

ASSESSMENT AND SPATIAL DISTRIBUTION OF WATER QUALITY CONSTITUENTS IN LAKE ECOSYSTEM USING SENTINEL-2 DATA AND MODELLING

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ABSTRACT

An inland lake is an essential component of the freshwater environment and must be monitored to prevent the quality of the lake's water from deteriorating. Turbidity and total suspended matter (TSM) are crucial water quality assessment factors. A cutting-edge technical approach called remote sensing is utilized to keep an eye on the quality of lake water. To assess the lake water quality, the water quality constituents (WQC) model was developed using an empirical computation technique using spectral wavelengths (400-800 nm) from in-situ hyperspectral remote sensing measurements. The results show that the best appropriate models that are sensitive to the estimation of TSM ($R^2 = 0.8523$) and Turbidity ($R^2 = 0.9115$) were selected and incorporated into Sentinel-2MSI for WQC estimation. The spatial distribution of WQC is mapped, providing information on both the distribution and variations of WQC within the lake. The research has proven that it has the potential for regular monitoring of lake water through this technique.

Keywords: Spatial Distribution, WQC, TSM, Turbidity, Sentinel-2, Lake Water Quality, Spectral Wavelength.

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INTRODUCTION

One of the most significant sources of fresh water is a lake. It is also rich in biodiversity and plays a significant role in ecological environment improvement and regulation. Examining and monitoring the lake water quality is important.^{1,2} In recent decades, urban area growth and industrialization have deteriorated freshwater resources and influenced the food chain in freshwater ecosystems. Therefore, it is essential to maintain attention to the regional quality of lake water. The examination of main water quality constituents (WQC) are suspended particulate matter and turbidity that characterize the lake water quality. Among various water quality parameters, suspended particle matter is the most common issue in inland water bodies like lakes, estuaries, and rivers.^{3,4} In water, an increase in Turbidity also increases the concentration of suspended matter and is also detrimental to the natural characteristics of water sources like lakes.^{5,6} Traditional measurement approaches are mainly based on field measurement and have some limitations, such as being expensive, consuming more time, requiring more human resources, and having difficulty in spatial monitoring all over the lake.⁶ Monitoring the quality of the water on a spatial-temporal scale is not possible.⁷ Overcoming such limitations, remote sensing techniques are being applied to monitor the lake ecosystem and also give a broader perspective, enabling retrieval of data from difficult-to-access areas where sampling is required.⁷⁻⁹ The satellite remote sensing (SRS) technique has more advantages than the traditional method because it provides continuous observation and synoptic view over vast spatial and temporal monitoring.¹² Modern development in sensor technology and model development progress which provide new vision for inland water remote sensing.^{10,11,13} The Sentinel-2A/2B dataset has been used to derive the water quality information and map its distribution. It has 13 spectral bands, 3 different spatial resolutions, and also has a 5-day revisit period.^{20,29} study aims to develop a WQC model through spectral band computation to analyze and assess the water quality of the lake water using the SRS technique and also to generate a spatial distribution map of water quality constituents.

EXPERIMENTAL

Study Area

Kolavai Lake is the largest freshwater lake in the Chengalpattu district, Tamil Nadu. It has a 4.5m maximum depth and a total capacity of about 476.69 Mcft. It is filled with 60 percent of the rainfall that was

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contributed by the NE monsoon period. The lake is polluted by domestic sewage, agricultural waste, and industrial effluents. Every day it also receives an average of 1450 litres of municipal wastewater into the lake. The study area location is represented in Fig.-1.

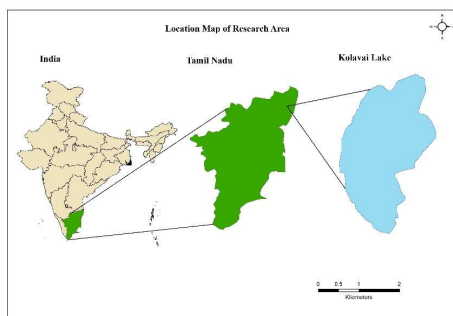


Fig.-1: Study Area Location

***In-vitro* Measurement**

In the laboratory, many water samples have been collected from different locations in the lake water and examined. The TSM concentration was determined by filtration of the obtained sample through a 47 mm diameter filter paper. Before filtering, the filtration paper was pre-weighed; that is, the initial weight was determined by observing the dry weight.²⁶⁻²⁸ Following filtering, it was cooled to ambient temperature and dried for two hours at 105 to 110 degrees Celsius. The filter's dry weight was determined, and by deducting the dry weight from the original weigh-in, the concentration of all suspended materials was computed.¹⁶⁻²¹ The Nephelo turbidity meter is used to test the turbidity of the water samples. Every water sample's level of turbidity was noted for the analysis. The analysis of the in-vitro samples is shown in Fig.-2(a-c).

