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Using MODIS remote sensing data for mapping the spatio-temporal variability of water quality and river turbid plume

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Abstract Fox River is the main source of land-based pollutants that flows into the southern Green Bay of Lake Michigan. Evaluation of water quality is normally based on time consuming and expensive in situ measurements. Remotely sensed data is an efficient alternative for field monitoring because of its spatial and temporal coverage. In this study, remote sensing imagery combined with in situ measurements of water quality were used to estimate an empirical relationship between water surface reflectance and water quality parameters including water turbidity and Total Suspended Sediment (TSS). Surface reflectance values is obtained from MODerate Resolution Imaging Spectroradiometer (MODIS) aboard the Aqua satellite. The empirical equations were derived from data over summers 2011–13 and show high correlation coefficients of equal to 0.83 and 0.87 for TSS and turbidity respectively. The validity of the proposed equations was tested for summer 2014 data. The NRMSE for prediction of measured data by the proposed equations are 0.36 and 0.3 for TSS and turbidity. Remotely sensed data was also used to produce water quality maps to improve our understanding of the spatio-temporal variations of Fox River turbid plume. The proposed approach can be extended to other coastal regions of Great Lakes and provide a framework to study pollution transportation in coastal areas.

Keywords Environmental remote sensing · Fox River · Lake Michigan · Modis · River plume · Total suspended sediment · Turbidity · Water quality monitoring

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Introduction

River plumes are major sources of pollutants, nutrients, and sediment into coastal areas, and play a significant role in biological and geochemical functioning of the coastal environment (Petus et al. 2014). Sediments and nutrients in water can degrade the quality of aquatic life in ecosystems by change in light penetration, species diversity, organic content, and productivity in the marine environments (Wood and Armitage 1997; Bilottaa and Brazier 2008). High concentration of inorganic matter can deteriorate algal life and microorganisms as well. Particles can fill in the gaps and holes that were previously habitats of aquatic organisms. Reduced photosynthesis would result in less oxygen and productivity in water. An indirect and important consequence of sediment intensification in water would disturb the food balance of aquatic life, especially fishes that are commercially and environmentally useful for the ecosystems (Moore 1989; Wang et al. 2007). Therefore, a fair understanding of the river plume could lead to developing better management scenarios of the lakes, rivers, coastal areas, and shorelines (Edition 2011; García Nieto et al. 2014; Corbari et al. 2016).

Turbidity can cost additional treatment processes in case of providing freshwater supplies from surface water bodies. Moreover, suspended sediments can decrease water quality by providing attachment sites for more contaminations such as heavy metals and toxic pollutants (Tchounwou et al. 2012). In coastal areas in which the economy is dependent on water recreational attractions, turbidity can also place a negative impact on the tourism industry (Bozec et al. 2008; De Juan et al. 2017). Accurate estimation of turbidity is crucial to plan and design environmental and restoration programs, to predict fate and transport of pollutants, and to estimate the sediment flux (Moreno-Madrinan et al. 2010). In this research, Total Suspended Sediment (TSS) and turbidity are considered as representations of the water quality and river plume.

River plume can influence the temperature, water quality, salinity, and vertical mixing and ambient velocities in the coastal region spreading through buoyant frontal motions (Nekouee et al. 2015a, b). Identifying the spatial extent of the area impacted by the land-based pollutants discharged through the river is necessary for management policies and environmental restoration plans. Therefore, it is essential to monitor the spatial and temporal variability of the river plume to protect water quality and coastal environment (Petus et al. 2014). For this purpose, determination of influenced area by river plume and controlling parameters on its variation is particularly important.

Located in the Midwest of US, Southern Green Bay supplies one-third of the total nutrient loading to Lake Michigan and has been designated as Area of Concern (AOC) by the US Environmental Protecting Agency. Fox River is the main source of land-based pollutants into southern Green Bay (Hamidi et al. 2015). Contaminants from Fox River are transported by currents and circulation all over the bay (Miller and Sylor 1993; Hamidi et al. 2013). Fox River is the main source of phosphorus to Lake Michigan (Dolan and Chapra 2012), but the bay is a very efficient nutrient trap, sequestering 70–90% of the total inputs via deposition and burial (Klump et al. 1997). Organic-rich suspended sediment from the river is the main cause of high oxygen depletion and consequently hypoxia in southern Green Bay (Klump et al. 2009). Transport of contaminated sediment and nutrients from Green Bay could potentially contaminate Lake Michigan wildlife and ecosystem whereas highly contaminated sediment is found in deposition within 10 km from Fox River (Manchester-Neesvig et al. 1996).

Fox River plume is influenced not only by the external forcing and drivers (such as bathymetry, the wind, and Coriolis effect) that shape the circulations and currents in Green Bay (Hamidi et al. 2012) but also by storms and discharges. This spatial and temporal variability makes direct measurement of water quality parameters expensive, time-consuming, and inefficient. In this situation, satellite remote sensing imagery is claimed to be a suitable alternative for monitoring water quality and river plumes in coastal regions (Petus et al. 2014).

With all the advances in visual computing (Tafti et al. 2014), satellite images provide a good source of information to study the quality of natural water resources. Several studies have addressed the problem of environmental water quality monitoring by modeling satellite imagery data of landscape spatial characteristics to investigate sources of contamination (Yan et al. 2005; Derek 2010). Remote sensing has been widely utilized to study water resources, and to monitor transport and dispersion of pollution in water bodies (Brekke and Solberg 2005; Yildirim et al. 2007; Shoghli et al. 2016; Haule et al. 2016). This can be a very useful tool for water quality modeling in lakes and coastal areas, especially in cases of insufficient observed data. However, the verification of the results would be a matter of concern due to lack of in situ measured data.

