Abayazid and El-Adawy (2019) over the Egyptian Coastal Lake presented with an approach for deriving the Dissolved oxygen (DO) by comparative analysis of multiple regression algorithms which were carried out using several combinations of optical parameters namely Turbidity, Chlorophyll-*a*, TSS and Temperature. The results showed successful statistically significant correlation in certain combinations considered, and the optimal results were established based on turbidity and natural logarithm of temperature with high R^2 value.

In a similar study by Song et al. (2011), over Central Indiana Water Supply Reservoirs estimated the Total phosphorus (TP) using hyperspectral remote sensing owing to its close association with Chl-a, Secchi disc transparency (SDT), turbidity and total suspended matter. Correlation analysis was performed to determine the sensitive spectral variables including TP, Chl-a, and SDT. The results indicated that TP had closer association with diagnostic spectral variables with R^2 ranging from 0.55 to 0.72.

Sharaf and Zhang (2017) also attempted to develop an integrated Landsat 8 band ratios and stepwise regression model to estimate the concentrations of non-optical SWQPs such as chemical oxygen demand, biochemical oxygen demand and dissolved oxygen by correlating with optical variables such as turbidity and total suspended solids. The study was carried out at Saint John River, Canada which finally showed better correlations between Landsat 8 surface reflectance and concentrations of SWQPs with a coefficient of determination equal to 0.85.

Arango and Nairn (2019) developed statistical water quality models that possess the capability in reliable estimation of optical water quality parameters like Total suspended solids (TSS), Chl-a and Secchi disc depth (SDD) with respect to non-optical water quality parameters like Total phosphorous (TP) and Total nitrogen (TN) in oligotrophic and eutrophic systems with the help of remote sensing images that were collected using a multispectral sensor. The study concluded that, with the employment of statistical water quality assessment and multiple linear regression models, the developed models were effective in predicting the optical and non-optical water quality parameters with increased prediction capability R^2 greater than 0.80.

Hasab et al. (2020) carried out the assessment of surface water quality parameters in Al-Hawizeh Marsh, Iraq on the basis of Remote sensing and GIS-based approaches. The Landsat 8 images were employed for predicting and assessing the spatial variations together with map distribution with respect to salinity, sulphate and calcium carbonate inside the Al-Hawizeh Marsh for duration of two seasons on the basis of mathematical modelling. The developed model for evaluating the salinity, sulphate and calcium carbonate showed the observations to be lowest during winter season but highest during autumn season. The observed values of correlation coefficient (R^2) corresponding to the real data with respect to mathematical models during the two seasons were 0.95, 0.96 and 0.92, respectively.

Mihu-Pintilie (2018) carried out a physico-chemical examination in Cuejdel lake basin that was realized on the basis of the monitoring programme that constituted the analysis of seasonal variations of thirteen leading physico-chemical parameters. Around thirty samples are taken for consideration in both spring season and autumn season. Corresponding readings were acquired from both in situ aquatic ecosystem and from the laboratory. The findings revealed that the degree of contamination by phosphorus and nitrogen compounds including nitrates, nitrites, phosphates, etc., were extremely lower and the value of nutrients revealed the natural function of the limnosystem.

It is evident from the study carried out in the Poyang Lake in China using empirical models, Sentinel-2A MSI band 7 is suitable for sediment-laden waters, while Sentinel-2A MSI band 4 is suitable for estimating the TSS in clear water (Liu et al. 2017). In a similar study by Toming et al. (2016) and Caballero et al. (2019), the dependence of the concentration of turbidity or suspended sediments on red and near infrared (NIR) regions was established. In another study by Alparslan et al. (2007), the blue, red, green, and NIR bands of Landsat-7 ETM were used in effectively monitoring the TSS concentrations of the reservoir behind Omerli Dam, Ustanbul. Hellweger et al. (2004) conducted a study with Landsat-5 TM images using regression models developed to measure the turbidity levels in the New York Harbour and found that the turbidity levels at the river run-off areas were correlated to the red band with coefficient of determination (R^2) = 0.78. Landsat -7/TM imagery over reservoirs of Shenzhen, China showed higher correlation coefficient of 0.626 between chemical oxygen demand (COD) concentration and reflectance values of band 1–3 by multiple linear regression approaches (Wang 2004).

The present study intends to develop the correlations between in situ data and reflectance data of various water quality parameters by regression-based techniques. Based on the available literature studies, stepwise regression was found to be most adequate for this study. The present study aims to (1) substantiate the application of Sentinel and UAV multispectral characteristics for analysing the water quality, and (2) develop algorithms to estimate the concentration of both optical and non-optical SWQPs using Stepwise regression (SWR) technique from UAV and Sentinel-2 reflectance data. The water body chosen for this present study is the Ukkadam Lake situated in Coimbatore, Tamilnadu, India (10.9917° North, 76.9722° East). The water samples were collected during the months of January and March 2021. The first in situ sampling was done on 03rd January 2021 and second series of sampling was carried out on 19th March 2021.

Materials and methods

Study site and water quality analysis

Ukkadam Lake is situated in Ukkadam, Coimbatore, Tamilnadu, South India. It lies between 10.9917° N latitude and 76.9722° E longitude. The lake occupies an area of around 1.295 km^2 with an average depth of 5.82 m. The lake consists of a total volume of 1,982,179.262 m^3 of water (https://en.wikipedia.org/wiki/ukkadam_lake).

The canals diverted from Noyyal river supply water to the Ukkadam Lake. Another lake, Selvachinthamani, located upstream in the north also provides sufficient water to the lake. The four sluice gates located at the south side of the lake release water to external use. The lake becomes polluted with effluents of sewage released from surrounding areas and is also encroached by water hyacinth to a considerable area. Some of the recent studies also highlighted the increasing pollution rate of this lake. A study carried out by Jeyaraj et al. (2016) revealed that the water quality of this lake was found to be polluted with reference to almost all the water quality parameters. Moreover, the water remains as alkaline nature with the total concentration of total dissolved solids (TDS) and turbidity to exceed the permissible limit, thereby concluding with the ultimate root cause of pollution as domestic and industrial discharges. Furthermore, another study carried out by Gowraraju et al. (2014) estimated the water quality index of this particular lake by National sanitation foundation—Water quality index (NSF-WQI) method. Here, all the measured parameters were found to be very much higher when compared to the permissible limit prescribed by the World health organization (WHO) and thereby seems to be unhealthy for public use.

In order to de-silt the lake and clear the encroachments, the Coimbatore corporation unveiled a plan in 2010 and subsequently conducted a series of studies. However, the study conducted in this paper is the first study intending to develop image processing algorithms for estimation of water quality parameters based on spectral characteristics of Sentinel-2 satellites and UAVs in Ukkadam lake. The satellite view of the Ukkadam lake is shown in Fig. 1.

The study can be basically classified as remote sensing analysis and water sampling analysis. The same is represented as a flow diagram in Fig. 2.

