DETECTION OF TOTAL DISSOLVED SOLIDS IN THE FOURTH REACH OF THE NILE RIVER BY USING LANDAST 8 IMAGERY

Dina M. Rifaat [1]; Noha S. Donia[2] and Ahmed M. A. Moussa[3]

1) Postgraduate student, Faculty of Graduate Studies and Environmental Research, Ain Shams University 2) Faculty of Graduate Studies and Environmental Research, Ain Shams University 3) Coastal Research Institute.

ABSTRACT

Field data collection is one of the most challenging tasks due to the difficulty accessing large areas of water bodies like rivers. Satellite images can be used to measure water quality over large areas of water bodies. Satellite data has been widely used to build Water Quality Parameters (WQPs) prediction algorithms. Total Dissolved Solids (TDS) are organic and inorganic substances in water and one of water quality parameter. These natural and artificial substances may affect water quality, health, and daily activities. Remote sensing makes tracking TDS easier. This study examines how Landsat 8 Operational Land Imager (OLI) images can estimate TDS in surface water along the fourth Nile River reach. Predicting TDS from satellite data is the study's final goal. The data were collected across the study area during four seasons, Feb. 2017, Aug. 2017, Feb. 2018, and Aug. 2018. The measured data are collected from seven places chosen to be located from El-Minya to Cairo. The data were divided into two main groups; twenty points were used to build a relation between the measured and reflected electromagnetic radiation of the Landsat 8 bands. While the other eight points were used through a linear equation of the band combination between Band 1 and 2 in cross-validation to test the accuracy of predicted TDS. The RMSE was high as 31, but it recommends using this model in similar conditions and using another correlation in different conditions and out-range data.

Keywords: Landsat imagery, Total Dissolved Solids (TDS), Nile River, Water Quality, and Remote sensing.

INTRODUCTION

Water is a vital natural resource for the preservation of both the environment and human life. With a total length of 6670 kilometers, the Nile River is the world's longest river. The Nile River has four reaches from Aswan to Cairo, where it splits into two branches that end in the Mediterranean Sea. The fourth reach selected to be the focus of our research.

This study area was chosen because it is the longest Nile River reach within Egypt. It is the most vulnerable to human manipulations, which harm its morphological and hydraulic efficiency, and it serves as an essential navigable waterway.

Water quality issues in Egypt differ by area and rely on elements including water flow rates, water uses, population density, sanitization practices, industrial discharges, instances of navigation, and agricultural runoff. As a result, worries about poor water management, declining water quality, and rising environmental degradation expenses are on the rise across the nation (INECO 2009, Ashour *et al*. 2009). Egypt's major water supply comes from the Nile River. One cannot overemphasise the historic concern for securing enough water for Egypt's existence and economic growth. However, unchecked sewage and industrial discharges have an immediate and long-term effect on the health of the water and the consumers (Ibrahim *et al*. 2009; Abdalla and Khalil 2018). According to African Development Bank report 2009, 80% of the nation's industrial waste is dumped into surface water bodies untreated, and no monitoring is carried out. Surface water resources are therefore thought to be among the most fragile water sources in Egypt (Sector 2009).an appropriate, efficient approach that aids in the prompt monitoring of these environmental consequences and fluctuations must be found immediately since the growing population places additional social, economic, and environmental demands on resources (Wu *et.al*. 2016, Baser 2019).

So maintaining and continuing water quality monitoring in the water resources is important (Goher et al. 2014). The traditional method of water quality monitoring and assessment entails collecting a large number of samples from the field and analyzing these samples in a laboratory; nevertheless, it is too time-consuming and expensive to conduct over a wider range of temporal and spatial scales. This traditional method yields accurate results but necessitates to a significant amount of time and resources (Yusop *et al.* 2011, González-Márquez *et al.* 2018). As a result, remote sensing can be used to scale up field observations since enormous areas can be continuously examined in a short amount of time (Somvanshi *et al*. 2012).

Variations in the concentration and character of suspended and dissolved particles, as well as other organic materials, change the optical properties of water, which can be assessed using satellite imagery (Pásler and Komárková, 2016 and Pavelsky and Smith, 2009).

Total Dissolved Solids (TDS) is one of the water quality parameters and used to measure water's salts and small amounts of organic matter. Remote sensing makes TDS monitoring easier (Ferdous *et al*., 2019). Remote sensing helps track TDS over a large area, which helps assess water quality (Bhateria and Jain, 2016). TDS levels affect water quality, health, and daily activities, so monitoring them is essential.

