Environmental Advances 5 (2021) 100097

Contents lists available at ScienceDirect

Environmental Advances

journal homepage: www.sciencedirect.com/journal/environmental-advances

A reflectance-based water quality index and its application to examine degradation of river water quality in a rapidly urbanising megacity

M Sufia Sultana [a,b,*], Ashraf Dewan [c]

[a] School of Environment, Geography and Geosciences, University of Portsmouth, Portsmouth PO1 3QL, United Kingdom
[b] Cranfield Water Science Institute, Cranfield University, Bedfordshire, MK43 0AL, United Kingdom
[c] Spatial Sciences Discipline, School of Earth and Planetary Sciences, Curtin University, Perth, WA, Australia

ARTICLE INFO

Keywords:
Dhaka
Urban river
Water quality
Landsat
Total suspended solids
Normalised Difference Water Quality Index

ABSTRACT

The water quality in rivers around Dhaka is deteriorating very fast given extensive sources of pollutants associated with rapid urbanisation and industrialisation. This paper introduced a water quality index (WQI) utilising Landsat bands 1 to 3 (0.45 to 0.67 μm) against band 5 (1.55 to 1.75 μm). The value of the proposed index varies from – 1 to + 1, whereby around 0 (small positive and negative) indicated probable contamination, if the water depth is around 2 m or above. This approach was developed using Landsat data to study long-term water quality change in the rivers surrounding Dhaka megacity, Bangladesh. The values were converted to total suspended solids (TSS) by utilising observed in-situ data, which showed a clear seasonal influence of water pollution, suggesting it reduces to the background level with the onset of high monsoonal river flows. However, long-term analysis showed that the rivers remain polluted throughout the year, particularly since 2011. The main reason for increasing river water pollution may be linked to the contaminant load which has increased extensively in recent years. The approach developed in this study may be used in other urban rivers, particularly in Asia.

Introduction

Asian countries, for example Bangladesh, India, China, Vietnam, and Malaysia, are experiencing a high rate of urbanisation, which is often demand-driven and unplanned. In Asia, it is projected that 55% of the population will live in urban settlements by 2030 (Choe and Roberts, 2011). Rapid urbanisation is continually altering land-cover and degrading hydrologically important wetlands and riverine areas, which are highly beneficial to water quality and flood control when they act as spatially distributed systems (Mitsch and Gosselink, 2000). Several studies have demonstrated the relationship between water quality degradation and unplanned urban growth, particularly in Bangladesh (Chowdhury et al., 2014; Hoque et al., 2014; Sakamoto et al., 2019; Whitehead et al., 2018). Investigation of urban river pollution may have implications for creating mitigation measures, as water quality degradation can lead to a number of environmental problems, including water-borne diseases (Dewan et al., 2013).

Although water quality is a complex issue extending from aesthetic, chemical to biological (Gholizadeh, Melesse, & Reddi, 2016), and is relatively difficult to retrieve from remotely sensed data, optical clarity (Goodin et al., 1993) provides an opportunity for mapping water quality. Total suspended solids (TSS) is considered as a water quality parameter that is interlinked with turbidity (Han, 1997; Lathrop, 1992), metal contents (Swain and Sahoo, 2017), Secchi disk transparency (Gholizadeh et al., 2016; Kloiber et al., 2002), and coloured dissolved organic matter (CDOM) (Griffin et al., 2018, 2011). Landsat multi-spectral satellite images are extensively used for mapping water quality by developing models from limited in-situ data (Gholizadeh et al., 2016). However, for long-term water quality analysis this approach is rare, despite the fact that satellite data have shown greater potential for effectively quantifying surface water quality (Bonansea, Rodriguez, Pinotti, & Ferrero, 2015; Griffin et al., 2011).