The operational features of the flow diagram in this study could be revealed using the following considerations:

Fig. 1 Sentinel-2 image of Ukkadam Lake

(1) This proposed research methodology could be basically classified as remote sensing analysis and water sampling analysis.
(2) For remote sensing analysis, the data from two sources were mainly acquired, which includes Level-1C (L1C) Sentinel-2 satellite images and UAV drone images.
(3) The 13 bands of Sentinel-2 images were re-sampled by nearest neighbour method to bring them to a uniform resolution of 10 m and the area of interest was determined.
(4) The subset of study was subsequently corrected to bottom of atmospheric (BOA) reflectance using the Case 2 regional coast colour (C2RCC) atmospheric correction processor in SNAP 8.0 software to obtain eight atmospherically corrected angular dependent water leaving reflectance (rhow) bands.
(5) Similarly, in case of UAV image capturing, the flight mission was planned using drone deploy software at a flight height of 300 feet so as to obtain 755 images which were finally sewed up together to obtain Orthomosaic image of high spatial resolution up to 3 cm.
(6) The geometric corrections, correction for lens distortions and camera tilts were also carried out with this software to finally attain an image of study area consisting of three bands.
(7) From these images, the reflectance values of various water sampling points were extracted using SNAP and ENVI software.
(8) The water samples from the Ukkadam Lake were collected at 16 strategic locations on the same day in which the satellite data and the UAV data were accessed and finally tested in the laboratory to obtain values for various surface water quality parameters.
(9) Finally, the validation of the developed stepwise regression models is done using 25% of in situ sampling results and accurate spatial distribution maps were generated accordingly.

Remote sensing analysis

For remote sensing analysis, two methods were adopted in this study. The Sentinel-2 data were obtained from the European space agency (ESA) Copernicus Open Access hub. The 13 spectral bands of Sentinel-2 range from the Visible (VNIR) and Near-infrared (NIR) to the Short wave infrared (SWIR). The multispectral bands of Sentinel-2 data and its corresponding spatial resolution are displayed in Table 1.

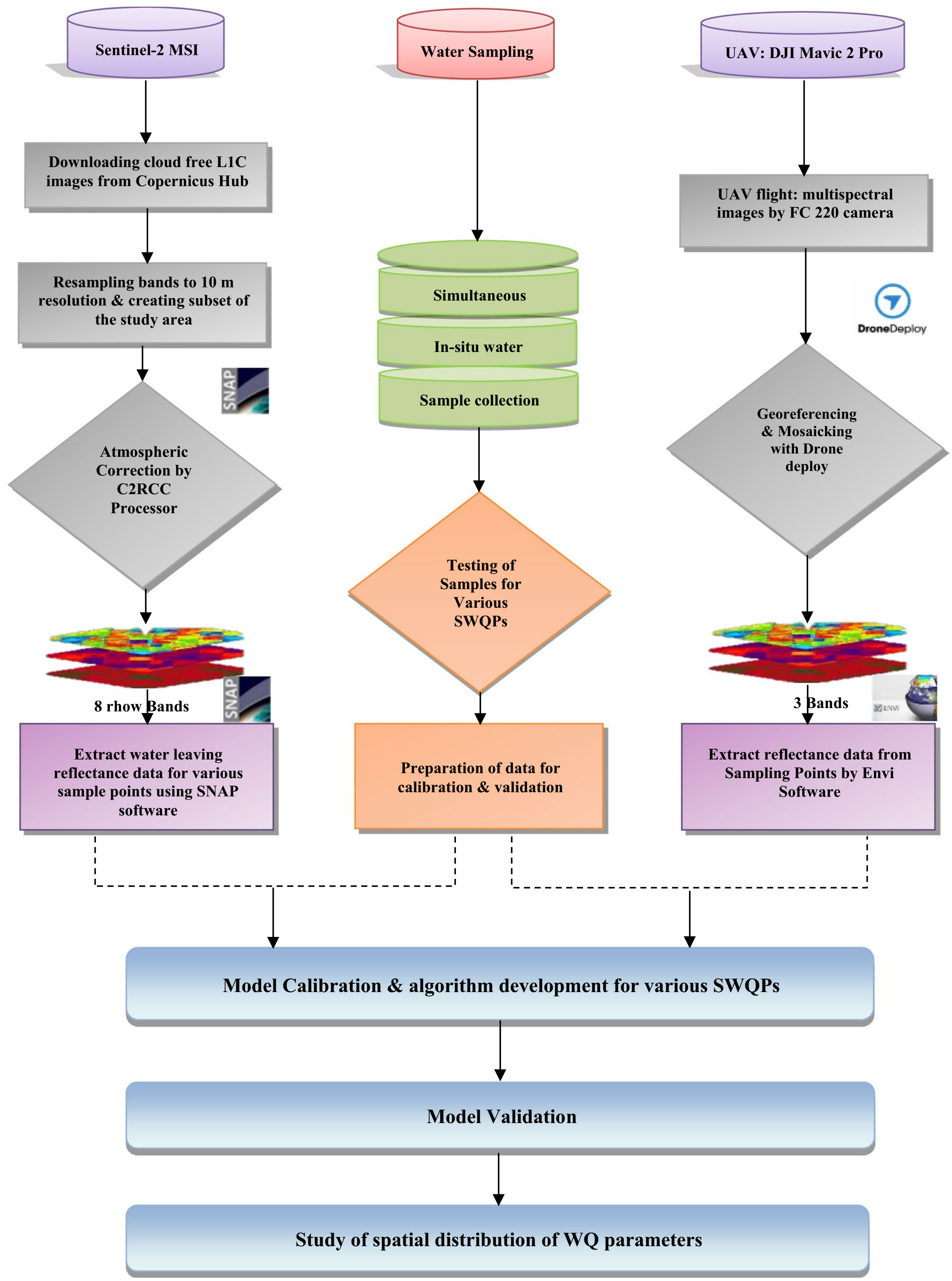


Fig. 2 Flow chart of methodology in the present study

Table 1 Sentinel-2 band details

Band number	Central wavelength (nm)	Spatial Resolution (m)
1	443	60
2	490	10
3	560	10
4	665	10
5	705	20
6	740	20
7	783	20
8	842	10
8a	865	20
9	945	60
10	1375	60
11	1610	20
12	2190	20

Pre-processing of Sentinel-2 satellite imagery

The Sentinel-2 imageries that are ortho-rectified, geo-located and radiometrically calibrated top-of-atmosphere (TOA) reflectance in Universal transverse mercator (UTM) projection with the WGS84 datum with less cloud cover were selected for this analysis. Since the 13 bands of Sentinel-2 images were not of the same resolution, the images were re-sampled by nearest neighbour method to bring them to a uniform resolution of 10 m and the area of interest is determined.

The varying atmospheric conditions and degradation of accuracy due to surface reflection adversely affect the remote estimation of lake water quality (Koponen et al. 2002). Hence, the S2 MSI images downloaded from Copernicus Hub-ESA, were subsequently corrected to Bottom of atmospheric (BOA) reflectance using the Case 2 regional coast colour (C2RCC) atmospheric correction processor in SNAP 8.0 software. It is a full spectrum version using a set of neural networks which were trained for simulated top-of-atmosphere reflectance (https://seadas.gsfc.nasa.gov/help/8.0.0/c2rcc/C2RCC Tool. html). C2RCC performs best for water bodies, achieving highest coefficient of determination and lowest root mean square deviation (RMSD) when compared with other processors like Acolite, l2gen, sen2cor, etc., (Warren et al. 2019). Finally, the atmospherically corrected angular-dependent water leaving reflectance (rhow) for various bands in the area of interest was extracted. The extraction of pixel information corresponding to the sampling points was done using ENVI and SNAP software. The atmospherically corrected image after C2RCC atmospheric processing is shown in Fig. 3.