The current study proposes a method for measuring TDS in surface water along the Nile River's fourth reach using satellite imagery.

MATERIAL AND METHODS

Study area description: The study area is located on the fourth Nile River tributary, which runs from El-Minya governorate to Cairo governorate. The study area spans four governorates: El-Minya, Beni Suef, El-Giza, and Cairo. The information was gathered over two years, in 2017 and 2018 (table 1). The TDS meter measured the TDS levels in seven surface water sample locations (Figure 1). The total measured data was 28 readings, divided into two groups based on cross-validation sampling: 20 readings (≈70%) for training and 8 readings (≈30%) for testing (table 2). The testing readings were detected to be two readings every season chosen randomly.

Table(1): Samples position and Total Dissolved Solids (TDS) measurements in different years.

samples	Longitude	Latitude	February 2017 TDS (mg/l)	August2017 TDS (mg/l)	February 2018 TDS (mg/l)	August 2018 TDS (mg/l)
S1	279042.0865	3112612.868	309	238	345	233
S2	280946.8957	3109145.199	307	254	344	234
S3	320200.568	3223437.156	301	242	339	240
S4	333662.6579	3286721.597	403	236	337	228
S5	334914.364	3296140.591	259	337	281	216
S6	330721.4874	3315664.381	242	212	247	200
S7	330446.6835	3331760.36	214	195	212	182

Vol. (51); Iss. (12); No. (6); Dec. 2022
ISSN 1110-0826
ONLINE ISSN 2636 - 3178

Figure(1): Location map for the collected water samples (from S1 in El-Minya governorate to S7 in Cairo governorate).

Vol. (51); Iss. (12); No. (6); Dec. 2022
ISSN 1110-0826
ONLINE ISSN 2636 - 3178

Table(2): Cross-validation sampling

Sample location	Test	validation	Date
S1	No	Yes	Winter 2017
S2	Yes	No	
S3	Yes	No	
S4	Yes	No	
S5	Yes	No	
S6	No	Yes	
S7	Yes	No	
S1	Yes	No	Summer 2017
S2	No	Yes	
S3	Yes	No	
S4	Yes	No	
S5	Yes	No	
S6	Yes	No	
S7	No	Yes	
S1	Yes	No	Winter 2018
S2	Yes	No	
S3	No	Yes	
S4	Yes	No	
S5	No	Yes	
S6	Yes	No	
S7	Yes	No	
S1	Yes	No	Summer 2018
S2	Yes	No	
S3	Yes	No	
S4	No	Yes	
S5	Yes	No	
S6	Yes	No	
S7	No	Yes	

Landsat 8 satellite data: Landsat 8 is operated by the United States Geological Survey (USGS) and National Aeronautics and Space Administration (NASA). It was launched in 2013 by Landsat, which was founded in 1972. Landsat 8 collects data in visible, near-infrared, shortwave, and thermal infrared spectrums. These data are used to generate detailed images of the Earth's surface to monitor urban growth, map land use and cover, study environmental changes, and observe natural disasters. Landsat 8 is well-known for its high-resolution imaging capabilities. Its two primary sensors, the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) produce detailed images with spatial resolutions of 30 meters for most visible, near infrared, and shortwave infrared bands and 100 meters for thermal bands. The USGS Earth Explorer website provides free downloads of all Landsat 8 data, to help researchers, educators, and the public to be able to access Landsat 8 data, it is now used in agriculture, forestry, geology, hydrology, and climate science. Landsat 8 is an effective tool for studying the Earth's surface and changes. Its high-resolution imaging and publicly available data have made it an indispensable resource for many applications and advanced fields of study.

Acquired Data: The Landsat 8 OLI images (path/row: 176/039-176/040-176/041) with the dates 10 February 2017, 14 August 2017, 10 March 2018, and 17 August 2018 were retrieved from the website of the United States Geological Survey (USGS). Table (3) provide information regarding the dates on which the satellite images used for the research were acquired.

Table(3): Acquisition Path/Row of Landsat 8 Operational Land Imager (OLI) satellite imagery.

