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# Feasibility of Using Landsat OLI Images for Water Turbidity Estimation in Gandoman Wetland, Iran

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**Abstract**

Change detection of wetlands is one of the essential requirements for the management and assessment of wetlands. Monitoring water quality is a crucial issue for assessing the environmental consequences of human interventions in wetland ecosystems. The present study aims to study the capability of satellite images in assessing the water turbidity and comparing their capability with ground sampling. Four stations in four directions were chosen in Gandoman wetland, located in Chaharmahal and Bakhtiari Province. Samples were taken three times in the wetland with the intervals of 30 days from September to December 2017. The turbidity index was calculated and the relationship between the data obtained from ground-based measurement and from satellite images was studied using linear regression analysis and correlation coefficient. The comparison between the amounts of turbidity observed in different stations in different months revealed that the turbidity value was at its highest point (214.49 NTU) in station number three in September, and its lowest point (2.25 NTU) in station number four in October and, therefore, there was a significant difference between the values ($p<0.05$). The results were also indicative of a significant correlation between the measured amounts of turbidity and the reflectance values of blue and red bands in the satellite images. Remote sensing techniques can overcome the limitations of traditional methods and be used as appropriate substitutes in monitoring the quality of water.

*Keywords:* Pollution; Water Resources; Monitoring; Landsat 8 OLI; Linear Regression.

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## 1. Introduction

Wetlands are complex and fragile ecosystems that hardly have the ability to self-purify (Engin et al., 2016; Yumun and Once, 2017). Wetlands are useful resources for supporting groundwater recharge, biodiversity, flood control, and the quality of water. Increase in the human population, anthropogenic activities, failure in the proper functioning of wastewater treatment plant, land use changes and the destruction of natural systems such as wetlands all lead to the increase of water pollution (Ahmed et al., 2017). Wetland water generally regulates functions such as conserving nutrients and filtering and cleaning pollutants (Alam et al., 2017).

With the extension of human communities over time and consequently, increase in the use of water resources, increasing changes in the qualitative features of water resources have occurred. Population growth and the pollution resulted from the emission of municipal, industrial and agricultural wastewater, leachate from landfills and surface runoffs are the factors that have resulted in water pollution and limitation of water resources (Masocha et al., 2017). Exploiting natural water resources requires raising awareness toward quantity and, more importantly, quality of water since water resources are the ultimate recipients of the pollution caused by human activities. Qualitative characteristics of water are among those factors that are important to be taken into consideration in planning for the management of water resources, assessing health factors of watershed basin, and making managerial modifications (Gigloo et al., 2013).

Wetlands have been identified as one of the most threatened habitats and received greater attention for monitoring the ecological functions (Ahmed et al., 2017). Many studies have reported that a decrease in the quality of water is a terrible threat to the society. To take corrective steps, it is required to assess the quality of water and provide a management system in which priority is given to monitor the quality of water (Mushtaq and Nee lala, 2016). As far as quality is concerned, water is defined in terms of physical, chemical and biological parameters. The conventional methods adopted to monitor the quality of water are generally expensive, time-consuming and not capable to give a proper temporal and spatial perspectives for the water resources from which few samples have been taken (Mohamed, 2015; Mushtaq and Nee lala, 2016). Water turbidity is an important index in defining the quality of water which, in turn, is a determining factor for other variables such as Chlorophyll a, total nitrogen and phosphorus, and trophic state (McCullough et al., 2012).