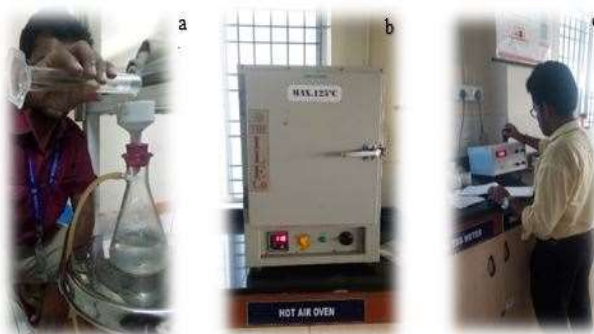


Fig.-2: (a) Filtering of Sample, (b) Drying of the filtered sample after filtration placed in a hot air oven and, (c) Turbidity observation of collected sample using Nephelo-turbidity meter

Remote Sensing Measurement

The water remote sensing reflectance ($R_{rs}(\lambda)$), is calculated as the ratio of water-leaving radiation (L_w) to down-welling irradiance (E_d).^{12,13,14} These radiance and irradiances are measured using a hyperspectral remote sensing (HSRS) sensor.

Satellite Data Acquisition and Process

High-resolution multispectral satellite imagery from the European Space Agency's Sentinel-2MSI was utilized in the study. It was obtained through the Copernicus portal and further image processing is carried out using SNAP.^{15,29} The atmospheric correction was processed using the sen2cor processor in SNAP, which provides reflectance data product.^{26,27} The retrieved processed data is used to estimate the water quality constituents (WQC) and its distribution monitoring mapping.

WQC- Retrieval Model Development

In this analysis, the spectroscopic reflectance wavelength bands such as blue (R_1), green (R_2), and red (R_3) up to NIR wavelength (R_8) were used to generate the WQC retrieval model. It was developed based on empirical determinations of various combinations between 400nm and 800 nm obtained from measured $R_{rs}(\lambda)$. The analyses were based on specific spectral properties of the component in the water column's

absorption and scattering, which governs reflectance.^{19,22-25} The developed models were performed for the statistical regression analysis with the water quality constituents.

RESULTS AND DISCUSSION

Water Quality Constituents- Analysis

In the research, the water quality constituents (TSM and Turbidity) were analyzed in the laboratory and evaluated and its results are illustrated in the following.

Table-1: WQC Analysis Details

WQC	Maximum	Minimum	Mean	SD	CV	MAD
TSM (mg/ltr)	11.77	4.16	8.15	2.46	0.30	1.98
Turbidity (NTU)	4	1	2.43	0.87	0.35	0.61

It was observed that there was a variation of suspended matter in the lake (4.17 - 11.71 mg/l). There are also similar turbidity levels from 1 NTU to 4 NTU, with a mean of 2.43 NTU. Also, other statistical parameter analyses, such as standard deviation (SD) of 2.46 & and 0.87 and coefficient of variables (CV) of about 0.30 and 0.35 respectively, for the WQCs (Table-1).

WQC Model Analysis

In the water quality constituent's model analysis, the spectral band ratio computation is done based on equation 1 and the model has been developed to estimate WQC concentration in the lake water.¹⁶. The developed model was applied to Satellite data like Sentinel-2MSI (S2MSI).

$$WQC \propto [R_2 / R_1] \quad (1)$$

The six developed models were evaluated with a statistical estimator and highly correlated models were selected and used to determine water quality constituent's concentration. It was assessed for performance using various accuracy estimators like RMSE, and MAPE^{16,17} are described in equations 2 and 3.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (X_{Estimated} - X_{Measured})^2}{N}} \quad (2)$$

$$MAPE = \frac{\sum_{i=1}^N \left(\frac{X_{Estimated} - X_{Measured}}{X_{Measured}} \right)}{a} \times 100 \quad (3)$$

A & a is the total amount of samples analyzed, $X_{estimated}$ indicates retrieved WQC from the developed model, and $X_{measured}$ is the observed WQC from the collected sample. In the analysis of WQC models, in the total suspended matter retrieval, the TSM 2 model shows a strong correlation with constituents having R^2 of 0.8523, Pearson coefficient of R (0.9232) with Adj R^2 of 0.8030. The other models TSM3 show another good correlation R^2 of 0.8136, Pearson coefficient of R (0.9020), and TSM1 shows moderate correlations R^2 of 0.7422, Pearson coefficient of R (0.8615) with Adj R^2 of 0.6562 as shown in Table-2.