Sensor	Path/Row	Date
Landsat 8 OLI	176/039	10 Feb 2017
	176/040	
	176/041	
Landsat 8 OLI	176/039	14 Aug 2017
	176/040	
	176/041	
Landsat 8 OLI	176/039	10 Mar 2018
	176/040	
	176/041	
Landsat 8 OLI	176/039	17 Aug 2018
	176/040	
	176/041	

Satellite data preprocessing: Preprocessing Landsat 8 data entails several steps that are required to convert raw satellite imagery into products suitable for a variety of applications and analytics. The following are the preprocessing steps:

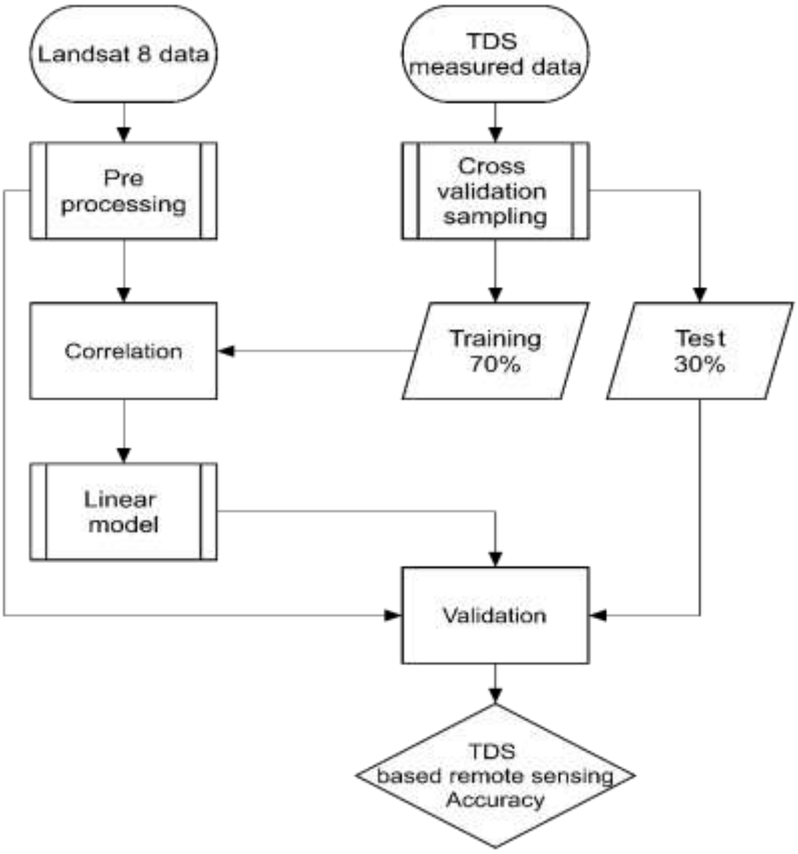
- **Radiometric calibration**: This ensures that the image's DN values are converted to reflectance values.
- **Geometric registration:** This step involves aligning the image with a consistent reference system.
- **Atmospheric correction:** This step removes atmospheric effects from the image, such as haze and clouds.
- **Surface reflectance correction**: This step corrects errors caused by the sun's angular position, atmospheric effects, and the Earth's surface.
- **Mosaicking**: This is the process of combining multiple images into a single image.
- **Cloud masking:** Removes clouds from the image with this step.

Vol. (51); Iss. (12); No. (6); Dec. 2022
ISSN 1110-0826
ONLINE ISSN 2636 - 3178

These steps are required to ensure the accuracy and consistency of Landsat 8 imagery and to prepare it for use in various applications.

Modeled TDS-based remote sensing data: Ions are often present in dissolved elements that are found in water. Since ions are electrically conductive, water is a good conductor of electricity. Using this principle, one may calculate the TDS of a given amount of water. When determining the amount of electricity that is conducted, a TDS meter's probe is dipped into the liquid being tested, and the resultant reading is converted from volts to parts per million (ppm) or milligrams per liter (mg/L) of total dissolved solids. This approach is utilized regularly and may be implemented in a reasonable amount of time, but it consumes time and money. The remote sensing data is collected and analyzed efficiently and using these data with acceptable accuracy has a high beneficiary.

The technique framework concentrated on using satellite imagery to map TDS throughout the main stem of the Nile River, collect modeled TDS values from maps, and compare them to measured TDS for specific places. The measured TDS data were divided using cross-validation sampling to build the model, train it, and validate it as is customary in machine learning, which analyses model performance. Figure (2) displays the proposed methodology's conceptual structure.



Figure(2): Framework of the implemented methods to monitor the Total Dissolved Solids (TDS) in the study.