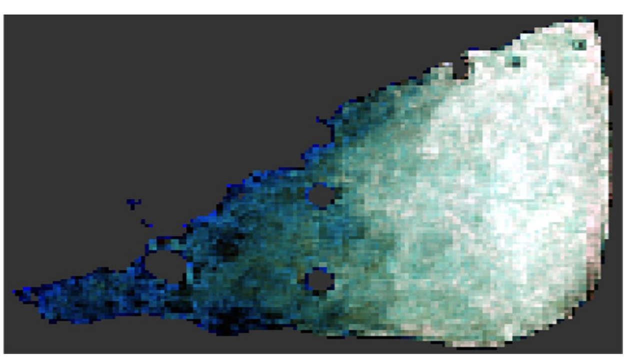


Fig. 3 Atmospherically corrected image after C2RCC atmospheric processing

Unmanned aerial vehicle imagery analysis

For unmanned aerial vehicle (UAV) image capturing, a commercially available DJI Mavic 2 Pro Quadcopter drone with FC220 RGB camera was used. The flight mission was planned using drone deploy software at a flight height of 300 feet to obtain the images of high spatial resolution up to 3 cm. The images were captured on the same day in which the Sentinel satellite passes over the study site, and the corresponding imageries were chosen for this analysis. On the day of analysis, a total number of 755 images were captured using the automated flight planning platform. The equivalent features of DJI Mavic 2 Pro Quadcopter drone used for this study are detailed in Table 2.

Pre-processing of Unmanned aerial vehicle imagery

The images captured using the UAV are combined together to obtain an ortho mosaic map using the Drone deploy

Table 2 Features of DJI Mavic 2 Pro Quadcopter drone

S. No	UAV Specifications	
1	Model	DJI Mavic Pro Platinum (M1X)
2	Maximum speed	40 mph
3	Maximum flight time	30 min
4	Stabilization	3-axis (pitch, roll, yaw)
5	Camera sensor	1/2.3″ (CMOS)
6	Effective pixels	12.35 M
7	Total pixels	12.71 M
8	Operating temperature	32° F—104° F (0 °C to 40 °C)
9	Navigation	GPS & Vision position-based navigation

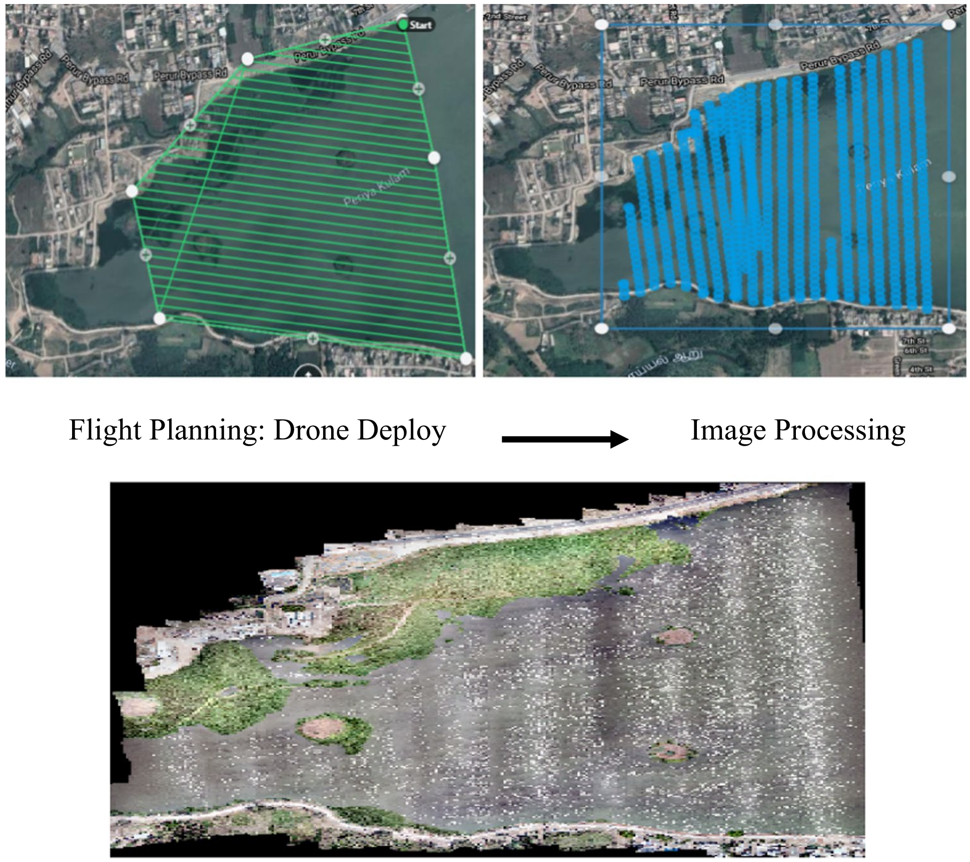


Fig. 4 Ortho mosaic imagery of Ukkadam Lake (3 cm resolution)

software. Geometric corrections, correction for lens distortions and camera tilts were also carried out with this software. As the flight altitude is 300 feets, the images captured were less influenced by the atmospheric effects. Hence, atmospheric correction was not applied to these UAV images, and finally, the raw digital numbers were extracted using ENVI software for further calculations. The different steps included in ortho mosaic imagery generating process using Drone deploy software were shown in Fig. 4.

Estimation of concentrations of surface water quality parameters

Regression analysis is a proven predictive modelling technique which correlates the reliance of a dependent variable to a group of independent variables. It is a process to analyse the dependence of variables that were not treated to have symmetrical correlation.

Here, the aim is to obtain a prediction of one variable, given the values of the others (Bartholomew et al. 2010). Several types of regression techniques are available like logistic regression linear regression, ridge regression, polynomial regression and stepwise regression. Stepwise regression (SWR) technique is the most suitable option for this study, as the variables are quantitative, which means the water quality parameters are measurable and the independent variables (surface reflectance values of bands/band ratios) are not highly correlated with each other.

In this study, the scope of using Sentinel-2/UAV reflectance values in predicting water quality parameters was identified using this SWR technique. The sampling points were divided into two datasets: 75% of the total sample

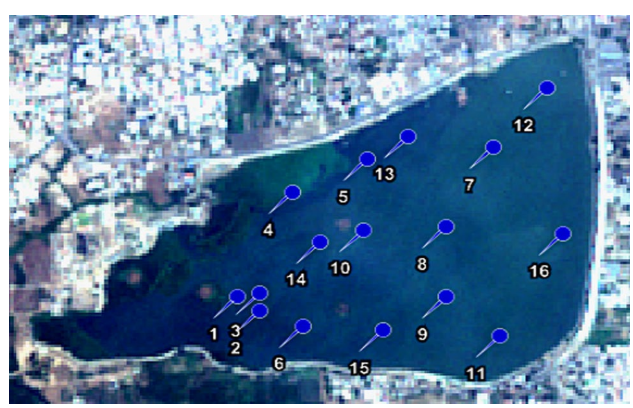


Fig. 5 Sentinel-2 image of Ukkadam Lake with 16 water sampling points

was used for standardization, while the remaining 25% of samples were implemented to validate the models. The performance of the developed models was evaluated by using regression lines' equations, R^2 and significant P value. The model categories were identified as follows (Chang et al. 2001):

- Category 1: Accurate prediction if $0.80 \le R^2 \le 1.00$
- Category 2: Satisfactory prediction if $0.50 \le R^2 < 0.80$
- Category 3: Unacceptable prediction if $R^2 < 0.50$

Water sampling and laboratory analysis

The water samples from the Ukkadam Lake were collected from 16 strategic locations on the same day in which the satellite data and the UAV data were accessed from the study site. Figure 5 shows the Sentinel 2 satellite image of Ukkadam Lake with various water sampling points.