Pioneer works started in 1970s to propose empirical relationships between TSS and remotely sensed radiance (λ) (Klemas et al. 1974; Johnson 1975; Munday and Alfoldi 1979; Curran and Novo 1988). Thereupon, this relationship has been the subject of investigation (Jupp et al. 1994; Fraser 1998; Yu et al. 2014), in which TSS and turbidity used to assess the quality of water. Remotely sensed data in combination with in situ measurements of suspended sediment, water quality parameters, and turbidity is an efficient way to study the river plume and estuarine system (Petus et al. 2010; Dogliotti et al. 2015; Garabaa and Zielinski 2015). Rostom et al. (2016) used hyperspectral remote sensing data to analyze turbidity of Mariut Lake in northern Egypt. Hou et al. (2017), have studied the relationship between concentrations of observational TSS/turbidity and surface reflectance of satellite data for 15 years and 102 large water bodies to investigate the trends of change in sediment volume and mass balance.

To date, remote sensing techniques have not been able to measure phosphorus directly since it is not recognized as an optically active variable. So monitoring of such parameters could be possible indirectly through modeling other water quality variables that are optically active such as TSS and chlorophyll-a. Although previous water quality studies have mostly concentrated on remote sensing modeling of optically active variables (He et al. 2008), some others have been tried to focus on investigating other nutrients such as phosphorous, nitrogen, oxygen, etc. (Wang et al. 2004; Xie et al. 2007; Wu et al. 2010; Yang et al. 2011).

Although attempts to estimate the phosphorus concentrations in lakes and reservoirs have achieved limited success, a recent research shows progress in the prediction of total phosphorous (TP) from satellite imagery data (Gao et al. 2015). As there is evidence of correlation between TP and optically active parameters like chlorophyll (Dillon and Rigler 1974), TSS (Alam et al. 2016), and Dissolved Organic Matter (Gao et al. 2015), it is possible to use TSS or any other optically active parameter as a proxy to estimate phosphorus concentration from remote sensing observations.

Although it is an area of interest for many researchers and several empirical methods have been suggested in recent years, it is important to have a specific algorithm and equation to relate water turbidity with reflectance from remotely sensed data for any geographical and limnologic conditions. Water turbidity and reflectance are strongly dependent on physical, biological, and mineral composition of particles (Bowers et al. 2007; Moreno-Madrinan et al. 2010).

This study focuses on the Fox River turbid plume discharged into southern Green Bay, located in North-Western Lake Michigan. In situ water quality data is used along with the MODIS remote sensing images to relate the water surface reflectance to its turbidity and suspended sediment concentration. This provides a reliable source to study and monitor the Fox River plume and water quality in Green Bay using satellite imagery. This approach helps improve our knowledge about the spatial extents of highly turbid and nutrient-rich Fox River plume and its seasonal and inter-annual variations. This paper is intended to be a point of departure for use of remote sensing data for delineation of the river plume extent, determination of water quality stressors, and related imposed risks to the Southern Green Bay ecosystem.

Materials and methods

Area of study

Area of study is located in southern part of Green Bay as shown in Fig. 1. Green Bay, a major embayment in the north-western part of Lake Michigan, is oriented along a northeast-southwest axis with a length of 160 km, a mean width of 22 km, and a mean depth of 15.8 m (Mortimer 1979). The shallow depth and constricted nature of Green Bay reduces mixing and exchange flow with the main body of Lake Michigan (Lathrop Jr. et al., Lathrop et al. 1990), making the southern part of the bay a trap for river effluent and sediment. Green Bay basin is about one-third of the watershed of the lake and receives approximately one-third of the total nutrient loading to the Lake Michigan basin (Hamidi et al. 2012).

Green Bay has a long history of hyper-eutrophication (Bertrand et al. 1976). Hypoxia within lower Green Bay and the Fox River has been a problem for decades, and recent evidence suggests that this problem may be worsening (Klump et al. 2009). Hamidi et al. (2015) studied the large-scale currents and circulation in the bay that influence the variation and transportation of biogeochemical loads from tributaries, mixing, and residence time.

Fox River plume has long been recognized as a major source of phosphorus in the Lake Michigan Basin, and the bay receives nearly 70% of its annual load of phosphorus (700 metric tons) from Fox River. Most of this phosphorus is deposited in the sediments and Green Bay acts as a nutrient trap for the external phosphorus inputs before flowing into Lake Michigan (Klump et al. 2010). Monitoring phosphorus changes is important for controlling eutrophication in lakes, and coastal areas (Seker et al. 2003). Phosphorous variability is an issue in Lake Michigan and Green Bay area since it can unbalance the aquatic life and coastal ecosystems (Klump et al. 1997; Danz et al. 2007).

Field data

TSS and water turbidity are two parameters that can show the extent of river plume in coastal regions. Measurements of TSS are time-consuming, costly, and provide information for single points in space and time. Yet, these sparse measurements are used to develop an empirical model that ties water surface reflectance values obtained from remotely sensed data with water quality parameters. In situ measurements of water quality parameters, used in this research, are provided by Green Bay New Water (Erin Wilcox personal communications). Figure 1 shows the stations within southern Green Bay at which TSS, turbidity, and total phosphorous (TP) values at water surface are measured. Geographic coordinates of these stations are listed in Table 1.