Table-2: Models Details for Retrieving the TSM and Turbidity (WQC)

WQC Model	Spectral Bands	Equations	R^2	R	Adj R^2
TSM1	SB ₄ /SB ₃	TSM = 25.786x - 4.7914	0.7422	0.8615	0.6562
TSM2	SB ₆ /SB ₃	TSM = 27.444x - 4.6416	0.8523	0.9232	0.8030
TSM3	SB ₇ /SB ₃	TSM = 31.774x - 6.9875	0.8136	0.9020	0.7515
TURB1	SB ₇ /SB ₃	TUR = 15.231x - 4.7839	0.4264	0.6530	0.2352
TURB2	SB ₆ /SB ₃	TUR = 16.678x - 5.2714	0.6533	0.8082	0.5377
TURB3	SB ₄ /SB ₃	TUR = 14.989x - 4.88	0.9115	0.9547	0.8820

The turbidity retrieval model was developed and observed that the TURB3 model showed a strong correlation with R^2 of 0.9115. TURB1 shows a weak correlation R^2 of 0.4264, Pearson coefficient of R (0.6530), whereas TURB2 shows a moderate correlation R^2 of 0.6533, a Pearson coefficient of R (0.8082) for this model.

WQC Analysis

In the water quality constituent analysis, total suspended matter and Turbidity are important water quality variables. Water turbidity is mainly dependent on the suspended particles in the lake. Due to its complex nature, there is a change in the radiations of lake water and its color variations.^{18,21}

Table-3: Analysis of WQC (Measured, Model, and S2MSI)

S.No.	WQC (TSM vs Turbidity)	R ²	R	Adj R ²	Slope	Intensity
1	In-vitro Measured	0.7281	0.8532	0.66	0.36335	-0.457
2	Model	0.8571	0.9257	0.821	0.4907	-1.505
3	S2MSI	0.8291	0.9105	0.786	0.36243	0.2139

The analysis was done to assess the relationship between TSM and the Turbidity of water derived from the laboratory measurement, model, and satellite data (S2MSI), and its details are shown in Table-3. In this analysis, it was observed that a good correlation was obtained in in-vitro measurement analysis with a Pearson coefficient R of 0.8532. These WQC parameters derived from the model and S2MSI were analyzed and there is a strong relationship obtained between TSM and turbidity relationship having R² of 0.8570 and 0.8291 respectively and other details of relationships are shown in Table-4. These variables have Pearson coefficient of R (0.9257 & 0.9105) for both the model and S2MSI respectively. The retrieved water quality constituents of both TSM and turbidity concentrations were analyzed for accuracy evaluation through linear relationship computation.

Table-4: Accuracy Analysis of WQC – obtained from Measured, Model, and S2MSI

S. No	Analysis of WQC	RMSE	MAPE
1	Measured TSM vs Model TSM	2.72	21.91
2	Measured TSM vs S2MSI TSM	5.53	40.26
3	Measured Turbidity vs Model Turbidity	0.56	14.01
4	Measured Turbidity vs S2MSI Turbidity	2.42	48.03

It was evaluated through accuracy assessment parameters such as RMSE and MAPE; its details are shown in Table-4. It was noted that the good result obtained is R² of 0.8657 and as shown in Fig.-3(a), and it also has RMSE of 2.72 mg/l, MAPE of 21.91%. It also evaluated for S2MSI retrieved TSM and measured TSM has R² of 0.8215 shown in Fig.-3(b). The accuracy of this analysis has an RMSE of 5.53 mg/l and MAPE of 40.26%. The important variable of water quality is Turbidity and it was evaluated between measured Turbidity and retrieved from the model and S2MSI which has R² of 0.8178 and 0.7502 shown in Fig.-3(c & d). The accuracy for this analysis has RMSE (0.56 mg/l & 2.42 mg/l), and MAPE (14.01 % & 48.03%). The well-correlated and accurate obtained model (TSM and Turbidity) was adopted for spatial distribution analysis of WQC.