The samples were collected during the months of January and March of the year 2021. The first in situ sampling was done on 03rd January 2021, and the second series of sampling was carried out on 19th March 2021. The sampling methodology from a water body mainly depends upon various factors like size of the water body, depth of water column and the flow rate (water quality sampling techniques (usgs.gov)). The water bodies which are shallow and well mixed, only requires surface (0–1 m) water sampling (field sampling programme (water quality (gov.au)). Here, in this lake, as most of the water sampling positions were shallow in depth, the lake water will be in well mixed-up condition. From the boat, the sampler bottle was dipped by hands to just below the water surface (typically 0.30 m–0.50 m depth) and by holding the sampler bottle in downstream position. Moreover, as the hands were covered with a plastic disposable glove, the contaminations from surface films were avoided. Whatever vessel was being used for water sample collection, it should possess the ability to face the water currents, therefore, the water samples were taken from the front of the vessel, preferably while moving slowly in forward direction to minimize the contamination caused by the boat itself (Apte et al. 1998).

In this study, all the water sampling points were taken only from the clear surface water area, and also the portions covered by aquatic vegetation were not taken into consideration as the vegetation portion will restrict the true reflectance of the water. Furthermore, the sampling positions were precisely determined by a hand-held GPS receiver, obtaining the exact co-ordinate values. The sampling points were mainly selected along the vicinity of the outfall as all the untreated household as well as industrial sewages might accumulate around these locations making it a pollutant hotspot. Moreover, no weather perturbations were observed in between the time span of field water sampling and satellite overpassing, which might cause alterations in the values of water quality parameters.

The water samples which were stored in a dark container with cooler were subsequently taken to laboratory analysis for the estimation of TDS, Potential of hydrogen (pH), Electrical conductivity (EC), Biological oxygen demand (BOD), COD, DO, Total organic carbon (TOC), TSS, Nitrate and Turbidity. The BOD, COD & TOC tests were carried out according to IS3025; Bureau of Indian Standards. Here, the BOD results were obtained after 3 days (https://law.resource.org/pub/in/bis/S02/is.3025.44.1993.pdf) of incubation procedure & COD by titration method (https://law.resource.org/pub/in/bis/S02/is.3025.58.2006.pdf). Also, the instruments including water analyser 371 were used for testing pH, EC, TDS, DO, and DR/890 colorimeter was used for analysing TSS and turbidity in this analysis.

These parameters were particularly selected for this study based on the codal provisions and guidelines published by the World Health Organization and Bureau of Indian Standards corresponding to water quality assessment. A turbidity meter denotes the turbidity based on the amount of light scattered by the particles in the water column. Testing for COD helps to quantify the amount of organics present in a water sample. A strong oxidant was used to react with all the organic matters in the sample. BOD is the measure of dissolved oxygen required by the aerobic organisms present in the water body for the breakdown of organic materials present in 5 days at a temperature of 20 °C. Also, the level of dissolved oxygen (DO), which is an indicator of free oxygen present in the water samples, was estimated. TOC, which indicates the amount of carbon found in an organic compound is mainly a nonspecific indicator of water quality, was measured with a total organic carbon analyser.

Table 3 SWQP results from the study

SWQP	January and March 2021			
	Mean	Max	Min	Std. Dev
Turbidity (NTU)	55.08	150	6.2	62.13
TSS (mg/L)	357.92	624	200	162.09
DO (mg/L)	4.49	5.8	3	0.79
BOD (mg/L)	46.42	92	17	23.23
COD (mg/L)	94.25	150	48	27.90
Nitrate (mg/L)	19.73	27	12	5.18
TOC (mg/L)	34.50	56	23	9.26
TDS (mg/L)	889.58	1,196	600	194.02
pH	8.50	8.80	8	0.24
EC (μs/cm)	724.08	757	700	18.79

Results and discussion

The spectral data from Sentinel-2 satellite and UAV were collected from the test site and processed to extract the concentrations of both optical and non-optical SWQPs. The key findings of this study were discussed in the subsequent sections.

Concentration of surface water quality parameters

The summary of water analysis results corresponding to the in situ samples which were collected from 16 points synchronous with the UAV flights and Satellite overpass are given in Table 3. Here, even though 10 parameters were tested and analysed, due to low correlation and coefficient of determination values, the parameters such as TDS, pH and EC were eliminated from further algorithm development stages.

Correlation of optical and non-optical surface water quality parameters

The non-optical parameters which were considered in this study showed positive correlation with the optical parameters. Most of the non-optical parameters like DO, BOD and COD showed a high level of correlation with turbidity which is an optical parameter, while TOC correlates with TSS as shown in Table 4.

Thus, even though it was believed that non-optical parameters do not directly affect the light signals measured by satellite sensors, it could be seen that the optical parameters affect the light reflectance. An indirect relationship can thus be established between non-optical water quality parameters and light reflectance data, based on which the estimation models were developed.

Evaluation of relationship between Sentinel-2 and surface water quality parameters

A scatter plot diagram was used to summarize the relationship between two sets of data. The Y axis of the graph corresponds to the values of various surface water quality parameters (dependent variable) and X axis represents the reflectance values of the bands which showed the highest correlation with the parameter (independent variable). Here, the regression line drawn after plotting the scatter diagram represents the relationship or correlation between the two variables. The direction of the slope of the line specifies the correlation as positive or negative; an upward sloping line indicates the positive correlation and a downward slope represents the negative correlation between the datasets. And finally, the equation given in each case represents the equation of the line plotted.

Figure 6 shows the correlation between sentinel-2 rhow bands/band ratios with in situ testing results of various water quality parameters. All the water quality parameters chosen in this study have shown significant correlations with coefficient of determination (R^2) greater than 0.5, and with p values less than 0.05. Sentinel-2 bands such as coastal aerosol (B1), blue (B2), red (B4), red edge (B5, B6, B7) and NIR (B8A) have contributed in the development of algorithm models for various surface water quality parameters. Furthermore, the band ratios were much helpful in model development due to its ability to enhance the spectral contrast between various targets. C2RCC processor generates rhow bands, i.e. atmospherically corrected angular dependent water leaving reflectance which plays an integral part in developing algorithms for water quality parameters with direct band correlations.

It is evident from Fig. 6e that TSS shows strong correlation with red edge bands and NIR bands with R^2 value of 0.727 and p value of 0.001, respectively. The optical parameter turbidity shows good correlation with blue, coastal aerosol and red edge bands with R^2 value of 0.777 and p value of 0.015, respectively. These results are found to be matching with the earlier literature reported by Moore (1980), Pavelsky and Smith (2009), and Gholizadeh et al. (2016), where it was seen that the reflectance in the red region increases with increase in turbidity of water. Non-optical water quality parameters like BOD, COD and DO showed strong correlations with blue band (B2) with high R^2 values. This is in agreement with the earlier studies by Mushtaq and Nee (2016) that the non-optical water quality parameters like

Table 4 Correlation matrix of optical and non-optical parameters

Parameter		Optical		Non-Optical			
		Turbidity	TSS	DO	BOD	COD	TOC
Optical	Turbidity	1	0.403	−0.879	0.951	0.821	0.430
	TSS	0.403	1	−0.395	0.395	0.507	0.834
Non-Optical	DO	−0.879	−0.395	1	−0.965	−0.934	−0.532
	BOD	0.951	0.395	−0.965	1	.908	0.503
	COD	0.821	0.507	−0.934	.908	1	0.66
	TOC	0.430	0.834	−0.532	0.503	0.66	1