The field data covers summers of 2011–2014. The analysis presented in this paper is limited to days with no cloud coverage over Green Bay and its adjacent area. Previous research shows that the existence of water vapor after floods can reduce the correlation between in situ water quality parameters and reflectance measured by satellites (Moreno-Madrinan et al. 2010). Therefore, if even the adjacent areas of the bay are covered with cloud on an image or if the image is obtained on immediate day after a flood event, that image is not used for analysis in this research since water vapor content can be potentially high over the bay. We used 118 set of field data for TSS and turbidity over 24 days with no cloud during summer 2011–2014. In Fig. 2 dates that have in situ measurements and no cloud coverage are shown with the number of data pairs in each date. To consider loading of the nutrients in Green Bay, data of Fox River discharge is also driven from U.S. Geological Survey (USGS) database (http://waterdata.usgs.gov/nwis/sw/) for the selected time period.

MODIS 250 m imagery

MODIS images are suitable for water turbidity monitoring because of their temporal and spatial resolution (Lillesand 2002). MODIS is a powerful imaging sensor, which was installed on two satellite platforms; Terra and Aqua launched

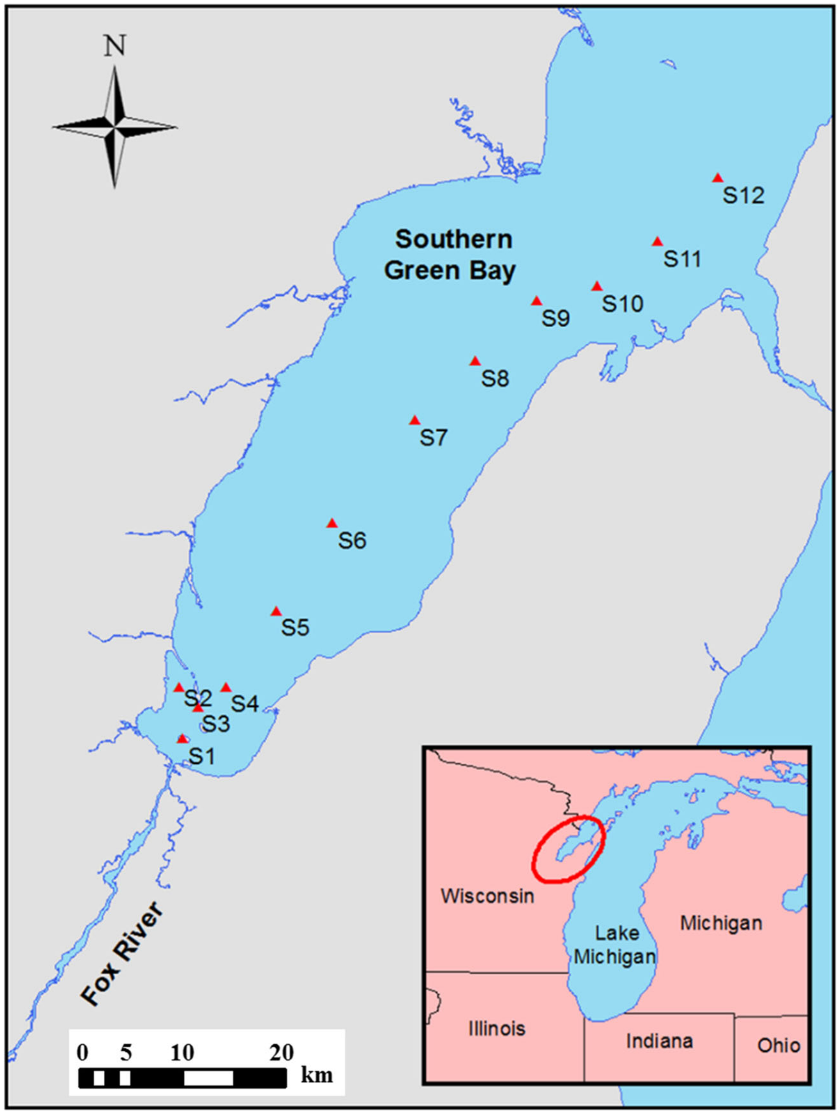


Fig. 1 Study area and location of in situ measurement stations

Table 1 Geographic locations of field stations

Stations	Latitude (deg.)	Longitude (deg.)
S1	44.557	−87.995
S2	44.596	−88.000
S3	44.581	−87.980
S4	44.596	−87.951
S5	44.653	−87.900
S6	44.718	−87.843
S7	44.795	−87.758
S8	44.839	−87.696
S9	44.883	−87.633
S10	44.894	−87.571
S11	44.928	−87.508
S12	44.975	−87.446

in 1999 and 2002 respectively. These two satellites carry multiple sensors and are part of NASA's Earth Observation System (EOS) of satellites [http://eospso.nasa.gov]. The orbits of Terra and Aqua satellites are designed so that they revisit any location on the earth's surface approximately every 1 to 2 days, which means that the temporal resolution of MODIS imagery is very suitable for spatiotemporal studies of the river plume. Each MODIS image is comprised of 36 imaging bands ranging in wavelength from 400 to 14,400 nm and in spatial resolution from 250 to 1000 m. There are many applications for MODIS data varying from atmospheric to ocean and land sciences.