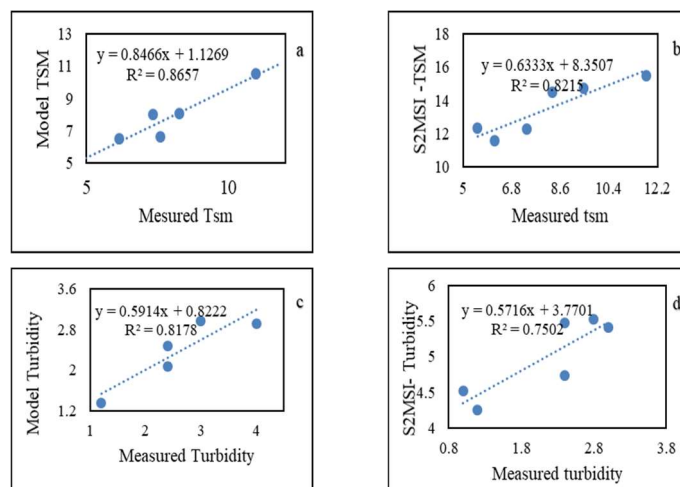


Fig.-3: Scatter plot analysis between Measured WQC, Model WQC, and S2MSI WQC a) Measured TSM vs. Model TSM b.) Measured TSM vs. S2MSI TSM c.) Measured Turbidity vs. Model Turbidity and d.) Measured Turbidity vs. S2MSI Turbidity.

Spatial Distributions Analysis of WQC

The variations in spatial distribution patterns of WQCs were obtained from Sentinel 2 MSI across Kolavai Lake. The Sentinel 2 MSI provides greater spatial information differences than other satellite sensors like MODIS because of its better spatial resolutions.^{6,22-24} In the WQC distribution analysis, it was classified into four classes Very High, High, Moderate, and Low, based on the concentration of water quality constituents in the lake, and its details are shown in Table-5.

Table-5: Distribution Classification Pattern of WQC

S. No	Class	TSM (mg/l)	Turbidity (NTU)
1	Very High	>18	>7
2	High	14-18	5-7
3	Moderate	13-14	4-5
4	Low	<13	<4

The eastern part of the lake had a lower concentration of TSM (<13 mg/l) as well and Turbidity (<4 NTU) was observed and shown in Fig.-4 (a & b). The middle part of the lake had a moderate and high range of TSM (13-14 mg/l & 14-18 mg/l) and moderate turbidity (4-5 NTU) was detected in Fig.-4 (a & b). The western part of the lake had variations in TSM concentrations from high to very high (>18 mg/l) near lake bunds, and the north-western parts of the lake had lower concentrations observed and shown in Fig.-4 (a). The turbidity distribution pattern analysis inferred that there a very high turbidity concentrations (>7 NTU) and high were observed in the north and south portions of the waterbody, as shown in Fig.-4(b). The spatial variations map, which depicts the spatial changes in WQC, indicated the distribution changes in water quality. The wind carries the ambient pollutants, which then dissolve in water. Agricultural pollutants also build up on the eastern side of the lake.