Long-term historical data, particularly on the water quality of rivers and wetlands, are lacking in this region. As a result, assessing the level of pollution is often carried out using a few point-source measurements (Karn and Harada, 2001). It is critical for management planning to understand spatial dynamics of the degree of pollution in rivers and the rate at which they are deteriorating. Here, we take Dhaka as an example megacity that characterised by its vast interweaved river networks, which act as the 'kidneys' of the city by carrying the pollution load and floodwater downstream (Hafiz et al., 2017) (Figure 1). Excessive pollution load is likely to exceed maximum attenuation capacity of the

* Corresponding author.
E-mail address: mst-sufia.sultana@cranfield.ac.uk (M.S. Sultana).

https://doi.org/10.1016/j.envadv.2021.100097
Received 4 May 2021; Received in revised form 7 July 2021; Accepted 12 August 2021
Available online 14 August 2021

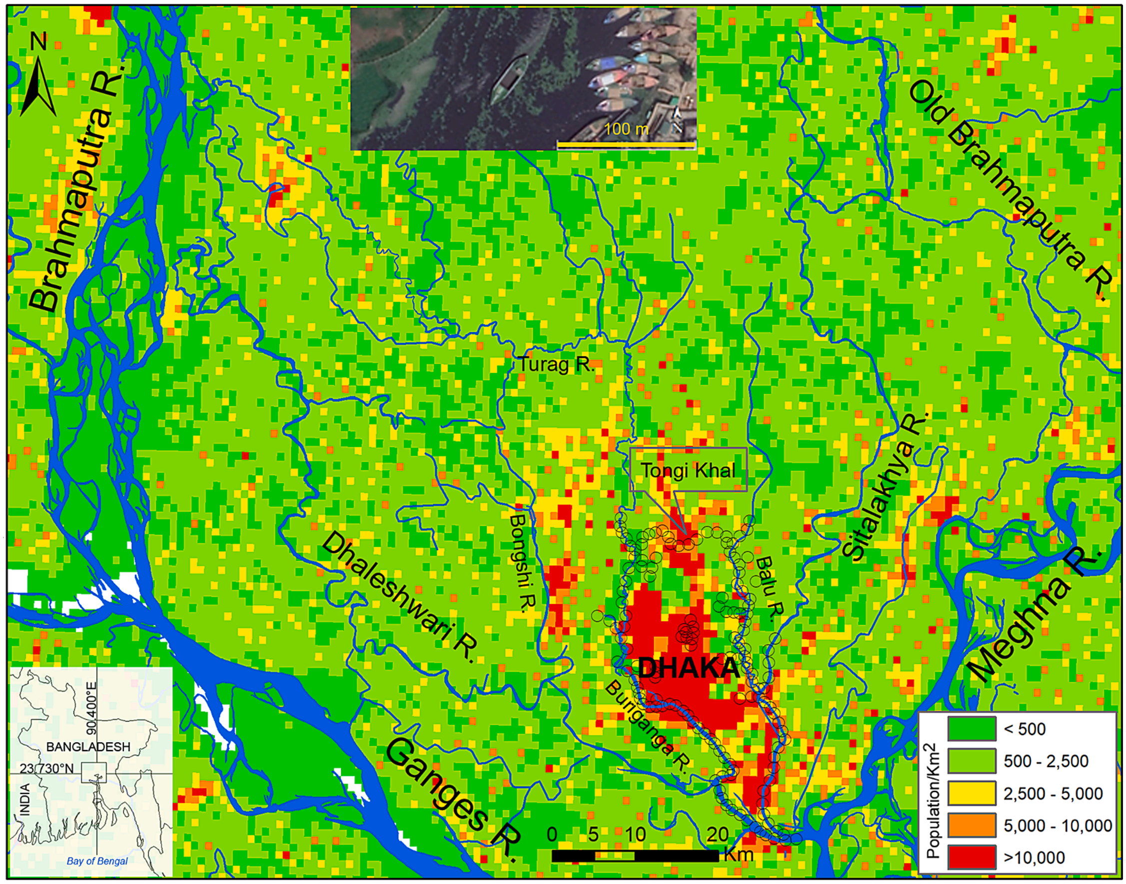

Fig. 1. The study area along with sub-regional river networks. The background layer indicates population density based on Landscan data (Bright et al., 2017). Dhaka is surrounded by the Turag-Buriganga to the west and Balu-Sitalakhya Rivers to the east. These rivers are connected by a non-natural canal Tongi khal. Open circle on these rivers indicates the water quality retrieval points. Inset image shows common floating objects (boats with foams, floating debris, and water hyacinth) found in the Dhaka Rivers taken from Google Earth Pro. The western side of Dhaka is well connected with one of the major rivers, the Brahmaputra, while the eastern side is merely getting any substantial contribution from major rivers.

waterways, if urban development continues at its current rate and style. Although several studies have looked into land-cover change ((Corner et al., 2014); Dewan and Yamaguchi, 2009), only a few have examined water quality over a year (Chowdhury et al., 2014; Rahman and Hossain, 2008) and rarely any study looks into the long term changes. There is considerable evidence that increased human activity has dramatically degraded river water quality, especially during the dry season (Hoque et al., 2014; Pramanik and Sarker, 2013; Rahman and Hossain, 2008), but there is a lack of assessment of long-term variations. The purposes of this work are to develop a water quality index based on spectral reflectance that can be used to assess overall water quality, and apply the index to assess long-term river water quality in Dhaka using freely available Landsat multispectral data.