The Land Processes Distributed Active Archive Center (LP DAAC) is an organization that processes MODIS data, archives, and distributes 68 different data products such as surface reflectance, surface temperature, and vegetation index [https://lpdaac.usgs.gov]. LP DAAC is a partnership

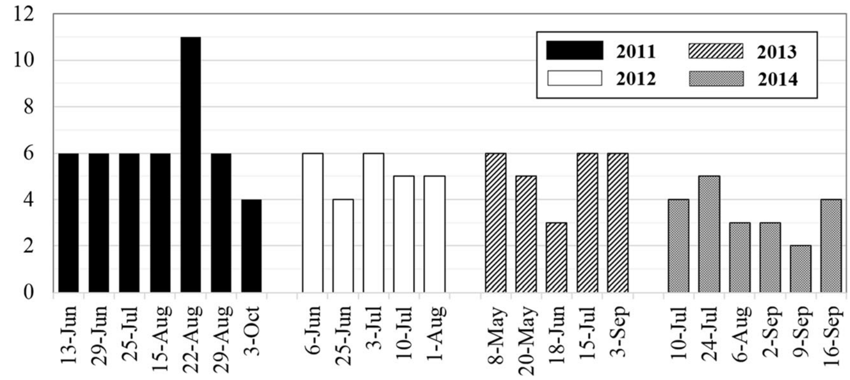


Fig. 2 Dates that both field and satellite data are available (vertical axis shows number of pairs of data in each date)

between the USGS and the National Aeronautics and Space Administration (NASA) and is a component of NASA's Earth Observing System Data and Information System (EOSDIS).

Landsat can provide images with finer resolution, however, most of the available images acquired by this satellite and other similar sensors overlap with cloudy days in the study area. Therefore, MODIS Aqua surface reflectance product (code named MYD09GQ) is used for its suitable spatial (250 m) and temporal (one image per day) resolution. Additionally, application of MYD09GQ data in assessment of turbidity and TSS of water bodies has been tested in recent studies, which resulted in significant correlation of imagery and observational field data (Chen et al. 2015; Hou et al. 2017).

MYD09GQ product is primarily intended for land applications and the atmospheric correction may not be valid for open ocean applications (Doxaran et al. 2009). Yet in highly turbid water bodies, the surface reflectance products are useful since water is a good reflector of sun's radiation (Petus et al. 2014). Band 1 of the MYD09GQ image has a spatial resolution of 250 m, temporal resolution of 1 day, and is centered at 645 nm wavelength. The reflectance in this wavelength is sensitive to mineral suspended matters and turbidity in water (Bowers et al. 2007). Therefore, after cloud analysis and visual investigation of the images, MODIS Aqua band 1 of the MYD09GQ product for the days with available in situ measurements and no partial or full cloud coverage was selected.

Data analysis procedure

MYD09GQ is a level-2 MODIS product (i.e. atmospherically corrected and geo-located) and therefore has a sinusoidal projection. This projection is usually changed to a more intuitive one in a preprocessing step. The field data used in this study has geographic coordinates associated with them (latitude and longitude). Therefore, the MYD09GQ band 1 images needed to be reprojected to the geographic coordinate system so that all the data would be in the same projection frame.

LP DAAC provides various tools for searching, downloading, and re-projecting MODIS data products. In this study, LP DAAC's Web-based MODIS Reprojection Tool (also known as MRT Web Tool) is utilized. This online tool allows browsing through MODIS products, searching for data based on dates, and re-projecting to geographic coordinates. All of MYD09GQ band 1 images of months of May through September of 2011–2014 were initially downloaded for this research using MRT Web tool.

Field data containing the location of sampling stations along with associated TSS and turbidity values are tabulated based on the dates of observation. Therefore, images acquired on days coinciding with field measurements are selected for model development. These images are selected among the bulk-downloaded images of the 4 years.

A MATLAB script has been developed and used to extract the reflectance values from selected images at the desired locations, which coincide with the in situ measurement stations. The reflectance values are then used in conjunction with the in situ TSS and turbidity measurements to establish an empirical formula, which is presented in the next sections.

The water surface reflectance is not linearly related to the concentration of TSS, but it increases with increase in TSS concentration and turbidity (Curran and Novo 1988). To develop an empirical relationship between water quality parameters (here turbidity and suspended sediment) and reflectance, measured data obtained on water surface during summers 2011–2013 by Green Bay New Water is used while the 2014 data is used for evaluation of the method. The proposed empirical relation can be used in water quality studies for the Green Bay area instead of expensive and time-consuming field measurements.

Image quality assessment and cloud contamination

To obtain reliable results, image quality assurance information was checked for atmospheric corrections of images and other quality issues. It is also necessary to discard images with cloud contamination over the study area because in the presence of clouds, all optical remotely sensed images contain information about the clouds rather than the earth's surface below.

To achieve this, MYD06_L2 data were used to investigate cloud coverage in the study area. This dataset is a MODIS daily global level-2 cloud product containing data acquired from Aqua with 1 km resolution and is derived from MODIS cloud mask product MYD35_L2 [http://modis-atmos.gsfc.nasa.gov/MOD35_L2]. Cloud fraction is a subset of MYD06_L2 data and was analyzed to examine the cloud coverage in the study area. Cloud fraction is the percentage of land in each pixel covered by clouds, such that cloud fraction of 1 means the pixel is completely covered by clouds and 0 means no cloud exists in that pixel [http://modis-atmos.gsfc.nasa.gov/MOD06_L2].