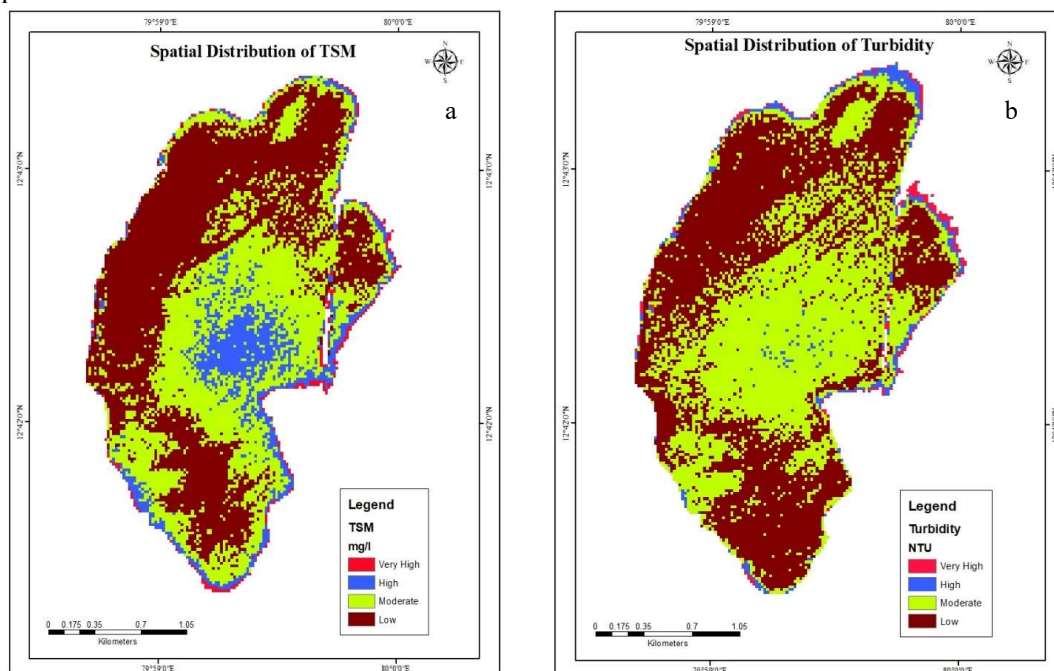


Fig.-4: Spatial Distribution of WQC a.) TSM b.) Turbidity

This developed approach is effective for both synoptic and continuous environmental monitoring of the lake. A rise in urbanization and population growth leads to stochastic anthropogenic nutrient supplies to the water, resulting in the depletion of aquatic oxygen supply. Some sources like industries, agricultural practices, municipalities, and surrounding homes directly hiked the water deterioration rate.^{26,28} This threat is mainly due to an increase in the rate of nutrient concentrations, phytoplankton biomass, and oxygen saturations. It causes a rapid water quality reduction and risks the lake ecosystem.

CONCLUSION

Water quality constituents are analyzed in the research and developed WQC remote sensing model using empirical relationship analysis between different measured remote sensing reflectance and measured TSM and turbidity values. The highly correlated model was selected and applied to S2MSI data for retrieving the TSM and Turbidity. The result indicates these spectral wavelengths (Green-B3, Red-B4, and VNIR-B6) are sensitive to water quality constituents (TSM and Turbidity) characteristics. It also infers that there is a relationship between TSM and Turbidity. The distribution changes in water quality were shown in the spatial variations map that represents the spatial changes in WQC. The quality of the lake water is deteriorating due to the discharge and accumulation of debris from the adjacent agriculture and residential areas. The ambient contaminants are carried by the wind and dissolved in water. Additionally, agricultural contaminants are accumulated on the lake's eastern side. To prevent the lake environment from degrading, the appropriate precautions and regulations should be adopted. The HSRS approaches have proved to be suitable for continuous and synoptic monitoring of the lake environment.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS

All the authors contributed significantly to this manuscript, participated in reviewing/editing and approved the final draft for publication. The research profile of the authors can be verified from their ORCID ids, given below:

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REFERENCES

1. A. Mahdy, S. Hilt, N. Filiz, M. Beklioglu, J. Hejzlar, D. Ozkundakc, E. Papastergiadou, M. Scharfenberge, R. Sorf and K. Stefanidis, *Aquatic Science*, **77(1)**, 499(2015), <https://doi.org/10.1007/s00027-015-0394-7>
2. J. Mc Grane Scott, *Hydrological Sciences Journal*, **61(13)**, 2295(2016), <https://doi.org/10.1080/02626667.2015.1128084>
3. S. Garima, T. Priya and M. Pallavi, *Rasayan Journal of Chemistry*, **15(3)**, 1867(2022), <https://doi.org/10.31788/RJC.2022.1537012>
4. K.L. Carder, F.R. Chen, J.P. Cannizzaro, J.W. Campbell and B.G. Mitchell, *Advances in Space Research*, **33(7)**, 1152(2004), [https://doi.org/10.1016/S0273-1177\(03\)00365-X](https://doi.org/10.1016/S0273-1177(03)00365-X)
5. A. Subba, S. Jha, M. Pandey, K. G. Dolm and Ajeya Jha, *Rasayan Journal of Chemistry*, **16(2)**, 746(2023), <https://doi.org/10.31788/RJC.2023.1628116>
6. K. Boudeffa, F. Fekrache and N. Bouchareb, *Rasayan Journal of Chemistry*, **13(1)**, 168(2020), <https://doi.org/10.31788/Rjc.2020.1315255>
7. K. Dornhofer K, A. Goritz A, P. Gege, B. Pflug and N.Oppelt, *Remote Sensing*, **8(11)**, 1(2016), <https://doi.org/10.3390/rs8110941>
8. V. Dutta V, D. Dubey and S. Kumar, *Science of the Total Environment*, **743(140756)**, 1(2020), <https://doi.org/10.1016/j.scitotenv.2020.140756>