Study area description

Dhaka megacity - a polycentric urbanized area - is located in central Bangladesh and has an area of about 1500 km^2 (Hassan and Southworth, 2018(Corner et al., 2014). The entire area of Dhaka is generally sloping southward and drained by tributaries and distributaries of the Ganges, Brahmaputra and Meghna (GBM) Rivers. These tributaries and distributaries are not only draining the ca. 2 m rainfall (80% of it falls between June and September) received every year, but also divert excessive monsoon flows of the GBM rivers downstream via the Buriganga-Dhaleswari-Sitalakhya river systems, as well as over 650 million m^3 of domestic wastewater (assuming 100 L/person/day) produced annually by the city dwellers, on top of untreated or partially treated industrial effluents and faecal waste. The current study (ca. 1100 km^2) focuses on the 110 km length of rivers (Turag-Buriganga, Balu-Sitalakhya and a canal, Tongi Khal, connecting Turag and Balu Rivers) around the main part of Dhaka city – the central region of Detailed Area Plan (DAP) (Figure 1). The main characteristics of Tongi Khal is that it has a bidirectional flow i.e., during monsoon it works as a tributary of the Balu river while in the dry season it becomes a tributary of the Turag river (Whitehead et al., 2018). The rivers are up to 500 m wide (and not less than 50 m), while the depth varies across the channel, but the mid-channel depth is nowhere < 2 m. The Buriganga River is the deepest, up to 10 m, and widest (Hafiz et al., 2017). Most of the rivers' bed is characterised by silty-muddy sediments.

Dhaka accommodates over 18 million people, which has doubled since 2000 and is projected to be over 27 million by 2030 (Swapan et al., 2017; UN, 2015). Approximately 500,000 rural people migrate to Dhaka every year because of rapid industrial growth, construction, and services (Choe and Roberts, 2011). Most of the migrants work in garments and manufacturing industries, which have been proliferating in the peripheral floodplain locations, prone to seasonal flooding. These industries, which account for 74% of the national total, are mostly unregulated and often dump their waste into the rivers and floodplains (Sakamoto et al., 2019). Untreated sewage and industrial effluents are primary causes of pollution in and around Dhaka city (Pramanik and Sarker, 2013).

Table 1
Landsat data, rows 43 and 44 of path 137, used in this study. There is a difference in band spectral coverage between Landsat 5 and 8 but they overlap and have the same spatial (i.e. 30 m) resolution. 'X' indicates no analysis done for that time.