In this study, to determine cloudy pixels a threshold value of 0.01 (1%) is selected for cloud fraction. If more than 80% of the pixels in the area of modeling has a cloud fraction value of 0.01 or less that day will be considered as a clear one (Sima et al. 2013). By doing so, several dates were determined to be clear for the modeling. In the next step, dates with the amount of clear pixels between 70% and 80% in the true-color MODIS aqua images were examined visually. These true color composites are available online [http://ge.ssec.wisc.edu/modis-today] for visual purposes. In addition, images with cloud fraction value of more than 0.01 over the measurement stations were not used in the modeling. At the end, images for days with clear cloud status and available field data were selected for analysis. The overlap of dates with filed data and images with no cloud cover was 24 days that we used for this research.

Results and discussion

Relationship between reflectance and particle concentration

In general, the concentration of mineral suspended sediments has a good correlation with reflectance coefficient in the red part of the spectrum (Bowers et al. 2007). In this wavelength, absorption of solar radiation by Colored Dissolved Organic Material (CDOM) is much smaller (Bowers et al. 2007) than absorption by clear water, therefore higher reflectance is expected from turbid water. In this research, surface reflectance values obtained from band 1 of MODIS images (MYD09GQ products) are used which are associated with the red part of the spectrum.

Fox River plume and pollution from the watershed is a serious concern in summer seasons, and the environmental problems are getting worse by thermal stratification (Hamidi et al. 2015). On the other hand, in winter the southern portion of the bay is fully or partially covered by ice, thus field measurements and remotely sensed data are confined to the months of summer.

Regression was used to estimate a mathematical relationship between water surface reflectance and in situ water quality parameters in southern Green Bay for three years separately and also together. After exclusion of all dates with cloud contamination, 97 pairs of in situ TSS and remotely sensed observations are selected for all stations shown in Fig. 1. Using regression method, a relationship is proposed between in situ measurement and water surface reflectance obtained from band 1 of MYD09GQ. Figure 3 shows this relationship

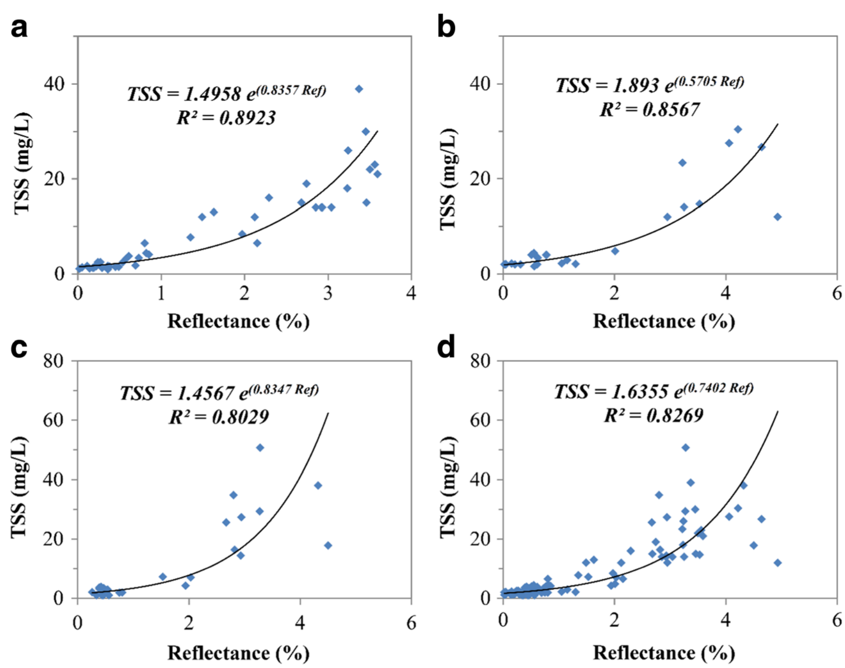


Fig. 3 Relation between reflectance in band 1 MODIS and in situ data for TSS in **a**) 2011, **b**) 2012, **c**) 2013, and **d**) three years combined

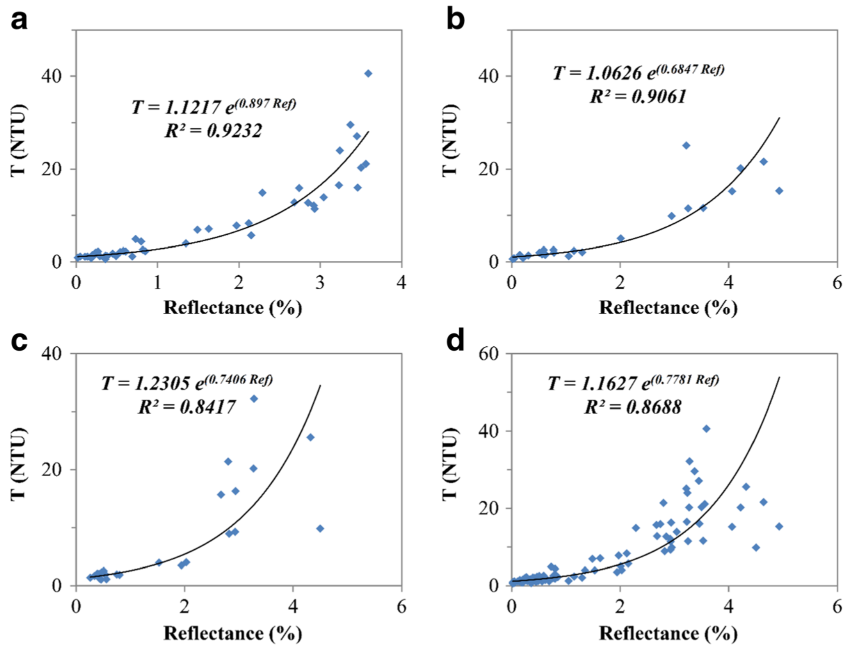


Fig. 4 Relation between reflectance in band 1 MODIS and in situ data for turbidity in **a**) 2011, **b**) 2012, **c**) 2013, and **d**) three years combined