Remote sensing and Geographic Information System (GIS) have been generally used in study of water quality. Remote sensing as a method for monitoring water quality was introduced in 1978 when Coastal Zone Color Scanner (CZCS) was launched; however, the first satellite started in 1961 (Chawira et al., 2013). Wetlands affect such physical aspects of water as color in much the same way as they affect people and their financial activities (Abdelmalik, 2016). Factors such as agricultural activities in the area, and seasonal changes are effective in the amount of pollution (Yumun and Once, 2017). Part of the pollutants are analyzed through biological processes and others, such as heavy metals, because of being poisonous (Migani et al., 2016) and not being able to self-purify, may be accumulated in suspended particles and sediments and, thereby, enter into the food chain (Feng et al., 2017). This will cause many problems particularly for the aquatic animals in the region and decreases their normal lifespan (Liao et al., 2016). To prevent and control water pollution, it is necessary to implement plans for monitoring surface water resources (Markogianni et al., 2014). In-situ measurements of qualitative parameters of water entail collecting water samples from different areas and analyzing them in laboratories; this is a time-consuming and expensive process (Sharif et al., 2014). However, remote sensing techniques are potent enough to overcome the limitations of traditional methods and are appropriate substitutes for monitoring the quality of water; they allow for displaying the results in terms of temporal and spatial scales, and are appropriate especially for wider areas (Mumtaz Bhatti, 2008). In recent studies about the pollution of the environment, geographic information system has been increasingly used to detect the sources of the pollutants. Geographic information system is used as a perfect tool for the interpretation, processing and presentation of the data (Moore et al., 2015). Remote sensing is from among those methods of data collection that keep the direct physical contact with the objects to be measured at a minimum. From this perspective, they are in contrast with ground methods in which human agent is responsible for data collection and analysis. Geographic information system and remote sensing provide appropriate tools for supervising and monitoring the patterns of change in wetlands and determining their state (Rebelo et al., 2009). Recent advances in remote sensing will facilitate the study of patterns of change in vegetation, land cover, and their management (Zomer et al., 2009). Turbidity is defined as the haziness of water, which is the result of the accumulation of suspended sediments in water. An increase in turbidity and its aftermaths will change the composition of the aquatic animals' community.

Turbidity is one of the important factors that can be used to assess the water quality and also to determine the amount of suspended sediments. It represents an optical determination of water clarity (Constantin et al., 2016). The kind of turbidity that is caused by suspended solids can result in a decrease in the amount of light that passes through water (Rangzan et al., 2012). Determining turbidity is one of the common procedures taken to evaluate the quality of water. In an area with a large number of dams, taking samples even from small parts for evaluating the quality of water is costly. Satellite remote sensing is a powerful tool for assessing the quality of water in large areas. Since 2013, a new satellite of the Landsat series is available, called Landsat-8 OLI, which was designed with similar characteristics to Landsat-5 and Landsat-7 ETM+ sensors in terms of spatial resolution (Yepez et al., 2018). The OLI (Operational Land Imager) sensor on Landsat-8 has the potential to meet the requirements of remote sensing of water color (Wang et al., 2019). The main objectives of this study are to investigate the water turbidity through ground-based measurement and compare the findings with those obtained from satellite images in Gandoman wetland. The innovation is that remote sensing was not used for quantifying water turbidity in this area. The main hypothesis of this study is that satellite images could be used for assessing water turbidity.

## 2. Materials and Methods

### 2.1. Study Area

Gandoman wetland as one of the wetlands of Aqyalaq drainage basin, located not far from Choqakhor wetland. A part of the water getting out of Choqakhor wetland falls into this wetland. The wetland is situated near Gandoman, a town in Borujen County, Charmahal and Bakhtiari Province, Iran. The minimum altitude of the wetland from the sea level is 2219 meters. It is located between 31° 49' N to 31° 53' N and 51° 05' E to 51° 07' E. The area of the wetland exceeds 1200 hectares; however, taking the encroachments into consideration, the area is reduced to 980 hectares. In high-water seasons, the depth of the wetland reaches an average of 30 centimeters. The majority of the lands have low infiltration capacity and mild slope of 0 to 2 percent. The level of sweat underground water is high and at the depth of 75-120 centimeters. The name of this wetland is recorded in the list of 10 best wetlands for bird-watching in Iran and its name is also recorded in the International Waterfowl Research Burea in London. The permanent water coverage is around 700 hectares (Mokhtari and Ghaderi, 2008). Figure 1 shows the location of study area.