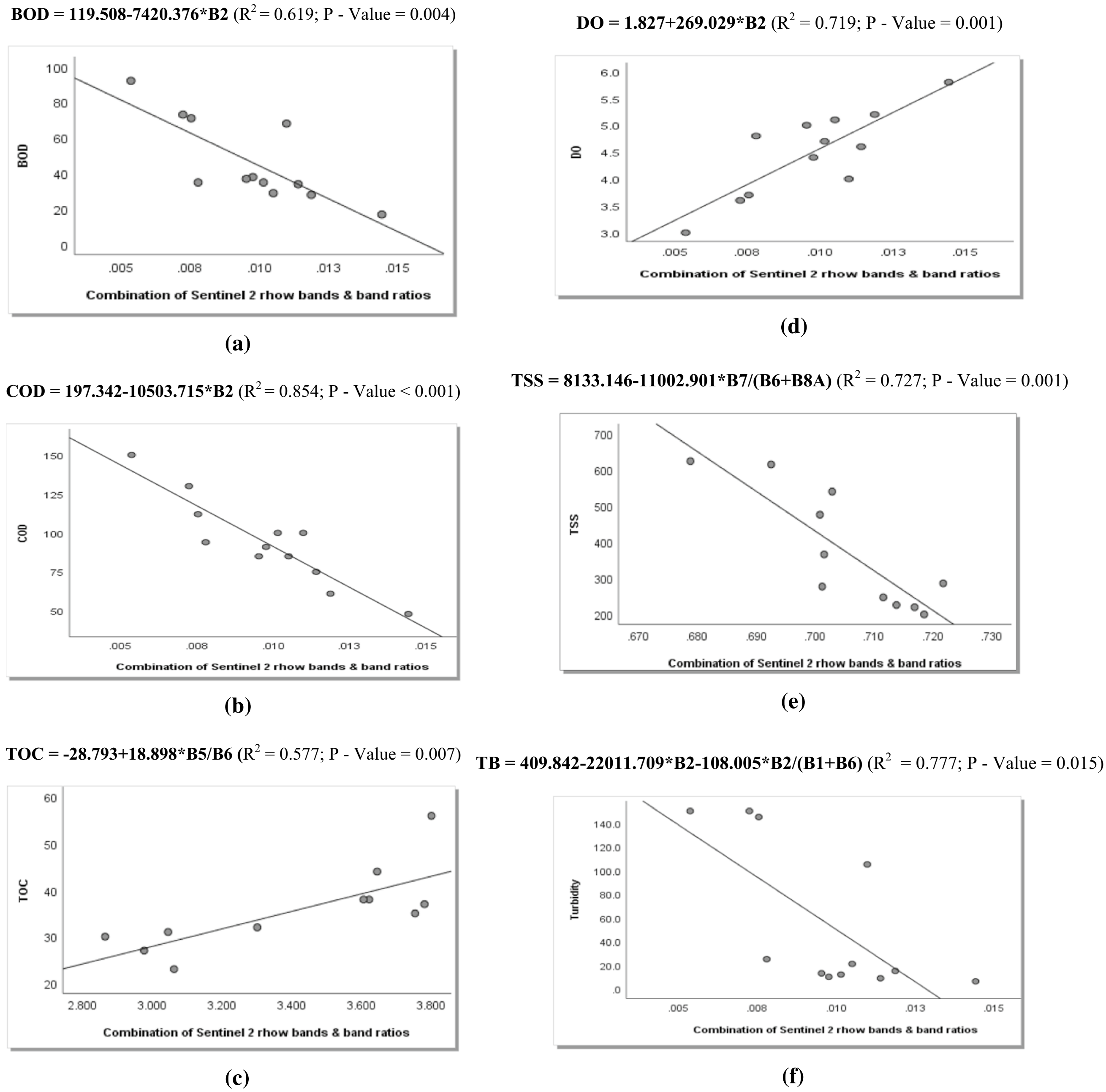


Fig. 6 Sentinel-2 estimation models for **a** BOD, **b** COD, **c** TOC, **d** DO, **e** TSS, and **f** Turbidity using the SWR technique based on calibration dataset

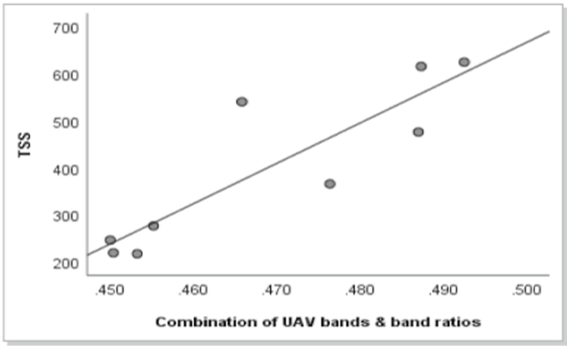
COD were strongly correlated with the single OLI band 2 (Blue) of Landsat 8.

Evaluation of relationship between surface water quality parameters using dataset from Unmanned aerial vehicle

Figure 7 shows the correlation between various bands of UAV with in situ testing results of SWQPs. Due to the low spectral resolution (3 bands) of UAV, limited correlations were obtained with respect to various SWQPs. TSS showed strong correlation with red, green, blue bands with R^2 value equals to 0.779 and significance (p) value of 0.002. Similarly, the COD and TOC also showed good correlations with red and blue bands with R^2 value of 0.556 and an optimal p value.

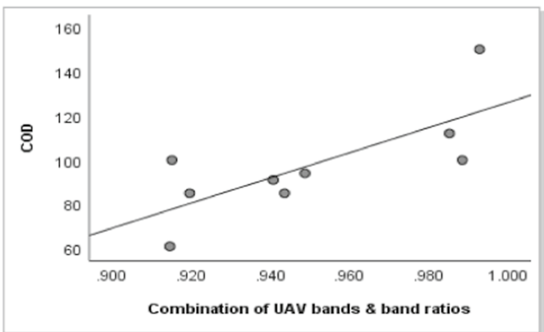
Only a few studies were carried out in analysing the SWQPs using UAV with a majority of research works that were conducted over optical water quality parameter

TSS=8535.594*B3/(B1+B2)-3602.206 (R^2 = 0.779; P - Value = 0.002)



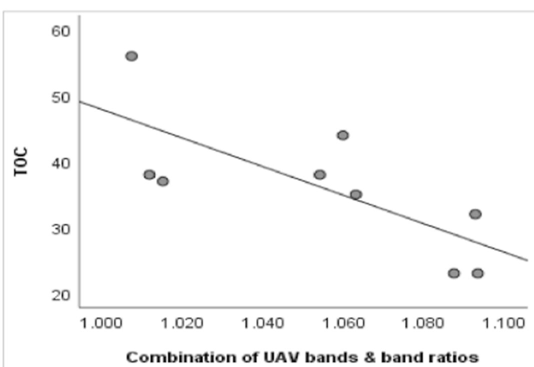
(a)

COD= -443.832+569.964*B3/B1 (R^2 = 0.556; P - Value = 0.021)



(b)

TOC= 265.732-217.790*B1/B3 (R^2 = 0.556; P - Value = 0.021)



(c)

Fig. 7 UAV estimation models for **a** TSS **b** COD **c** TOC

studies. The novelty of the present study lies in establishing significant correlations of algorithmic models with reasonable acceptance limits, proving the capability of data obtained using UAVs in non-optical surface water quality determination.

Validation of Sentinel-2 and Unmanned aerial vehicle-based stepwise regression models

The surface reflectance data from Sentinel-2 and UAV together with 75% of in situ sampling test results were correlated to generate various algorithms of SWQPs using stepwise regression technique. The validation of the developed SWR models was done using 25% of in situ sampling results. Using the algorithms, SWQPs were predicted for various sampling points and validated with the actual laboratory results.