Sl No.	Year	Type of Image	Wet Season	Dry season
1	1994	Landsat 5	17 Oct 1994	X
2	1999	Landsat 5	15 Oct 1999	X
3	2005	Landsat 5	15 Oct 2005	16 Jan 2005
4	2008	Landsat 5	23 Oct 2008	13 Mar 2008
5	2011	Landsat 5	30 Sep 2011	02 Feb 2011
6	2015	Landsat 8	25 Sep, 27 Oct, 28 Nov, 30 Dec, 2015	28 Jan, 13 Feb, 17 Mar, 18 Apr 2015
7	2017	Landsat 8	16 Oct 2017	X
8	2018	Landsat 8	X	21Feb 2018

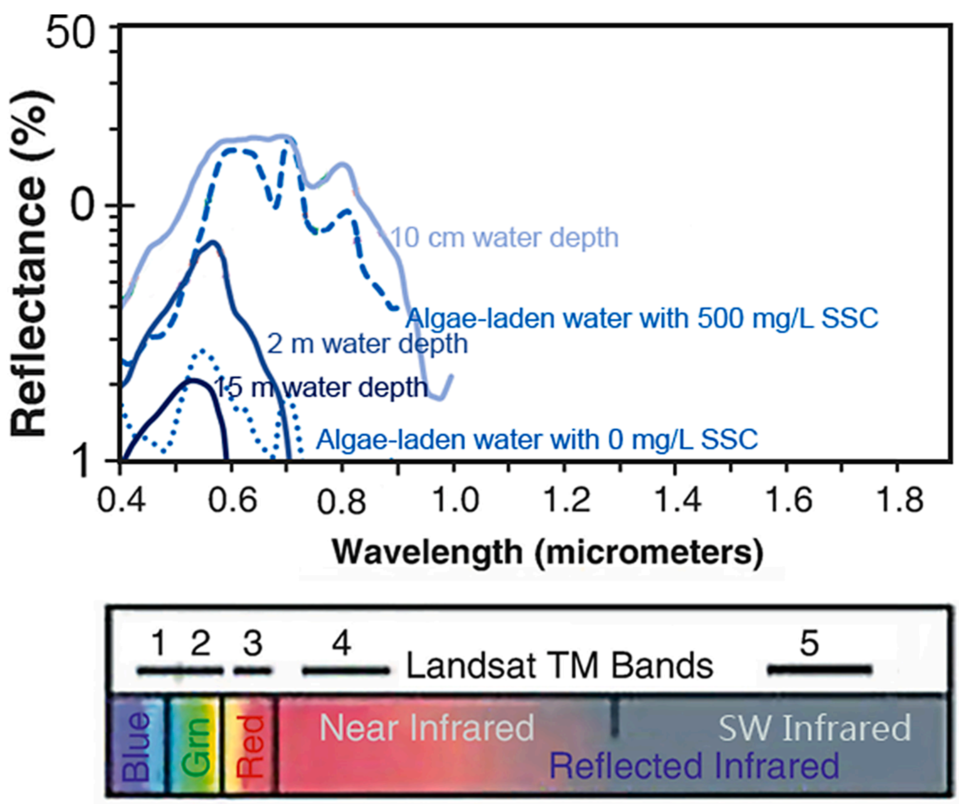

Fig. 2. Spectral bands and reflectance of various substance including water modified after Schowengerdt (2007) considering work of Han (1997), Lafon et al (2002). This is showing various influence of reflectance of water. Note that Y axis is in logarithmic scale.

Data and methodology

Data

A total of 34 scenes from Landsat 5 and 8 sensors were used. They represent Level 2 data, which are calibrated radiometrically and corrected for atmospheric differences. Essentially, Level 2 product provides an estimate of the surface reflectance as it would be measured from the ground (Masek et al., 2006; Vermote et al., 2016). They were downloaded from USGS data distribution portal, Earth Explorer (https://earthexplorer.usgs.gov/ accessed 01 March 2018) for multiple years, starting from the 1990s (Table 1). Cloud-free images of February and October were obtained for each year to reflect the dry and wet seasons, respectively. However, cloud-free images were not always found, as a result, data of the nearest date was used. More images were obtained in 2015 due to the availability of cloud-free data, which were used to demonstrate seasonal and monthly variations in water quality.