The regression analysis was used to build the linear model. It represents the relationship between a dependent (response) variable and one or more independent variables (predictor variables) and is modeled by regression analysis. Based on the independent variables, it predicts the dependent variable. The dependent-independent connection is modeled using linear regression. Find the line that best fits the data and use it to generate predictions. Estimating

Vol. (51); Iss. (12); No. (6); Dec. 2022
ISSN 1110-0826
ONLINE ISSN 2636 - 3178

model parameters from a sample of data and evaluating the model on a separate test set are both parts of regression analysis. Model fit is evaluated using R-squared and mean-squared error.

Regression analysis is frequently used to model and predict real-world occurrences in many domains, including economics, finance, biology, and engineering. The relationship between the dependent variable and the independent variables was examined for a linear relationship and served as the foundation for the variable correlation. The dependent variable (in our study is the TDS measured data) and independent variable (in our study is the bands value) have a linear relationship. Simple linear regression models were used to analyze linear relationships. To assess the model's goodness of fit, the square of the Coefficient of Determination (R2) was calculated. It accepts numbers ranging from 0 (completely random) to 1 (all the points lie precisely on the regression line). However, the value (R2) is computed each time an additional independent variable is introduced.

Correlation R and R-squared are two important measures in statistical analysis. Correlation measures the strength of the relationship between two variables, while R-squared measures the amount of variation in the data that is explained by the model.

The spectral band values at each measurement station were extracted from images for use as independent variables in regression models (Saleh 2017). Only the single pixel value for each sampling station was extracted. By calculating the Pearson Correlation (r) using the correlation coefficient and using simple linear regression (R2) to identify the highly correlated value between the two sets of variables (spectral and ground data for seven sampling stations in four different seasons), the correlation between the spectral bands of Landsat-8 images and the in situ

Vol. (51); Iss. (12); No. (6); Dec. 2022
ISSN 1110-0826
ONLINE ISSN 2636 - 3178

TDS measurements were investigated in order to evaluate the nature and strength of the relationships table (4). The best index was then selected.

Table(4): Table 4: Pearson Correlation (r), Coefficient of Determination values (R2) and prediction model of Total Dissolved Solids (TDS) between field data and spectral data.

TDS index (x)	r	R2	Prediction model
Band1	0.36	0.1277	y = 1859.6x + 8.042
Band2	0.37	0.1364	y = 1912.1x + 46.303
Band3	0.35	0.1254	y = 1655.88x + 50.53
Band4	0.32	0.1022	y = 1382.45x + 97.415
Band5	0.21	0.0433	y = 423.02x + 243.44
Band6	0.23	0.0539	y = 993.18x + 239.78
Band 7	0.21	0.0429	y = 1492.5x + 239.39
B1×B2	0.37	0.1363	y = 7031x + 153.06
B1-B2	0.17	0.03	y = -11145x + 532.35
(B1*B2)/(B1-B2)	0.4	0.1605	y = 179.72x + 144.57

The band index of (b1*b2)/(b1-b2) was chosen and used due to its higher R2 named the TDS index. At the same time, the resulting linear model was indicated as TDS = 179.72(TDS index) + 144.57. This linear equation was built based on the relation between Landsat 8 data and 70% of measured TDS data.

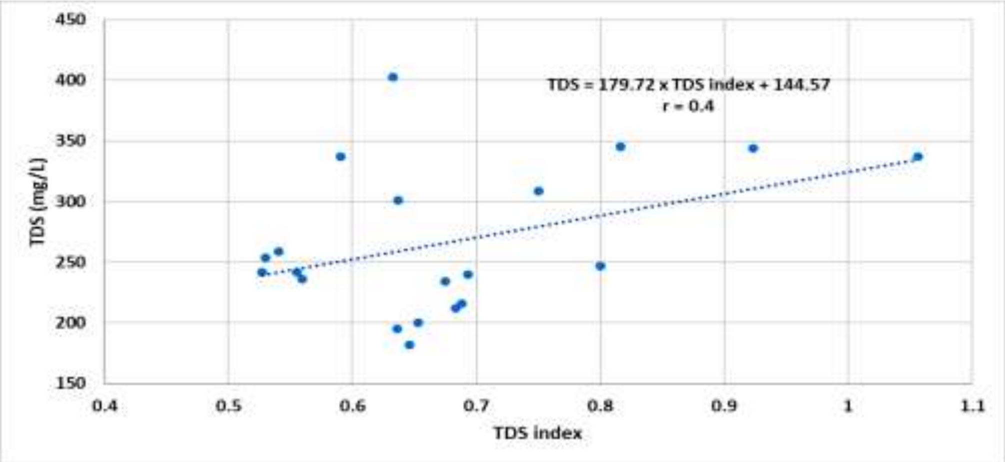
$$TDS\ index = \frac{b1 \times b2}{b1 - b2} \qquad \text{Eq (1)}$$

Where, b1 and b2 represent bands 1 and 2 of the Landsat 8.