In case of Sentinel-2 based SWR models, strong correlation was established between the predicted and measured surface water quality parameter values with coefficient of determination (R^2) more than 0.8. Table 5 shows the validation data of sentinel-2 band using stepwise regression models. Table 6 shows the validation of predicted SWQPs from UAV-based SWR models, and the measured test results which showed good correlation with $R^2 > 0.80$ thereby validating this present study.

Spatial distribution maps of Sentinel-2 and Unmanned aerial vehicle based on stepwise regression models

With the help of SNAP software, the algorithms derived from stepwise regression models were applied to every pixel of the Sentinel-2 and UAV images to develop accurate spatial distribution maps for various surface water quality parameters over Ukkadam Lake.

Figures 8 and 9 show the respective spatial distribution maps of sentinel-2 and UAV-based SWR models. It was observed from the above figures that DO varies between 2.09 mg/l and 6.93 mg/l and in most of the points, the DO value is between 4 and 5 mg/l, from which it was evident that the aquatic life is partially strained. The BOD and COD values were observed to be high throughout the lake which shows clear evidence of industrial pollution. Another important parameter considered, TOC, was seen to vary between 20 mg/l and 45 mg/l. As TOC is the sum of Dissolved organic carbon (DOC) and Particulate organic carbon (POC) present in the water, its increased value indicates high rate of organic material decomposition (Richard et al. 2000), (https://www.elgalabwater.com/blog/ total-organic-carbon-toc). It was also seen that, the turbidity and TSS values were optimal in some of the sampling points while showing peak values in those parts of the lake with inlets from industries and construction sites.

Table 5 Validation of Sentinel 2 data using stepwise regression models

Algorithms	SWQP		Point 13	Point 14	Point 15	Point 16	Validation Correlation (R^2)
119.508–7420.376*B2	BOD	Predicted	63.80	74.17	72.81	18.27	0.821
		Measured	55.00	62.00	81.00	28.00	
197.342–10,503.715*B2	COD	Predicted	118.48	133.17	131.24	54.04	0.896
		Measured	126.00	115.00	122.00	67.00	
1.827 + 269.029*B2	DO	Predicted	3.85	3.47	3.52	5.50	0.908
		Measured	4.20	3.50	2.90	5.80	
-28.793 + 18.898*B5/B6	TOC	Predicted	41.30	40.58	36.87	27.77	0.868
		Measured	37.00	44.00	32.00	21.00	
8133.146–11,002.901*B7/ (B6 + B8A)	TSS	Predicted	479.23	467.60	404.27	216.16	0.81
		Measured	420.00	388.00	448.00	184.00	
409.842–22,011.709*B2-108.005*B2/(B1 + B6)	Turbidity	Predicted	88.12	120.30	127.50	3.21	0.853
		Measured	107.00	94.00	153.00	9.75	

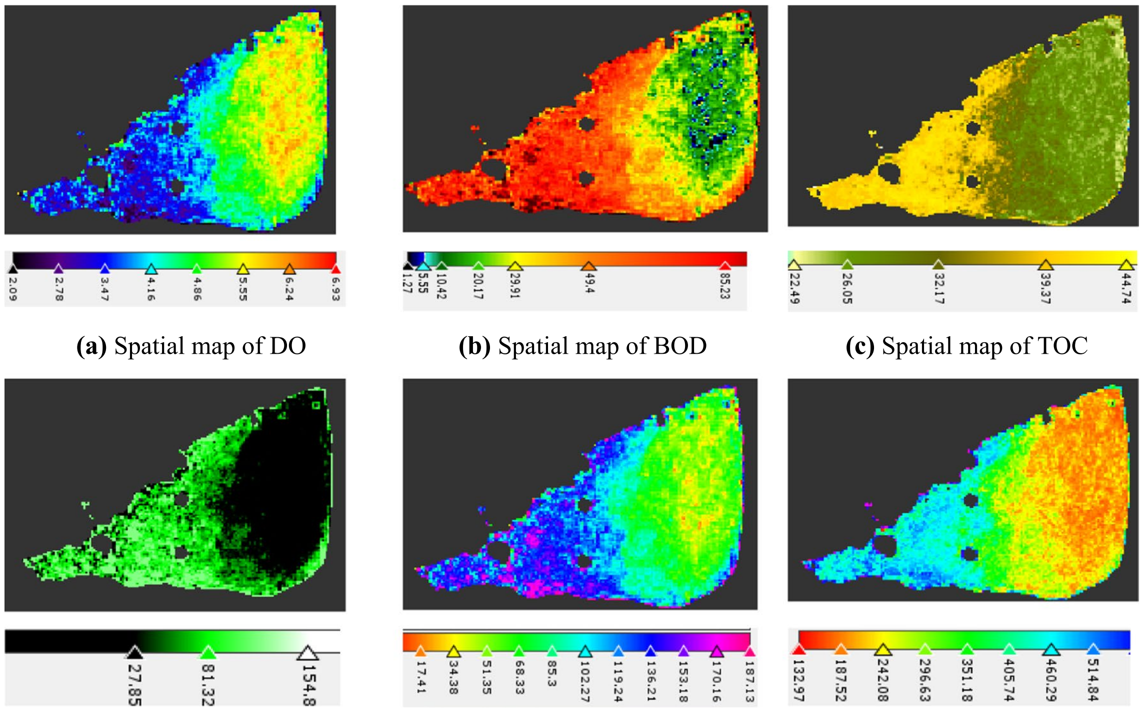
Table 6 Validation of UAV data based on stepwise regression models

Algorithms	SWQP		Point 13	Point 14	Point 15	Validation Correlation (R^2)
8535.594*B3/(B1 + B2) − 3602.206	TSS	Predicted	330	280	510	0.86
		Measured	420	388	448	
-443.832 + 569.964*B3/B1	COD	Predicted	110	92	112	0.804
		Measured	126.00	115.00	122.00	
265.732–217.790*B1/B3	TOC	Predicted	35.02	29.45	47.94	0.88
		Measured	37	44	32	

Discussions on the findings

In this paper, the reflectance values from both Sentinel-2 and UAV were analysed for obtaining the correlations between band values or combination of band values with various surface water quality parameters. The surface reflectance data generated from Sentinel-2 satellite imagery with C2RCC atmospheric correction give specific water leaving reflectance as output. Furthermore, the wide spectral resolution of the satellite imagery has stimulated the formation of algorithms to predict SWQPs like COD, BOD, DO, TSS, TOC and Turbidity with reasonably increased correlations when compared to UAV imagery.

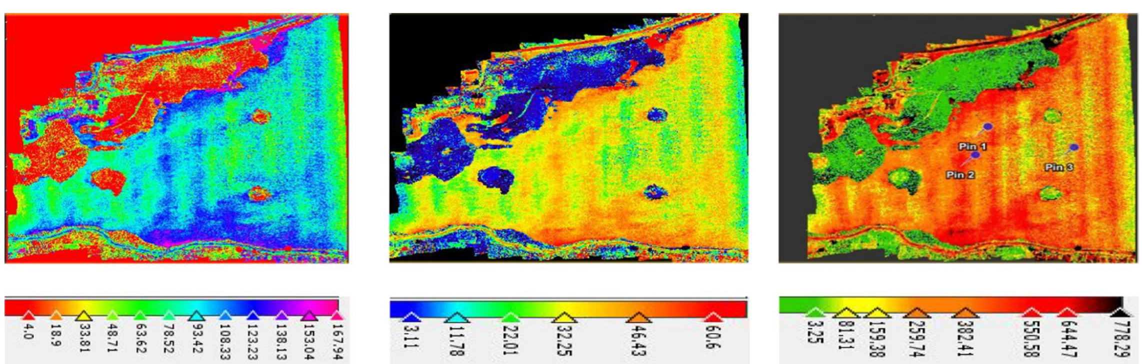
In this present study, BOD was tested in laboratory after the incubation of samples with microbes, measuring the depletion of oxygen directly resulting from biological activity aided by organic matter in the samples. Samples containing higher concentration of organic matter resulted in increased microbiological activity, which led to greater oxygen depletion. COD is likewise a measure of organic matter and oxygen demand, where the depletion of oxygen demand is through chemical oxidation and non-biological activity. TOC on the other hand measures the amount of carbon resulted from the generation of CO_2 because of oxidation reaction. On analysing the test results of various water quality parameters as shown in Table 4, it could be clearly inferred that non-optical parameters like BOD and COD can be correlated to optical parameter like turbidity, and TOC is non-optical with TSS in this present study area. This is further evident in the algorithms generated from Sentinel-2 satellite. Here, the water quality parameters like BOD, COD and Turbidity can be determined from the blue band of Sentinel-2, while the parameters TOC and TSS can be determined from the red edge bands.