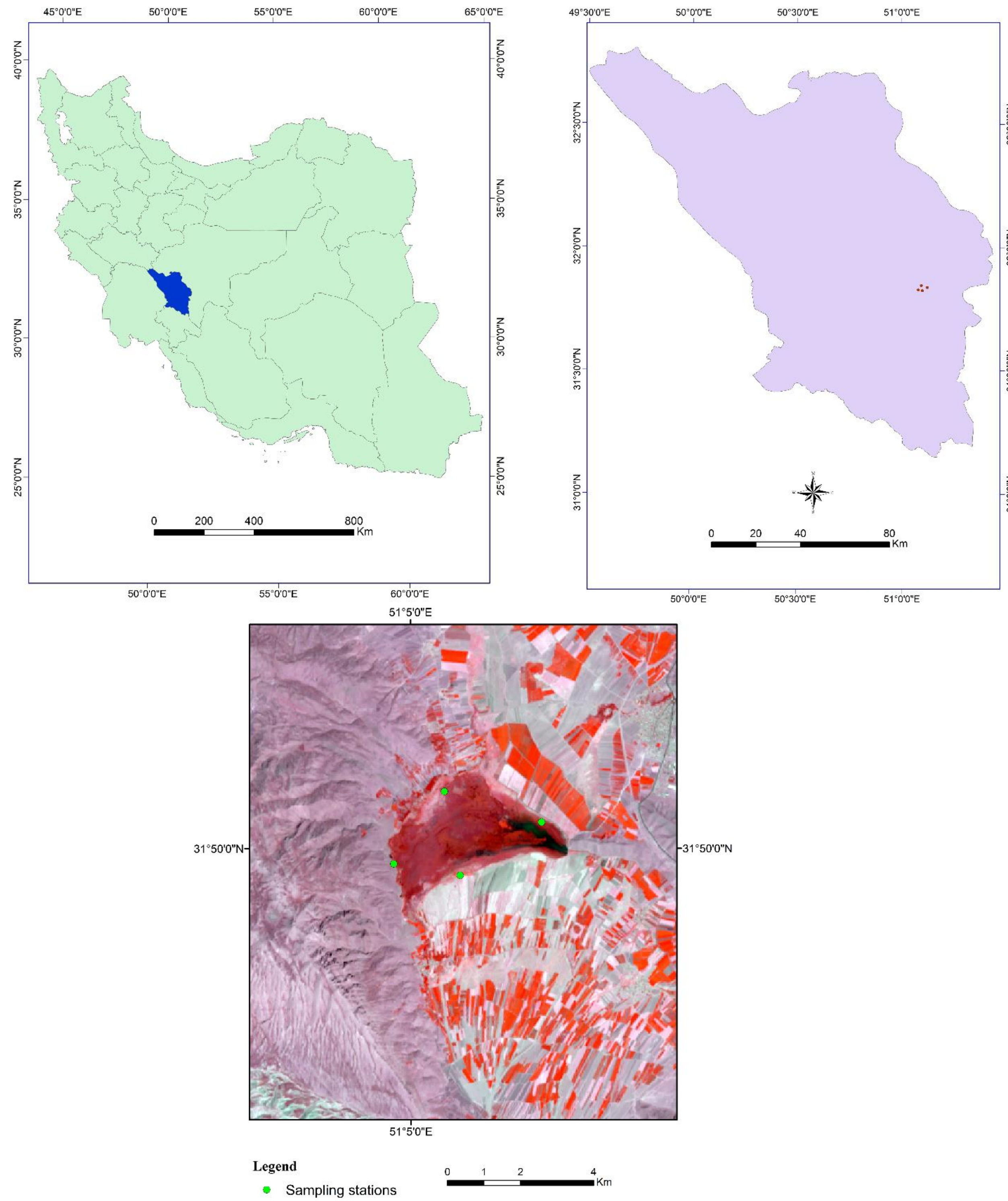


**Figure 1**. Location of study area

## 2.2. Methods

In the present study, Landsat OLI (2017) and Landsat TM (2000) images were used. OLI has a deep blue visible channel that is designed specifically for water resources and coastal zone analysis (Hancock, 2015). The images were georeferenced. They are available in the U.S. Geological Survey website. The image pertaining to the year 2017 was downloaded using Ortho Photo download application; therefore, geometric correction was not needed. Geometric correction of the Landsat TM image of the year 2000 was performed using ground control points and topographic maps on a scale of 1:2500. To do so, 32 ground control points, which were mostly such landmarks as junctions and known buildings, with an appropriate dispersion were used. The images were georeferenced using first degree polynomial model. After performing geometric correction, the intended area for investigation was separated creating AOI in ERDAS Imagine 8.4 software. Figure 2, shows the flowchart of the study.