Vol. (51); Iss. (12); No. (6); Dec. 2022
ISSN 1110-0826
ONLINE ISSN 2636 - 3178

RESULTS

Remote sensing-based TDS Model: The relation between TDS (mg/L) and TDS index derived from satellite data was built as shown in figure (3). The linear relationship was indicated based on slope and aspect, 179.27 and 144.57, respectively. The correlation coefficient of TDS data with the TDS index was as high as 0.4, representing a moderate correlation.

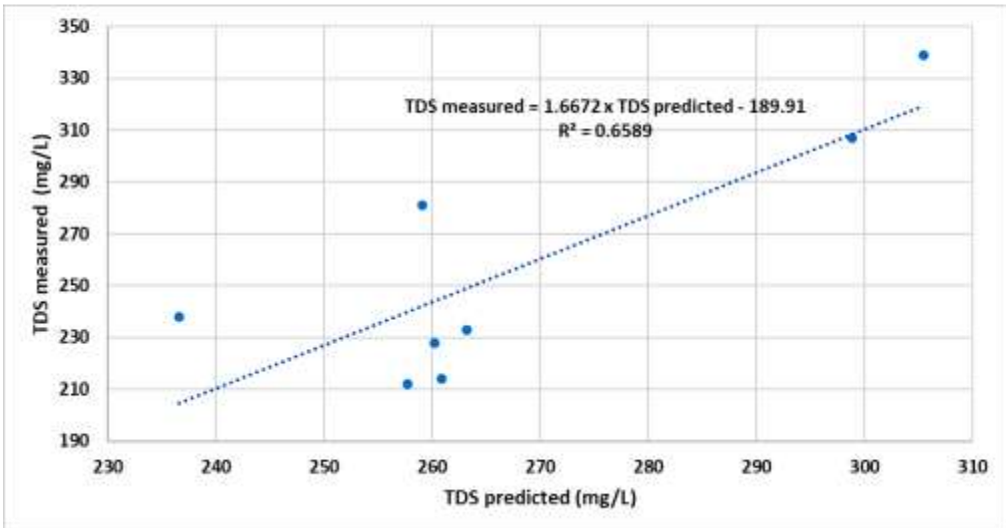


Figure(3): the correlation between Total Dissolved Solids (TDS) and TDS index derived from satellite data.

Model validation: Linear regression models are evaluated using The Root Mean Squared Error (RMSE) and R2. RMSE compares observed(measured) and predicted dependent variable values. It is the square root of the average squared difference between predicted and observed values. Lower RMSE values indicate a better model-data fit.

R-squared represents the proportion of dependent variable variation explained by independent variables. It ranges from 0 to 1, with 1 indicating a perfect fit and 0 indicating that the model does not explain dependent variable variation. R-squared, a goodness-of-fit metric, is used to compare models.

During four seasons, the cross-validation sampling method was used to validate the model results. The chosen data is indicated in table (1). Because the RMSE was as high as 31, and indicated a positive outcome, the TDS index was successfully used to derive TDS measurements in the area under investigation. On the other hand, the R2 indicates good results, and its value was relatively high at 0.66 (figure 4). This indicates that the results were good and acceptable to use. The linear equation between measured and predicted TDS could be used to calibrate the results if needed.



Figure(4): the relationship between measured and predicted Total Dissolved Solids (TDS).

Vol. (51); Iss. (12); No. (6); Dec. 2022
ISSN 1110-0826
ONLINE ISSN 2636 - 3178

DISCUSSION

TDS measures the inorganic and organic content of water, which has an impact on water, taste, and aquatic life. TDS monitoring is required for water and resource management. TDS is commonly measured remotely. Remote sensing is a low-cost, non-invasive method for monitoring TDS in real time over large areas (Ferdous *et al.*, 2019).

In comparison, remote sensing can monitor TDS in large bodies of water where in situ measurements are difficult. Water quality, management, and TDS dynamics are all improved by remote sensing. Remote sensing can assess and manage water quality as technology advances, protecting water resources and aquatic ecosystems.