The data products come from the two scenes, rows 43 and 44 under WRS (Worldwide Reference System) path 137. There is a difference in spectral coverage between Landsat 5 and 8 but they overlap and have the same spatial (i.e. 30 m) resolution (Vermote et al., 2016). The equivalent bands between the images (Landsat 5 and 8) i.e., bands 1-7 except 6 (thermal band) of Landsat 5 and bands 2-7 of Landsat 8, were stacked with an image processing software (Hexagon Geospatial, 2016), which allowed multispectral images to be created that were then mosaicked to create a single image of each date for the study area (Supplementary Information, SI hereafter, Figure S1).

Mosaicked Landsat images were masked out to isolate waterbodies from built-up and vegetation categories by applying the water body delineation algorithm (Eq. 1) of Xu (2006). Here, a threshold value of 0 (to 1) was used, which has been proven to identify water bodies unequivocally (Campos et al., 2012). This also removes any pixels within the river where there were floating objects (e.g., boats, vegetation), common in Asian urban rivers (see inset in Figure 1).

To convert mosaicked Landsat multi-spectral 'water body' data to TSS (Total Suspended Solids), measured field data were used (Chowdhury et al. 2014). The data were collected from water samples during 2011 Feb 02 (± 7 days of satellite overpass). Chowdhury et al. (2014) mapped TSS values (mg/L) at a spatial scale of the channel width for 02 Feb 2011 by developing an algorithm to predict total suspended solids