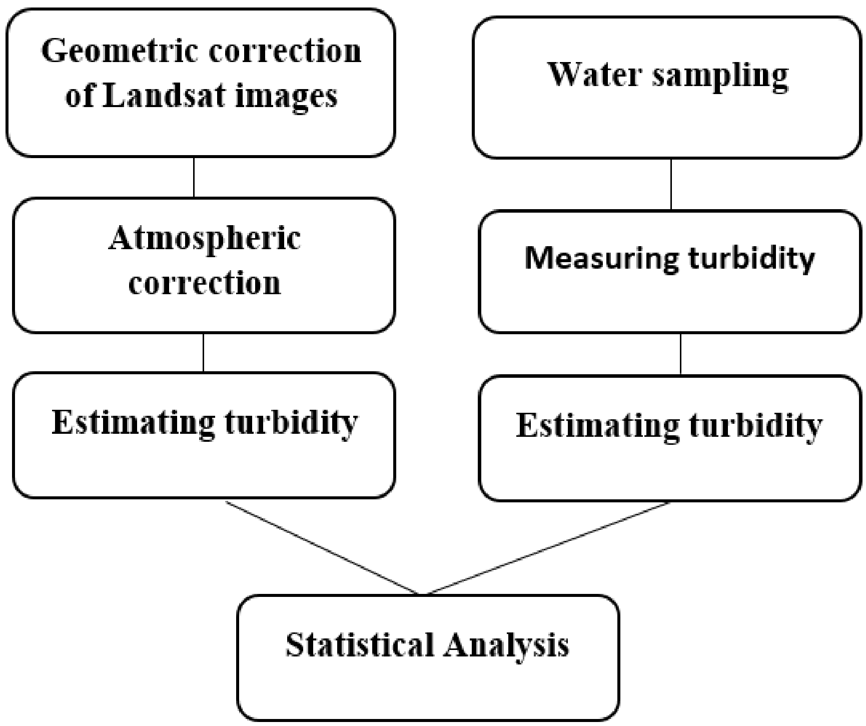


**Figure 2.** Flowchart of the study

## 2.3. Water sampling

Water samples were gathered three times from the depth of 20-30 centimeters from four stations (north, south, east and west) on the fifteenth day of each month. In the same location, water and air temperature were measured. The depth of water in the sampling area was between 50 to 80 centimeters. Before delivering the water samples to the laboratory for analysis, they were kept in special containers in a cool and dark place so as to minimize any negative effect on the quality of the water. During this fieldwork, GPS 76csx with an accuracy of three meters was used to determine and record the coordinates of sampling stations.