Measurements of TDS in different locations (figure 1) were used to investigate using satellite imagery and spectral characteristics as estimators for TDS through linear regression analysis. The correlation coefficient of TDS data with the TDS index was high as 0.4, representing the strength and direction of a relationship between two variables in linear regression. Pearson correlation coefficients of 0.4 indicate a moderately positive linear relationship. Both variables are increasing but at different rates. Correlation coefficients are higher in more robust relationships.

RMSE and R-squared are used to evaluate a linear regression model. Data-fitting models have a high R-squared and a low RMSE. A model with a high R-squared may overfit the data, have missing variables, or have an incorrect functional form. Although the RMSE was as high as 31, it is recommended that this model be used in conditions that are analogous to those found in the data, while another correlation is used in conditions that differ from those found in the data.

Several studies were carried out worldwide to assess and monitor water quality in large size of water bodies (rivers, reservoirs and lakes) using remote sensing techniques such as:

El- Rawy *et al.* (2020) used remote sensing data and in situ measurements to monitor the water quality in the Ismailia Canal, Nile Delta, Egypt. The linear regression equations were developed, and they achieved a strongly positive correlation between the most appropriate spectral band ratios and the measured in situ water quality parameters. As comparison to traditional ground methods, the difference between the computed and measured values can be compared with minimum cost and time savings.

Taher *et al.* (2021) the spatial and temporal variations in surface water quality were evaluated in the Nile River of Damietta Region, Egypt using multivariate statistical techniques.

Aboalazayem *et al*. (2022) Found that the resolutions of the Landsat 8 OLI satellite allowed us to successfully determine and estimate the spatial–temporal distribution of water quality parameters along Aswan high dam reservoir.

Al-Mayah (2018) used Different Environmental Indices, Remote Sensing Technique and Geographical Information System to Evaluate Water Quality in Al-Gharraf River Southern of Iraq and found that the comparison between the real values of water quality parameters for the twenty-one stations of the Al-Gharraf River and the GIS maping proved the success of the GIS maping in predicting the water quality parameters at any location along the river.

Ibrahim *et. al*. (2018) used GIS techniques to monitoring Surface Water Quality for River Nile, Egypt. Through the collection of 15 water samples, the GIS approach analysed the water quality index of the Rosetta branch and its drains. Understanding water quality and creating appropriate management strategies for ecosystem conservation are the two goals of this study.

The final weight values are what divide water into the four categories of excellent, good, moderate, and poor. Finally, the spatial variations of major water quality parameters were estimated, and all values were integrated.

El-Zeiny and El-Kafrawy (2017) technologies of remote sensing and GIS have been successfully utilized to assess water pollution in Burullus Lake, egypt. Landsat OLI image dated 2015 has provided the necessary spectral data to this study.

Maliki *et al.* (2020) the research presented the potential of integrating Landsat 8 OLI data analysis and field survey data. Satellite data and water samples were collected nearly simultaneously to assess the salinity of the Shatt al-Arab river in Basra province, Iraq. The correlations between different indices with TDS in six stations along the river were calculated using regression analysis. The results confirmed that the predicted model was suitable for investigating effects of salinity in the Shatt al-Arab river. Elaboration of OLI data using spectral index algorithms provides a powerful Tool for retrieving salinity in the surface waters.

Ferdous *et al*. (2019) used different band compositions of Landsat 8 OLI, and it is simple to determine the salinity level in term of TDS level of surface water in Coastal Bangladesh. Regression analysis with field values identified seven band compositions (blue, green, red, blue and green, blue and red, green and red, blue and green and red). The relationship between Landsat and ground-referenced data was used in several studies.

González-Márquez *et al*. (2018) proved that the Models created from Landsat 8 images can be an extremely effective tool for monitoring water quality parameters and depth in El Guájaro reservoir, Colombia.

These studies used similar techniques; however, generated models for TDS estimation were not comparable because generated models are empirical models limited to the area and environment.

CONCLUSIONS

Data from remote sensing are now needed to find solutions for water resource concerns and to analyze water quality on a large scale. This study looked at the possibility of using Landsat 8 OLI data to extract the TDS index, which could be used to predict TDS based on satellite data. Satellite data and water samples were collected during four seasons in two years, 2017 and 2018. A cross-validation sampling method was used to divide the samples into two parties: 70% for training and 30% for testing. The efficiency of the suggested model was evaluated using the coefficient of determination values (R2) and Root Mean Square Error (RMSE). The results indicated that acceptable RMSE with 31, nonetheless, it is advised that this model be used in comparable settings and another correlation be used in different situations and out-of-range data. The findings revealed that the TDS level of Nile River surface water was effectively detected using the TDS index.