(a) Spatial map of DO **(b)** Spatial map of BOD **(c)** Spatial map of TOC

(d) Spatial map of Turbidity **(e)** Spatial map of COD **(f)** Spatial map of TSS

Fig. 8 Spatial distribution maps of Sentinel-2 based SWR models



(a) Spatial map of COD **(b)** Spatial map of TOC **(c)** Spatial map of TSS

Fig. 9 Spatial distribution maps of UAV-based SWR models

Considering most of the practical real-world applications, the traditional in situ measurement and laboratory testing for analysing the water quality are both time consuming and expensive. SWR models from Sentinel/UAV possess increased potential to play pivotal role in continuous monitoring of water quality and to take appropriate action plans accordingly. However, the remote sensing data are readily available and local authorities could use these developed models to retrieve various surface water quality parameters of Ukkadam Lake in periods with weather conditions similar to those used for the generation of model and with reasonable accuracy together with reduced cost and time. The correction tools available and widespread spectral resolution thus play a very important role in the formulation of algorithmic models for retrieving the water quality parameters. The conventional models employing UAV imagery even though being more accessible, they face the shortcoming of reduced spectral resolution in UAV. Furthermore, the non-availability of a processor and necessity for generating a specific water reflectance have limited the development of predictive algorithms for acquiring additional water quality parameters.

Conversely, for future research, in order to additionally validate the applicability of this developed Sentinel-2 and UAV-based SWR algorithms, further studies are required for the analysis of these selected water quality parameters at various seasons together with different water sampling depths as well. The related consequences towards data interoperability, machine learning models and data sharing for reinforcement of interactions amid UAVs and satellites will also need to be assessed. Additionally, generating Sentinel-2-based water quality index models have to be explored which will assist in summarizing the complicated water quality data into simplified numerical values.

Conclusion

Several interesting findings related to the novel approach for monitoring the surface water quality using UAV and Sentinel-2 multispectral data were summarized in this paper. The water leaving surface reflectance data generated from Sentinel-2 imagery using C2RCC processor were used for analysing the water quality parameters. The wider spectral resolution of Sentinel-2 has enabled the formulation of algorithms to predict SWQPs including COD, BOD, DO, TSS, TOC and Turbidity with better correlations ($R^2 > 0.5$ and $p < 0.05$). Using UAV for the estimation of water quality was also explored and algorithms were generated for optical and non-optical parameters like TSS, COD and TOC with good correlations. Here, 75% of the sample data were used for generating the models, and the models so developed were validated using the remaining 25% data. The SWR models from both Sentinel-2 and UAV imagery on validation resulted in $R^2 > 0.80$ demonstrating increased reliability and accuracy of the models in predicting various water quality parameters.

Acknowledgements The authors would like to thank the authorities of Coimbatore Municipal Corporation for their support in the fieldwork activities and data collection.

Author's contribution All authors equally participated in overseeing the laboratory work, data analysis, and manuscript writing and review.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Availability of data and material Authors are willing to share data and material according to the relevant needs.

Declarations

Conflict of interest The authors declare no competing financial, professional and personal interests.

Consent for publication We declare that we consented for the publication of this research work.

References

Abayazid H, El-Adawy A (2019) Assessment of a non-optical water quality property using space-based imagery in Egyptian Coastal Lake. J Water Resour Prot 11:713–727. https://doi.org/10.4236/jwarp.2019.116042

Alparslan E, Aydöner C, Tufekci V, Tüfekci H (2007) Water quality assessment at Ömerli Dam using remote sensing techniques. Environ Monit Assess 135:391–398. https://doi.org/10.1007/s10661-007-9658-6

Alvado B, Sòria-Perpinyà X, Vicente E, Delegido J, Urrego P, Ruíz-Verdú A, Soria JM, Moreno J (2021) Estimating organic and inorganic part of suspended solids from sentinel 2 in different inland waters. Water 13:2453. https://doi.org/10.3390/w13182453

Apte SC, Batley GE, Szymczak R, Rendell PS, Lee R, Waite TD (1998) Baseline trace metal concentrations in New South Wales coastal waters. Mar Freshw Res 49:203–214. https://doi.org/10.1071/MF96121

Arango JG, Nairn RW (2019) Prediction of optical and non-optical water quality parameters in oligotrophic and eutrophic aquatic systems using a small unmanned aerial system. Drones 4:1. https://doi.org/10.3390/drones4010001

Bartholomew DJ (2010) Analysis and interpretation of multivariate data. Int Encycl Educ. https://doi.org/10.1016/b978-0-08-044894-7.01303-8

Bourouhou I, Salmoun F (2021) Sea water quality monitoring using remote sensing techniques: a case study in Tangier-Ksar Sghir coastline. Environ Monit Assess 193:557. https://doi.org/10.1007/s10661-021-09242-4

Caballero I, Stumpf R, Meredith A (2019) Preliminary assessment of turbidity and chlorophyll impact on bathymetry derived from Sentinel-2A and Sentinel-3A satellites in South Florida. Remote Sensing 11:645. https://doi.org/10.3390/rs11060645

Chang CW, Laird DA, Mausbach MJ, Hurburg CR (2001) Near-infrared reflectance spectroscopy–principal components regression analyses of soil properties. Soil Sci Soc Am J 65:480. https://doi.org/10.2136/sssaj2001.652480x

Cillero Castro C, Domínguez Gómez JA, Delgado Martín J, Hinojo Sánchez BA, Cereijo Arango JL, Cheda Tuya FA, Díaz-Varela R (2020) An UAV and satellite multispectral data approach to monitor water quality in small reservoirs. Remote Sensing 12:1514. https://doi.org/10.3390/rs12091514

El Mountassir O, Bahir M, Ouazar D, Ouhamdouch S, Chehbouni A, Ouarani M (2020) The use of GIS and water quality index to assess groundwater quality of krimat aquifer (Essaouira; Morocco). SN Applied Sciences 2:871. https://doi.org/10.1007/s42452-020-2653-z

Field sampling program (waterquality.gov.au)

Gholizadeh M, Melesse A, Reddi L (2016) A Comprehensive review on water quality parameters estimation using remote sensing techniques. Sensors 16:1298. https://doi.org/10.3390/s16081298

Gitelson A, Garbuzov G, Szilagyi F, Mittenzwey KH, Karnieli A, Kaiser A (1993) Quantitative remote sensing methods for real-time monitoring of inland waters quality. Int J Remote Sens 14:1269–1295. https://doi.org/10.1080/01431169308953956

Gowraraju N, Mayandi J, Polavakkalipalayam NM (2014) Water quality index of Ukkadam pond connected to River Noyyal, Coimbatore, Tamil Nadu, India. Malaya J Bio Sci 1:100–103