**Table 1.** The geographical position of the sampling stations

| January | December | November | October | September | Parameter | Months / Stations |
|---|---|---|---|---|---|---|
| 29.61±0.86$^{AB}$ | 27.47±0.93$^{AB}$ | 11.16±0.36 $^{C}$ | 16.97±0.43$^{C}$ | 12.72±0.04$^{D}$ | Turbidity | 1 |
| 27.72±0.38$^{B}$ | 24.05±2.17$^{cB}$ | 79.19±0.27$^{A}$ | 94.13±0.48$^{B}$ | 51.02±0.41$^{B}$ | | 2 |
| 31.02±1.42$^{A}$ | 28.38±0.87$^{A}$ | 48.64±0.02$^{B}$ | 127.91±1.26$^{A}$ | 214.49±0.91$^{A}$ | | 3 |
| 21.03±1.36$^{C}$ | 20.63±1.38 $^{C}$ | 2.48±.02$^{D}$ | 2.25±0.01$^{D}$ | 15.12±0.50 $^{C}$ | | 4 |
| 9.34±0.48$^{A}$ | 9.71±0.07$^{A}$ | 8.88±0.07$^{AB}$ | 5.88±0.04$^{B}$ | 7.45±0.01$^{B}$ | pH | 1 |
| 9.40±0.56$^{A}$ | 9.56±0$^{B}$ | 8.50±0.21$^{C}$ | 9.47±0.53$^{A}$ | 7.52±0.02$^{AB}$ | | 2 |
| 9.90±0$^{A}$ | 9.79±0.01$^{A}$ | 9.15±0.13$^{A}$ | 6.08±0.04$^{B}$ | 7.66±0.09$^{A}$ | | 3 |
| 9.75±0.07$^{A}$ | 9.77±0.02$^{A}$ | 8.72±0$^{B\ C}$ | 6.05±0.03$^{B}$ | 7.59±0.07$^{AB}$ | | 4 |
| 600.50±47.37 $^{C}$ | 570.50±43.13 $^{C}$ | 352.50±0.70$^{C}$ | 316.00±1.41$^{D}$ | 304.50±4.94$^{D}$ | EC | 1 |
| 872.00±7.07$^{A}$ | 824.00±7.07$^{A}$ | 268.00±1.41$^{D}$ | 984.00±.65$^{A}$ | 653.00±2.82$^{B}$ | | 2 |
| 758.00±2.82$^{B}$ | 726.00±9.89$^{B}$ | 580.00±8.48$^{A}$ | 669.00±1.41$^{B}$ | 914.50±0.70$^{A}$ | | 3 |
| 376.50±2.12$^{D}$ | 354.50±10.60$^{D}$ | 386.50±16.26$^{B}$ | 340.00±1.41 $^{C}$ | 339.50±2.12 $^{C}$ | | 4 |
| 0.10±0.02$^{A}$ | 0.06±0.05$^{A}$ | 0.96±1.07$^{A}$ | 0.70±0.14$^{A}$ | 0.13±0.07$^{A}$ | TSS | 1 |
| 0.06±.02$^{A}$ | 0.04±0.02$^{A}$ | 0.02±0.02$^{A}$ | 6.60±.84$^{A}$ | 0.04±0.02$^{A}$ | | 2 |
| 0.29±0.21$^{A}$ | 0.08±0.02$^{A}$ | 0.53±0.43$^{A}$ | 9.60±12.72$^{A}$ | 1.73±1.28$^{A}$ | | 3 |
| 0.05±0.01$^{A}$ | 0.12±0.11$^{A}$ | 0.05±0.01$^{A}$ | 0.70±1.14$^{A}$ | 0.24±0.11$^{A}$ | | 4 |
| 0.80±0.28$^{A}$ | 0.14±0.11$^{A}$ | 1.67±2.33$^{A}$ | 1.30±0.98$^{A}$ | 1.41±23.26$^{A}$ | TDS | 1 |
| 0.01±0.01$^{B}$ | 0.07±.04$^{A}$ | 0.81±0.09$^{A}$ | 0.64±0$^{A}$ | 18.49±23.26$^{A}$ | | 2 |
| 0.03±0.01$^{B}$ | 0.25±0.29$^{A}$ | 0.28±0.25$^{A}$ | 7.59±8.72$^{A}$ | 2.99±0.43$^{A}$ | | 3 |
| 0.05±0.01$^{B}$ | 0.18±0$^{A}$ | 0.15±0.01$^{A}$ | 0.10±0.08$^{A}$ | 1.15±1.56$^{A}$ | | 4 |

## 2.4. Measuring turbidity

Clay particles, sand particles, minerals, particles of organic materials, planktons and other microscopic organs which are suspended in the water and do not let the light transmit through water result in water turbidity. Turbidity is measured under controlled conditions comparing light intensity scattered by the sample with the light intensity scattered by the standard method. The more intense the scattered light at 90 degrees from the incident light beam, the higher the degree of turbidity. Bubbles, color and dirty glasses are from among intervening elements. To measure water turbidity, L21 Raspina Co. turbidimeter was used. Using the available standards and considering the turbidity range of the samples, the intended range was chosen, the standard was put in the related container of the turbidimeter, and the number was read. As the next stage, the samples were completely mixed so that no bubble existed in them. Then, they were put in the turbidimeter's cell, and the external surface of the cell was wiped and dried. Finally, it was put in the container and the number displayed was directly read and recorded.

2.5. Estimating turbidity using satellite images

After geometric correction, radiometric correction was applied to the images so that the numeric values of the pixels could be turned into reflectance values. Then, atmospheric correction was done to eliminate the negative effect of atmosphere on the images. Dark Object Subtraction method was used for atmospheric correction and the value of dark pixels was reduced using ATMOSC in the TerrSet; this helped the quality of the images to be enhanced. Then, the reflectance values in the bands of satellite images were extracted from sampling sites in different months starting from September 2017 and ending with January 2018.