REFRENCES

Abdalla, F., and Khalil, R. (2018): Potential effects of groundwater and surface water contamination in an urban area, Qus City, Upper Egypt. African Earth Sciences, 141:164-178.

Al-Mayah, W. T. (2018): Evaluating of Water Quality in Al-Gharraf River Southern of Iraq Using Different Environmental Indices. Remote Sensing Technique, and

Geographical Information System. Ph. D. Thesis, College of Science, University of Baghdad, Iraq.

Aboalazayem, M., Essam A. Gouda, Moustafa A. M. and Amr E. (2022): Suspended sediment concentration and water quality monitoring along aswan high dam reservoir using remote sensing. Nile Water Science and Engineering Journal, 13(1):35-49.

Ashour, A., Attar, S. E., Rafaat, Y., and Mohamed, M. (2009): Water resources management in Egypt. Journal of Engineering Sciences, Assiut University, 37 (2):269-279.

Baser, V. (2019): Optimization of Existing Solid Waste Landfill Sites Using Gis and Mcda: The Case of Giresun, Turkey. Fresen. Environ. Bull., 28: 9033-9043.

Bhateria, R., and Jain, D. (2016): Water quality assessment of lake water: a review. Sustainable Water Resources Management, 2:161-173. https://doi.org/10.1007/s40899-015-0014-7

El-Rawy, M., Fathi, H. and Abdalla, F. (2020): Integration of remote sensing data and in situ measurements to monitor the water quality of the Ismailia Canal, Nile Delta, Egypt. Environmental Geochemistry and Health, 42:2101-2120. https://doi.org/10.1007/s10653-019-00466-5.

El-Zeiny, A., and El-Kafrawy, S. (2017): Assessment of water pollution induced by human activities in Burullus Lake using Landsat 8 operational land imager and GIS. The Egyptian Journal of Remote Sensing and Space Sciences, 20:49-56.

Ferdous, J., Rahman, M. T. U., and Ghosh, S. K. (2019): Detection of total dissolved solids from Landsat 8 OLI image in coastal Bangladesh. Proceedings of the 3rd International Conference on Climate Change, 3: 35-44.

Goher, M. E., Hassan, A. M., Abdel-Moniem, I. A., Fahmy, A. H., and El-sayed, S. M. (2014): Evaluation of surface water quality and heavy metal indices of Ismailia Canal, Nile River, Egypt. Egyptian Journal of Aquatic Research, 40(3): 225-233.

González-Márquez, L. C., Torres-Bejarano, F. M., Rodríguez-Cuevas, C., Torregroza-Espinosa, A.C., and Sandoval-Romero, J. A., (2018): Estimation of water quality parameters using Landsat 8 images: application to Playa Colorada Bay, Sinaloa, Mexico. Applied Geomatics, 10:147-158.

Ibrahim, H. S., Ibrahim, M. A., and Samhan, F. A. (2009): Distribution and bacterial bioavailability of selected metals in sediments of Ismailia Canal, Egypt. Journal of Hazardous Materials, 168(2-3):1012-1016.

Ibrahim, M., Al-Zyoud, S., and Elhaddad, E. (2018): Surface water quality monitoring for river Nile, Egypt using GIS-techniques. Open Journal of Geology, 8 (2):161-173. doi:10.4236/ojg.2018.82010

INECO (2009): Institutional framework and decision-making practices for water management in Egypt, International Consultants Egypt.

Maliki, A. A., Chabuk, A., Sultan, M. A., Hashim, B. M., Hussain, H. M., and Al-Ansari, N. (2020): Estimation of total dissolved solids in water bodies by spectral indices case study: Shatt al-Arab river. Water, Air, and Soil Pollution, 231(9). https://doi.org/10.1007/s11270-020-04844-z

Pásler, M., and Komárková, J., (2016): Utilization of Landsat data for water quality observation in small inland water bodies. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLI-B8, 373-377.

Pavelsky, T. M., and Smith, L. C., (2009): Remote sensing of suspended sediment concentration, flow velocity, and lake recharge in the Peace- Athabasca Delta, Canada. Water Resources Research, 45(11).