and as one can see, although the three years have different average temperature and river discharges, the relationship between TSS and surface reflectance follows similar trends over three years. As the overall trend for the equations over three years are similar, it is reasonable to use the relationship obtained by combined data of three years as shown in Fig. 3d. Eq. 1 presents the empirical relation between the surface reflectance obtained from band 1 of MYD09GQ images and *TSS*:

$$TSS = 1.6355\ e^{0.7402 R_{rs}} \tag{1}$$

where R_{rs} is reflectance percentage and *TSS* is suspended sediment concentration in milligram per liter (mg/L).

Reflectance and turbidity

Turbidity is a commonly used index to determine the percentage of light penetration in water that consequently affects the photic depth in the water column. Photic depth indicates the depth in the water column in which gross primary productivity and respiration are equal. Turbidity has a direct influence on water quality, heat flux, thermal stratification, and hypoxia (Hamidi et al. 2015; Bravo et al. 2015).

Accurate estimation of turbidity is crucial to plan and design environmental and restoration programs, to predict fate and transport of pollutants, and to estimate the sediment flux (Moreno-Madrinan et al. 2010).

Following the same method used for TSS, Fig. 4 shows pairs of in situ turbidity data and its corresponding surface reflectance for summers of 2011 to 2013. A similar trend for variation of turbidity versus reflectance over all three summers can be observed in Fig. 4. Based on low interannual variation, the whole set of data is used as a reference to propose Eq. 2 to estimate turbidity based on atmospherically corrected reflectance in band 1 from MODIS Aqua sensor.

$$T = 1.1627\ e^{0.778 R_{rs}} \tag{2}$$

In this equation, R_{rs} is the surface reflectance obtained from band 1 of MYD09GQ images and T is water turbidity in NTU unit.

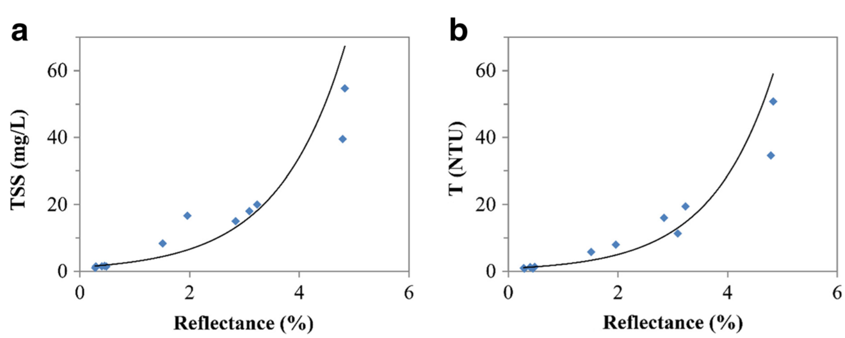


Fig. 5 Comparison of in situ TSS (left) and turbidity (right) data for summer 2014 with proposed equation based on 2011–13 data

Table 2 Cross-validation of the empirical relation considering data of 2011–2014

Training	Test	Mean R^2	Std. R^2	Mean Corr.	Std. Corr.
50%	50%	0.8199	0.0293	0.7451	0.0684
60%	40%	0.8182	0.0236	0.7609	0.0806
70%	30%	0.8192	0.0185	0.7637	0.0989
80%	20%	0.8204	0.0116	0.769	0.109
90%	10%	0.8184	0.0086	0.8384	0.1454

Validation of proposed method

To validate the empirical equations, suggested for TSS and turbidity, the reflectance for stations with measurements in summer 2014 was extracted from remotely sensed data following the same procedure described in Section 2.4. Comparison of TSS and turbidity values obtained from Eqs. 1 and 2 for 2014 images with the in situ measured TSS and turbidity values provides a reliable way to validate the level of accuracy of these empirical equations. Figure 5 shows the proposed equations along with the pairs of in situ data and surface reflectance for 2014. In this figure, there is a good agreement between the proposed empirical method and 2014 in situ data. It is important to note that the empirical relations were developed without use of 2014 data. The correlation coefficient between measured data and proposed equation is about 0.95. This shows the reliability of the method and equations suggested in this research to study Fox River plume and spatiotemporal variation of water quality parameters in southern Green Bay.

Normalized Root Mean Square Error (NRMSE) is a parameter, which is used for comparison of two sets of data. The goodness of fit between measurements and model predictions of TSS and turbidity was quantified in terms of NRMSE. The NRMSE between observed and modeled data is estimated using Eq. 3 for time series of observed ($x_{i,1}$) and modeled ($x_{i,2}$) values of TSS and turbidity.

$$NRMSE = \frac{1}{std}\left(\sum_{i=1}^{n}\frac{\left(x_{i,1}-x_{i,2}\right)^2}{n}\right)^{1/2} \tag{3}$$

In this equation, *std.* is the standard deviation of the observed values. Calculation shows the *NRMSE* is 0.36 and 0.3 for TSS concentration and turbidity respectively.