Landsat 8 has been widely used in water and coastal area management. Landsat 8 OLI has been innovated with 12 bits of radiance resolution in comparison with 8 bits for Landsat 5 TM and Landsat 7 ETM (Quang et al., 2017). OLI has a deep blue visible channel that is designed specifically for water resources and coastal zone analysis (Hancock, 2015).

2.6. Statistical analysis

The values of turbidity in different stations were compared using randomized complete block design in SAS 9.4. To analyze the data two-way ANOVA was used, and to compare the means Duncan test with a confidence level of 95% was conducted. Excel software was used to draw diagrams. To determine the relationship between the reflectance values and the measured amounts of turbidity, regression analysis was applied. In so doing, the measured turbidity and the amount of reflectance were considered as dependent and independent variables, respectively.

## 3. Results

3.1. Statistical Analysis

The randomized complete block design was used to compare the mean values of turbidity in different months. The results are reported in Table 2.

**Table 2.** The comparison of mean values of turbidity in different months and different stations

| TDS | TSS | EC | PH | Turbidity | | Factors / Months |
|---|---|---|---|---|---|---|
| 5.56±11.73$^{A}$ | 0.54±0.88$^{B}$ | 526.7±266.20$^{AB}$ | 7.36±0.09$^{C}$ | 67.11±88.62$^{A}$ | Months | September |
| 2.46±4.63$^{A}$ | 4.94±6.33$^{A}$ | 614.4±291.99$^{AB}$ | 7.02±1.61$^{C}$ | 66.46±55.97$^{A}$ | | October |
| 0.72±.09$^{A}$ | 0.39±0.60$^{B}$ | 396.8±122.34$^{B}$ | 8.81±0.27$^{B}$ | 35.37±32.79$^{A}$ | | November |
| 0.16±0.13$^{A}$ | 0.07±0.05$^{B}$ | 618.8±190.37$^{AB}$ | 9.70±0.10$^{A}$ | 25.13±3.44$^{A}$ | | December |
| 0.22±0.37$^{A}$ | 0.12±0.13$^{B}$ | 651.8±199.52$^{A}$ | 9.59±0.37$^{AB}$ | 27.35±4.17$^{A}$ | | January |

As Table 2 presents, the comparison of turbidity amounts in different months and different stations revealed that station number three had the highest amount of NTU (214.49) in September and station number four had the lowest amount of NTU (2.25) in October. A significant difference between these amounts was observed ($p<0.05$).

As it is observed in Table 2, the values of turbidity were studied and compared from September 2017 to January 2018. The highest and lowest values were observed in September with 67.11 NTU and in December with 25.13 NTU, respectively ($p<0.05$). These factors did not have significant differences in different months.

3.2. Estimating turbidity using satellite images

The results of regression analysis and the correlation analysis between the values of reflectance in satellite images and turbidity revealed that the highest amount of correlation was between the values of reflectance of red and blue bands and turbidity. As shown in Figures 3 and 4, the correlation coefficient of more than 0.9 was observed between the measured turbidity and the values of reflectance of red and blue bands.