Saleh, A. M. (2017): Evaluation of different soil salinity mapping using remote sensing indicators and regression techniques, Basrah, Iraq. Journal of American Science, 13:85-89.

Sector (2009): Country Profile. African Development Bank. 213.

Somvanshi, S., Kunwar, P., Singh, N., Shukla, S., and Pathak, V. (2012): Integrated remote sensing and GIS approach for water quality analysis of Gomti River, Uttar Pradesh. International Journal of Environmental Science, 3: 62.

Taher, M. E. S., Ghoneium, A. M., Hopcroft, R. R., and ElTohamy, W. S. (2021): Temporal and spatial variations of surface water quality in the Nile River of Damietta Region, Egypt. Environmental Monitoring and Assessment, 193(3): 128. doi:10.1007/s10661-021-08919-0

Wu, R. J., and He, X. F. (2016): Monitoring Land Use/Land Cover Change Around a Plain Reservoir Along South-North Water Transfer Project-Eastern Route, China. Fresen. Environ. Bull. 25(1):345-354.

Yusop, S. M., Abdullah, K., San, L. H., and Bakar, M. N. A., (2011): Monitoring water quality from Landsat TM imagery in Penang, Malaysia. Proceeding of the 2011 IEEE International Conference on Space Science and Communication (IconSpace), Penang ,Malaysia, July, 249-253.

اكتشاف إجمالي المواد الصلبة الذائبة في الحبس الرابع لنهر النيل باستخدام صور لاندسات8

دينا محمد رفعت(١)– نهي سمير دنيا(٢)– أحمد مصطفي أحمد موسي(٣)
١) طالب دراسات عليا، كلية الدراسات العليا والبحوث البيئية، جامعة عين شمس ٢) كلية الدراسات العليا والبحوث البيئية، جامعة عين شمس ٣) معهد بحوث الشواطئ

المستخلص

يعد جمع البيانات الميدانية من أكثر المهام تحديًا نظرًا لصعوبة الوصول إلى مساحات كبيرة من المسطحات المائية مثل الأنهار. يمكن استخدام صور الأقمار الصناعية لقياس جودة المياه على مساحات كبيرة من المسطحات المائية. تم استخدام بيانات الأقمار الصناعية على نطاق واسع لبناء خوارزميات التنبؤ بخصائص جودة المياه (WQPs). المواد الصلبة الذائبة الكلية (TDS) هي مواد عضوية وغير عضوية في الماء وأحد معايير جودة المياه. قد تؤثر هذه المواد الطبيعية والاصطناعية على جودة المياه والصحة والأنشطة اليومية. يجعل الاستشعار عن بعد تتبع المواد الصلبة الذائبة أسهل. تبحث هذه الدراسة كيف يمكن لصور لاندسات ٨ تقدير المواد الصلبة الذائبة في المياه السطحية على طول الحبس الرابع لنهر النيل. الهدف النهائي للدراسة هو توقع إجمالي المواد الصلبة الذائبة من بيانات الأقمار الصناعية. تم جمع البيانات عبر منطقة الدراسة خلال أربعة مواسم، فبراير ٢٠١٧، أغسطس ٢٠١٧، فبراير ٢٠١٨، وأغسطس ٢٠١٨. تم جمع البيانات المقاسة من سبعة أماكن تم اختيارها لتكون موجودة من المنيا إلى القاهرة. تم تقسيم البيانات إلى مجموعتين رئيسيتين؛ تم استخدام عشرين نقطة لبناء علاقة بين الإشعاع الكهرومغناطيسي المقاس والانعكاس لنطاقات لاندسات ٨. بينما تم استخدام النقاط الثمانية الأخرى من خلال معادلة خطية لمجموعة النطاق بين النطاقين ١ و٢ في التحقق المتقاطع لاختبار دقة المواد الصلبة الذائبة المتوقعة. كان RMSE مرتفعًا ٣١ , لكنه يوصي باستخدام هذا النموذج في ظروف مماثلة واستخدام ارتباط آخر في ظروف مختلفة وبيانات خارج النطاق.

الكلمات المفتاحية: صور لاندسات، إجمالي المواد الصلبة الذائبة (TDS)، نهر النيل ، جودة المياه ، والاستشعار عن بعد.

Vol. (51); Iss. (12); No. (6); Dec. 2022
ISSN 1110-0826
ONLINE ISSN 2636 - 3178