To ensure the robustness of R^2 and correlation coefficient values for Eq. 1, cross-validation of the empirical relation was performed over the whole set of data for 2011–2014. Five experiments with different combinations of training data and test data were performed. Each experiment was run 100 times with the training and test data pairs selected randomly. Table 2 presents some statistics on R^2 and correlation coefficient that confirm that the values cited in Sections 3.1 are within acceptable range. All these tests show the ability of this method to predict the variation of water quality parameters based on remotely sensed data in southern Green Bay.

River plume dynamics

Fox River plume is a highly dynamic coastal structure, driven by meteorological forcing, Coriolis Effect, river discharge,

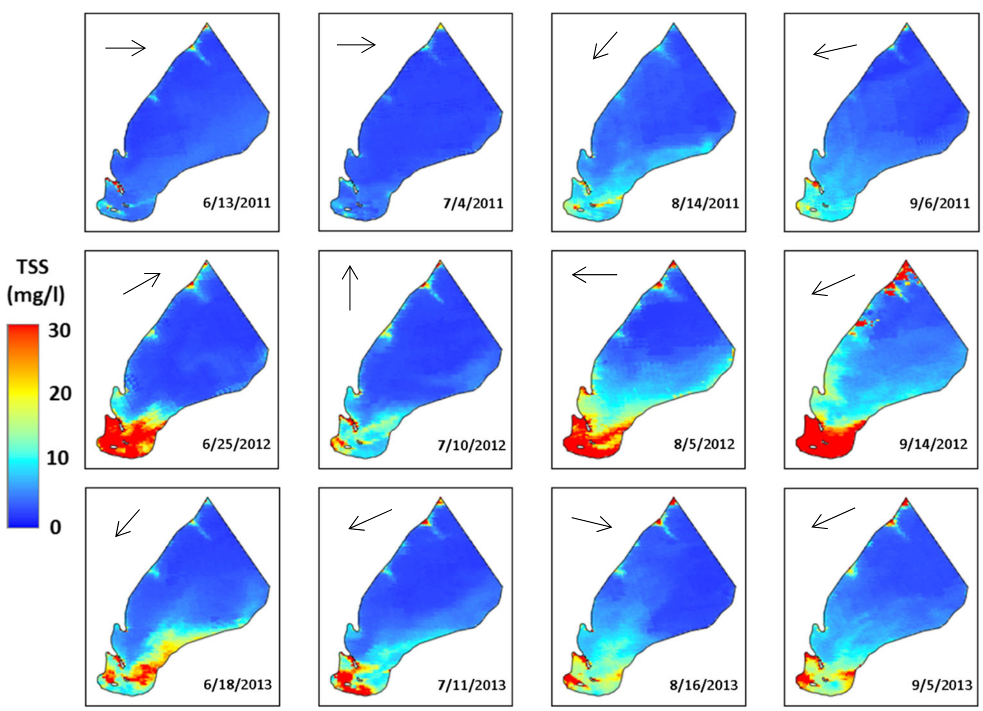


Fig. 6 Examples of Fox River plume. The arrows show the dominant wind direction at the same dates

and Bay bathymetry. Using Eq. 1 concentrations of TSS can be calculated for any day using only band 1 of the MYD09GQ image of that day. A color representation of the calculated TSS for all pixels of the bay provides a map of plume distribution associated with each day. Figure 6 shows the variation of plume for a selection of 12 days between summers of 2011–2013. This figure shows the high spatial and temporal variations of the plume in the southern portion of the bay. The area of the plume is mainly extended to the east side of the bay.

The area of the southern Green Bay affected by plume is also calculated here using a TSS of 5 mg/L as the threshold to define the plume. There is 97 pairs of data with cloud-free MYD09GQ images for the period of summers of 2011 through 2013. The variation of the area of the plume is between 12 to 180 km^2 for these days while 50% of the time the area of the turbid plume is more than 106 km^2.

Figure 7 shows the variation of Fox River discharge and concentration of TSS in three different locations inside the bay obtained using Eq. 1. From Fig. 7a a correlation between the increase of TSS concentration in station 4 and increase of discharge rate from the river can be seen (marked by arrows). The same argument is valid for TSS concentration in Stations 7 and 9 as shown in Fig. 6b.

The other point one can investigate from Fig. 7 is the decrease in the TSS concentration from south to the north of the bay. For a given date, June 20th for instance, the TSS concentration in Stations 4, 7, and 9 are approximately 40, 12, and 5 mg/L. This shows that the main source of sediment concentration and turbidity in the southern Green Bay is Fox River discharge, even though other factors such as wind driven wave, gyres, and circulation affect the TSS concentration.