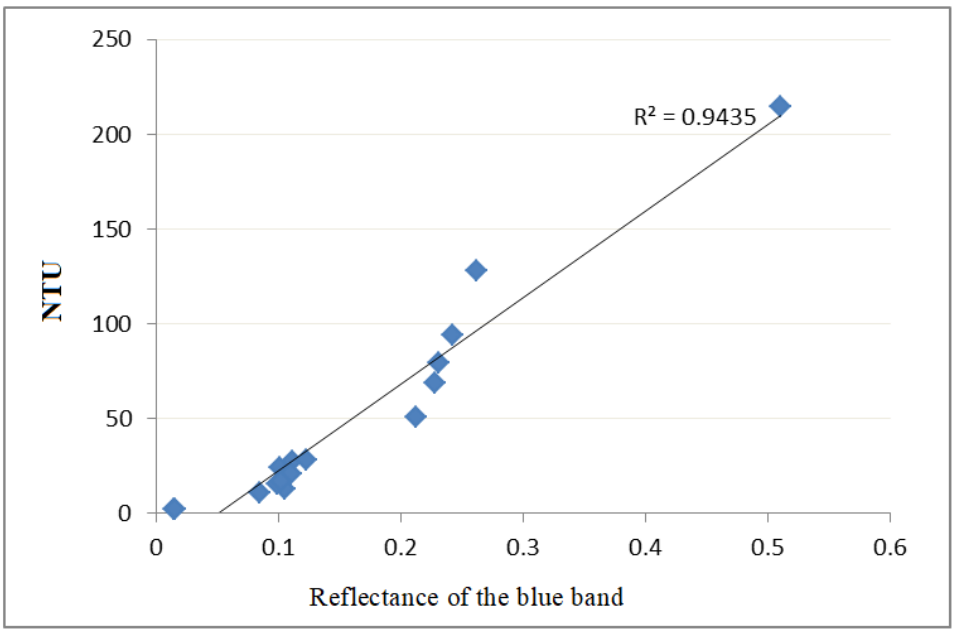


**Figure 3.** The correlation between the values of reflectance of the blue band and the measured turbidity

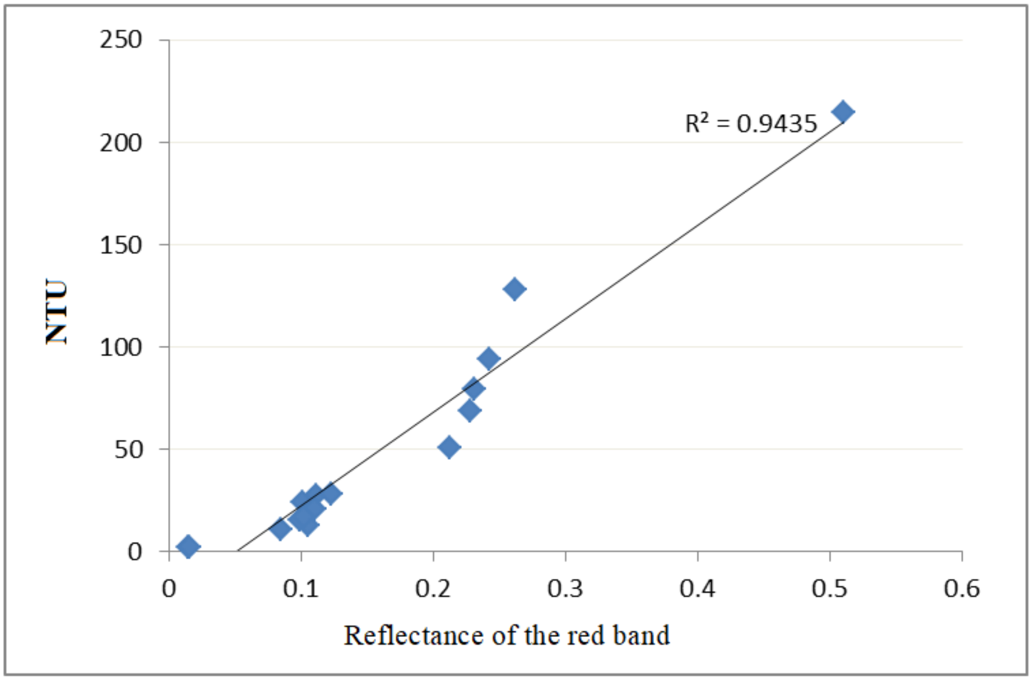


**Figure 4**. The correlation between the values of reflectance of the red band and the measured turbidityThe regression equation for the values of reflectance of the blue band and turbidity is as follows:

Turbidity: - 23.048 + 455.996 (Reflectance of the blue band) $R^2$= 0.94
The regression equation for the values of reflectance of the red band and turbidity is as follows:
Turbidity: - 21.616 + 378.974 (Reflectance of the red band) $R^2$= 0.97