Hasab HA, Jawad HA, Dibs H, Hussain HM, Al-Ansari N (2020) Evaluation of water quality parameters in Marshes Zone Southern of Iraq based on remote sensing and GIS techniques. Water Air Soil Pollut. https://doi.org/10.1007/s11270-020-04531-z

Hellweger FL, Schlosser P, Lall U, Weissel JK (2004) Use of satellite imagery for water quality studies in New York Harbor. Estuar Coast Shelf Sci 61:437–448. https://doi.org/10.1016/j.ecss.2004.06.019

https://en.wikipedia.org/wiki/Ukkadam_Lake

https://law.resource.org/pub/in/bis/S02/is.3025.44.1993.pdf (Assessed 21 September 2021)

https://law.resource.org/pub/in/bis/S02/is.3025.58.2006.pdf (Assessed 11 October 2021)

https://seadas.gsfc.nasa.gov/help/8.0.0/c2rcc/C2RCCTool.html

https://www.elgalabwater.com/blog/total-organic-carbon-toc

Jeyaraj M, Ramakrishan K, Jai Anandhi A, Arunachalam S, Magudeswaran P (2016) Investigation of physico-chemical and biological characteristics of various lake water in Coimbatore District, Tamilnadu, India. Orient J Chem 32:2087–2094

Kapalanga TS, Hoko Z, Gumindoga W, Chikwiramakomo L (2021) Remote-sensing-based algorithms for water quality monitoring in Olushandja Dam, north-central Namibia. Water Supply 21:1878–1894. https://doi.org/10.2166/ws.2020.290

Khaki M (2020) Satellite remote sensing in hydrological data assimilation. Springer, Cham. https://doi.org/10.1007/978-3-030-37375-7

Koponen S (2002) Lake water quality classification with airborne hyperspectral spectrometer and simulated MERIS data. Remote Sens Environ 79:51–59. https://doi.org/10.1016/s0034-4257(01)00238-3

Liu H, Li Q, Shi T, Hu S, Wu G, Zhou Q (2017) Application of Sentinel 2 MSI images to retrieve suspended particulate matter concentrations in Poyang Lake. Remote Sens 9:761. https://doi.org/10.3390/rs9070761

Mihu-Pintilie A (2018) The seasonal variation of physical-chemical parameters and water quality assessment (WQI). In: Natural Dam Lake Cuejdel in the Stânişoarei Mountains, Eastern Carpathians. Springer, Cham. https://doi.org/10.1007/978-3-319-77213-4_7

Minu P, Souda VP, Baliarsingh SK, Dwivedi RM, Ali Y, Ashraf PM (2020) Assessing temporal variation of coloured dissolved organic matter in the coastal waters of South Eastern Arabian Sea. Acta Oceanol Sin 39:102–109. https://doi.org/10.1007/s13131-020-1534-z

Mishra S, Stumpf RP, Schaeffer BA, Werdell PJ, Loftin KA, Meredith A (2019) Measurement of cyanobacterial bloom magnitude using satellite remote sensing. Sci Rep 9:18310. https://doi.org/10.1038/s41598-019-54453-y

Moore GK (1980) Satellite remote sensing of water turbidity/Sonde de télémesure par satellite de la turbidité de l'eau. Hydrol Sci Bull 25:407–421. https://doi.org/10.1080/02626668009491950

Mushtaq F, Nee Lala MG (2016) Remote estimation of water quality parameters of Himalayan lake (Kashmir) using Landsat 8 OLI imagery. Geocarto Int 32:274–285

Papenfus M, Schaeffer B, Pollard AI, Loftin K (2020) Exploring the potential value of satellite remote sensing to monitor chlorophyll-a for US lakes and reservoirs. Environ Monit Assess 192:808. https://doi.org/10.1007/s10661-020-08631-5

Pavelsky TM, Smith LC (2009) Remote sensing of suspended sediment concentration, flow velocity, and Lake Recharge in the Peace-Athabasca Delta. Can Water Resour Res. https://doi.org/10.1029/2008wr007424

Richard S, Seri CY, France VW, Bruno C (2000) Microbial decomposition of large organic particles in the northwestern Mediterranean Sea: an experimental approach. Mar Ecol Prog Ser 198:61–72. https://doi.org/10.3354/meps198061

Sharaf El Din E, Zhang Y (2017) Estimation of both optical and non-optical surface water quality parameters using Landsat 8 OLI imagery and statistical techniques. J Appl Remote Sens 11:046008. https://doi.org/10.1117/1.JRS.11.046008

Song K, Li L, Li S, Tedesco L, Hall B, Li L (2011) Hyperspectral remote sensing of total phosphorus (TP) in three central indiana water supply reservoirs. Water Air Soil Pollut 223:1481–1502. https://doi.org/10.1007/s11270-011-0959-6

Toming K, Kutser T, Laas A, Sepp M, Paavel B, Nõges T (2016) First experiences in mapping lake water quality parameters with Sentinel-2 MSI imagery. Remote Sens 8:640. https://doi.org/10.3390/rs8080640

Tóth VZ, Ladányi M, Jung A (2021) Adaptation and validation of a sentinel-based chlorophyll-a retrieval software for the Central European Freshwater Lake, Balaton. PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science. https://doi.org/10.1007/s41064-021-00160-1

Tsouros DC, Bibi S, Sarigiannidis PG (2019) A review on UAV-based applications for precision agriculture. Information 10:349. https://doi.org/10.3390/info10110349

Vercruysse K, Grabowski RC, Hess T, Lexartza-Artza I (2020) Linking temporal scales of suspended sediment transport in rivers: towards improving transferability of prediction. J Soils Sediments 20:4144–4159. https://doi.org/10.1007/s11368-020-02673-5

Verpoorter C, Kutser T, Seekell DA, Tranvik LJ (2014) A global inventory of lakes based on high-resolution satellite imagery. Geophys Res Lett 41:6396–6402. https://doi.org/10.1002/2014gl060641

Vertucci FA, Likens GE (1989) Spectral reflectance and water quality of Adirondack mountain region lakes. Limnol Oceanogr 34:1656–1672. https://doi.org/10.4319/lo.1989.34.8.1656

Wang Y (2004) Water quality change in reservoirs of Shenzhen, China: detection using LANDSAT/TM data. Sci Total Environ. https://doi.org/10.1016/s0048-9697(04)00100-7

Warren MA, Simis SGH, Martinez-Vicente V, Poser K, Bresciani M, Alikas K, Ansper A (2019) Assessment of atmospheric correction algorithms for the Sentinel-2a multispectral imager over coastal and inland waters. Remote Sens Environ 225:267–289. https://doi.org/10.1016/j.rse.2019.03.018

Water quality sampling techniques (usgs.gov)

Xiong J, Lin C, Ma R, Cao Z (2019) Remote sensing estimation of lake total phosphorus concentration based on MODIS: A case study of Lake Hongze. Remote Sens 11:2068. https://doi.org/10.3390/rs11172068

Yang B, Liu Y, Ou F, Yuan M (2011) Temporal and spatial analysis of COD concentration in East Dongting Lake by using of remotely sensed data. Procedia Environ Sci 10:2703–2708. https://doi.org/10.1016/j.proenv.2011.09.420

Yu X, Yi H, Liu X, Wang Y, Liu X, Zhang H (2016) Remote-sensing estimation of dissolved inorganic nitrogen concentration in the Bohai Sea using band combinations derived from MODIS data. Int J Remote Sens 37:327–340. https://doi.org/10.1080/01431161.2015.1125555