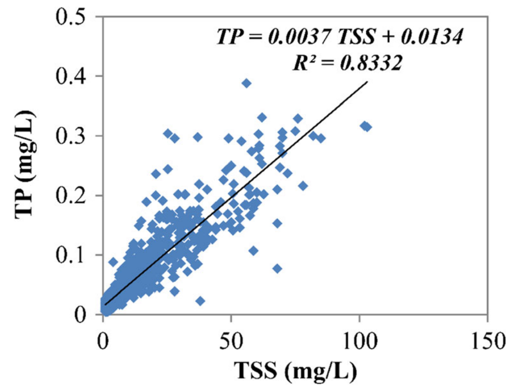


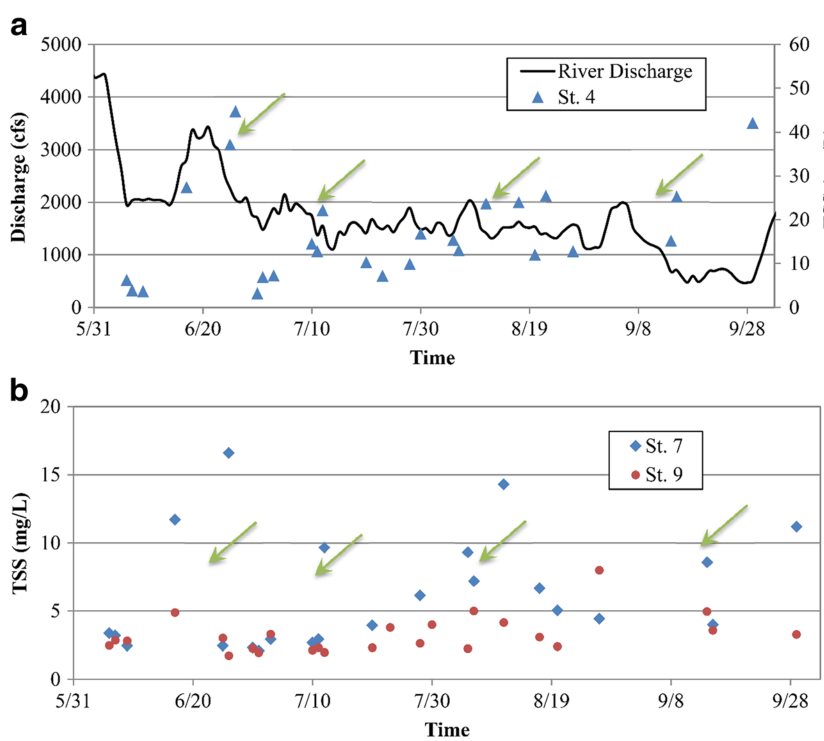
Fig. 8 Correlation between total suspended sediment and total phosphorus in the southern Green Bay

Indirect estimation of TP

As it is shown in Fig. 8, the correlation between TSS and TP observational data was tested in this study. There is a strong correlation that provides a framework to predict indirectly TP, which doesn't have direct optical properties and spectral characteristic, from TSS and reflectance. Eq. 4 shows the empirical relation between measured TSS and TP, calculated from 1100 pairs of data over summers 2011–13.

$$TP = 0.0037(TSS) + 0.0134 \tag{4}$$

Fig. 7 Correlation between river discharge and TSS concentration in three different stations in the bay



This relationship and estimated TSS could be used for further analyses to evaluate phosphorus concentration in the Green Bay. TP field measurement would be costly and in many instances not practical. Therefore, it is not possible to measure TP in many different locations or field stations and eventually a limited number of measurements would be obtained. It should also be noted that the TP evaluated using this method would be restricted to the surface of the water column since the calculation of TSS with remote sensing techniques is also valid for the upper layers. In addition, one should be aware of the errors in modeling TSS with imagery data and building a TP ~ TSS relationship. Nevertheless, this method can provide a general knowledge about TP circulation and a rough estimation of its variability in a large study area. It can also help to determine TP gradient as well as point sources of pollution, if any, in the modeling zone.

Summery and conclusion

In this research, the Fox River turbid plume—a major source of sediment and contamination to the Green Bay and Lake Michigan—was studied using the in situ measurements and satellite imagery data. Cloud contamination is a common barrier to the remote sensing modeling in the study area. To avoid this issue and in order to select the most appropriate satellite data temporal resolution of different available satellites was considered against the time of measurements. In this regard, MODIS data provides the most overlapping time. Surface reflectance values, obtained from band 1 of MYD09GQ images, were correlated to corresponding turbidity and TSS measured over summers of 2011–13 for 16 stations in Southern Green Bay. Derived empirical equations showed strong correlation between turbidity and TSS with surface water reflectance with correlation coefficients of 0.87 and 0.83, respectively. Proposed relationships were validated against measured data in summer of 2014. The NRMSE for prediction of measured data with the equations developed for turbidity and TSS are 0.3 and 0.36, respectively. Proposed model was used to estimate TSS in the Lower Green Bay area. Generated maps provide a spatiotemporal view of the variations of TSS which indicates the dynamic nature of the Fox River plume. It was shown that the turbidity and TSS concentration increase with an increase in river discharges. Additionally, it was also shown that the concentration of TSS increases in 3 specific stations as the river discharge increases. These types of analysis that model spatial and/or temporal variability in a large systems may probably need either huge amount of calculations or a dense network of monitoring stations. In either way, the analysis would be expensive and time-consuming, while remote sensing provides reliable and accurate estimations with less effort needed for data collection and computational processes. This study provides a framework to incorporate widely available remotely sensed data in water quality studies. In future analyses, the proposed empirical relations could be applied to other sites in the Great Lakes to check the validity and robustness of the proposed methodology. In addition to that, other water quality parameters could be targeted as the subject of the study. Obviously, more in situ measurements is required for further validations.

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