9. A.A. Gitelson, G. Dall'Olmo, W. Moses, D.C. Rundquist, T. Barrow, T.R. Fisher, D. Gurlin and J. Holz. *Remote Sensing of Environment*, **112**(9), 3582(2008), <https://doi.org/10.1016/j.rse.2008.04.015>
10. A. Gitelson, *International Journal of Remote Sensing*, **13**(17), 3367(1992), <https://doi.org/10.1080/01431169208904125>
11. Z.P. Lee, K.L. Carder, and R.A. Arnone, *Applied Optics*, **41**(37), 5755(2002), <https://doi.org/10.1364/AO.41.005755>
12. C.D. Mobley, *Applied Optics*, **38**(36), 442(1999), <https://doi.org/10.1364/AO.38.007442>
13. H. Liu, Q. Li, T. Shi, S. Hu, G. Wu and Z. Qiming, *Remote Sensing*, **9**(7), 1(2017), <https://doi.org/10.3390/rs9070761>
14. P. Murugan, R. Sivakumar and Savithri Bhat, *International Journal of Advanced Remote Sensing and GIS*, **9**(1), 3170(2020), <https://doi.org/10.23953/cloud.ijarsg.444>
15. A.Y. Morel and H.R. Gordon, *Boundary-Layer Meteorology*, **18**(4), 343(1980), <https://doi.org/10.1007/BF00122030>
16. A. Morel and L. Prieur, *Limnology and Oceanography*, **22**(4), 709(1977), <https://doi.org/10.4319/lo.1977.22.4.0709>
17. T. Nguyen, H. Thu, K. Katsuaki Koike and N.M. Trong, *Remote Sensing*, **6**(1), 421(2014), <https://doi.org/10.3390/rs6010421>
18. N. Sravanthi, Chuqun Chen, A.P. Yunus and J. Wu, *Regional Studies in Marine Science*, **24**(1), 303(2018), <https://doi.org/10.1016/j.rsma.2018.09.007>
19. S. Saadat, D. Rawtani and C.M. Hussain, *Science of the Total Environment*, **728**(138870), 1(2020), <https://doi.org/10.1016/j.scitotenv.2020.138870>
20. E. B. Stumpner, B.A. Bergamaschi, T.E. Kraus, A.E. Parker, F.P. Wilkerson, B.D. Downing, R.C. Dugdale, M.C. Murrell, K. D. Carpenter, J. L. Orlando and C. Kendall, *Science of the Total Environment*, **700** (134392), 1(2020), <https://doi.org/10.1016/j.scitotenv.2019.134392>
21. A. Amuthini Sambhavi, K. Nagamani and B. Gowtham, *Rasayan Journal of Chemistry*, **13**(3), 1871(2020), <https://doi.org/10.31788/RJC.2020.1335702>
22. D.P. Hader, A.T. Banaszak, V.E. Villafane, M.A. Narvarte, R.A. Gonzalez and E.W. Helbling *Science of the Total Environment*, **713**(136586), 1(2020), <https://doi.org/10.1016/j.scitotenv.2020.136586>
23. V. Garg, S. P. Aggarwal and P. Chauhan, *Geomatics, Natural Hazards and Risk*, **11**(1), 1175(2020), <https://doi.org/10.1080/19475705.2020.1782482>
24. Li Na, Shi Kun, Zhang Yunlin, Gong Zhijun, Peng Kai, Zhang Yibo & Zha Yong, *Remote Sensing*, **11**(2), 1(2019), <https://doi.org/10.3390/rs11020177>
25. H. Liu, Q. Li, T. Shi, S. Hu, G. Wu, and Q. Zhou, *Remote Sensing*, **9**(7), 1(2017), <https://doi.org/10.3390/rs9070761>
26. M. H. Gholizadeh, A. M. Melesse and L. Reddi, *Sensors*, **16**(8), 1(2016), <https://doi.org/10.3390/s16081298>
27. M. Elhag, I. Gitas, A. Othman, J. Bahrawi and P. Gikas, *Water*, **11**(3), 1(2019), <https://doi.org/10.3390/w11030556>
28. A. Göritz, S. A. Berge, P. Gege, H. P. Grossart, J. C. Nejstgaard, S. Riedel, R. Röttgers, and C. Utschig. *Remote Sensing*, **10**(2), 1(2018), <https://doi.org/10.3390/rs10020181>
29. K. Töming, T. Kutser, A. Laas, M. Sepp, B. Paavel, and T. Nõges, *Remote Sensing*, **8**(8), 640(2016), <https://doi.org/10.3390/rs8080640>

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