## 4. Discussion

This study showed that it is possible to determine the water turbidity using satellite images. This method not only is time saving and cost-effective but also enjoys a high degree of precision. The findings of this study are consistent with those reported in Alrababah, Alhamad (2006), Koutsias, Karteris (2003) and Sadr et al. (1995) that these studies support the usefulness of the data obtained from Landsat in determining turbidity considering their availability. Other researchers also acknowledged the applicability and usefulness of these images in determining turbidity. Dena et al. (2015) are among these researchers. They conducted a research article entitled "Monitoring lake water quality status of the Albufera de Valencia in Spain" and verified the usefulness of Landsat TM and +ETM images in the daily estimation of some of the parameters that have a role in the quality of water such as Chlorophyll A and turbidity. They used MODIS and Landsat TM and $ETM^+$. Mohammad (2015) used data from Landsat 5 and 7 for mapping the quality of water of the lake of Mosul Dam located in the northern part of Iraq. The purpose of the study was to extract a simple and accurate algorithm for assessing the parameters related to the quality of water. Measuring the quality of water entailed the measurement of temperature, turbidity, Chlorophyll A, nitrite, nitrate, phosphate, Total Organic Carbon (TOC), dissolved organic carbon, total dissolved solids and pH. The results of the spatial analysis revealed that it was possible to use TM5 and +ETM images for investigating the quality of the water of the lake of Mosul Dam. Abdelmalik (2016) also estimated the parameters involved in water quality through remote sensing in the Himalayan lake of Kashmir using images from Landsat 8 OLI. The purpose of the study was to extract a simple and accurate algorithm for assessing such parameters of water quality as DO, COD, pH, alkalinity, hardness, chloride, TSS, TDS, turbidity, electrical conductivity, and phosphate. The results indicated that remote sensing had a great potential in improving the way the quality of water was monitored and assessed. The study, further, revealed that satellite sensors could measure the values of sunlight's reflection from the surface of water in different wavelengths and these reflectance values usually showed a significant correlation with different parameters of water quality. Satellite images are devices that reduce the cost and energy needed for water sampling and determining such parameters as turbidity. The results of regression and correlation analyses between the reflectance of the bands of satellite images and the measured amount of turbidity revealed that the highest degree of correlation existed between the values of reflectance of blue and red bands and turbidity. The findings are in line with those obtained from the studies conducted by Hadjimitsis et al. (2006), McCullough (2012) and Kulkarni (2011) in which it has been confirmed that the most appropriate bands for investigating turbidity are blue and red bands. In a like manner, Lambriks and Nagel (2003) conducted a study to assess the potential of Landsat TM and $ETM_+$ satellite images in monitoring water turbidity in Kentucky Lake. The results of correlational study between the reflectance of images and turbidity indicated that there was a significant correlation between the red band and the values of turbidity. The findings are consistent with the findings of Nabizadeh, Binesh Barahmand, Nadafi, and Mesdaghinia's (2012) study in which the turbidity of water in a part of the southern coast of the Caspian Sea was studied. They found that it was possible to quantitatively estimate water turbidity using Landsat OLI and ETM images. Moreover, the results of the present study confirm those obtained from Aghighi et al.'s (2009) study. They conducted their study in Gorgan Gulf and reported that it was possible to use satellite images for estimating important parameters in water quality including turbidity. Turbidity is one of the important parameters that have a role in water quality. It can be claimed that it is the second most important parameter with BOD5 as the most important determining factor. In winters, when rainfall increases, water turbulence and runoffs streaming toward wetlands are the factors that add to water turbidity. Moreover, the depth of water is effective in water pollution and turbidity. The total amount of suspended solids is also a determining factor as an increase in this value leads to an increase in turbidity. In this study, the latter relationship was observed.

## 5. Conclusions

It is necessary to have long-term precise programs for monitoring water quality and managing wetlands. Remote sensing has an important and effective role in managing and monitoring water quality. Satellite images measure the values of sunlight's reflection from the surface of water. The reflectance of water depends on the concentration of water and those parameters involved in determining water quality, including turbidity. Therefore, the reflection of images is indicative of the amount of turbidity. The findings of regression analysis conducted to study the relationship between in-situ turbidity and turbidity of satellite images revealed that there was a significant relationship between the values of reflectance of red and blue bands and the measured turbidity.

Remote sensing techniques can overcome the limitations of traditional methods and be used as appropriate substitutes in monitoring the quality of water. They provide the possibility of displaying the results at varying temporal and spatial scales and are used especially in wider areas. The features of remote sensing include appropriate return period, high capacity in spatial segmentation, non-stop monitoring, and large-scale data collection. Such characteristics turn remote sensing into a new effective method for monitoring the quality of water. Spectral reflectance measured by the satellite remote sensing system has the relationship with a number of parameters of water quality. One of these parameters is turbidity. An increase in turbidity and its negative consequences in water mass lead to some changes in the composition of the aquatic animals' community. The turbidity that is the result of suspended solids can reduce the amount of light that passes through water.

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