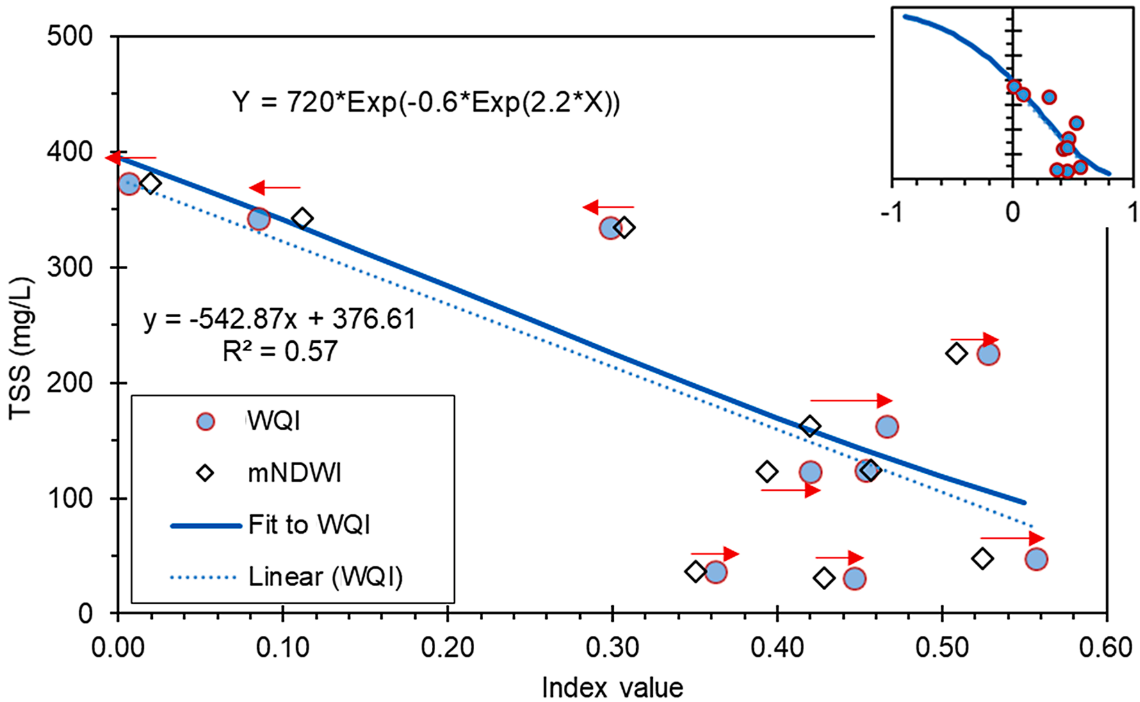

Fig. 3. Plot of WQI and TSS values, showing the separation between high TSS between mNDWI and proposed WQI. Inset shows the theoretical curve fit, which is an exponential curve that allows TSS to be estimated as TSS = 720*Exp(-0.6*Exp(2.2*Index)).

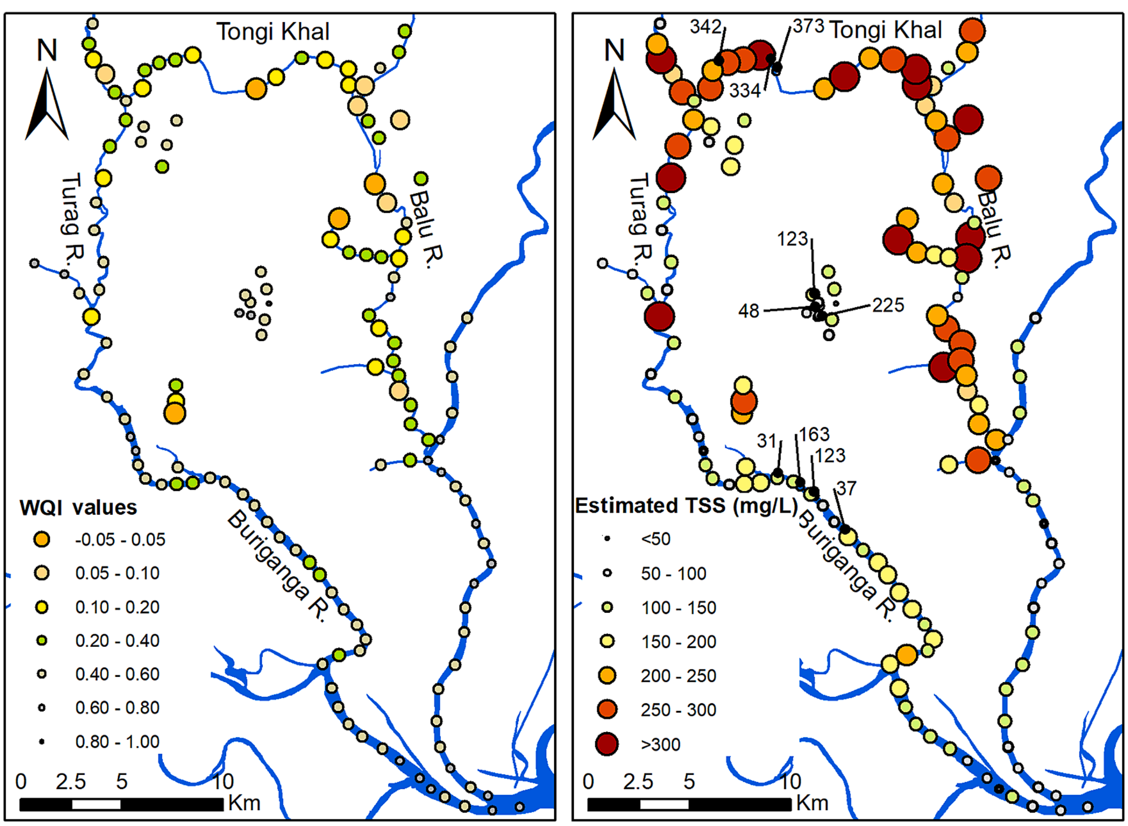

Fig. 4. Index values converted to TSS for February, 2011 indicating its spatial variability. The left panel shows the index values while right panel shows estimated TSS values. Note that observed TSS values are annotated in the right panel.

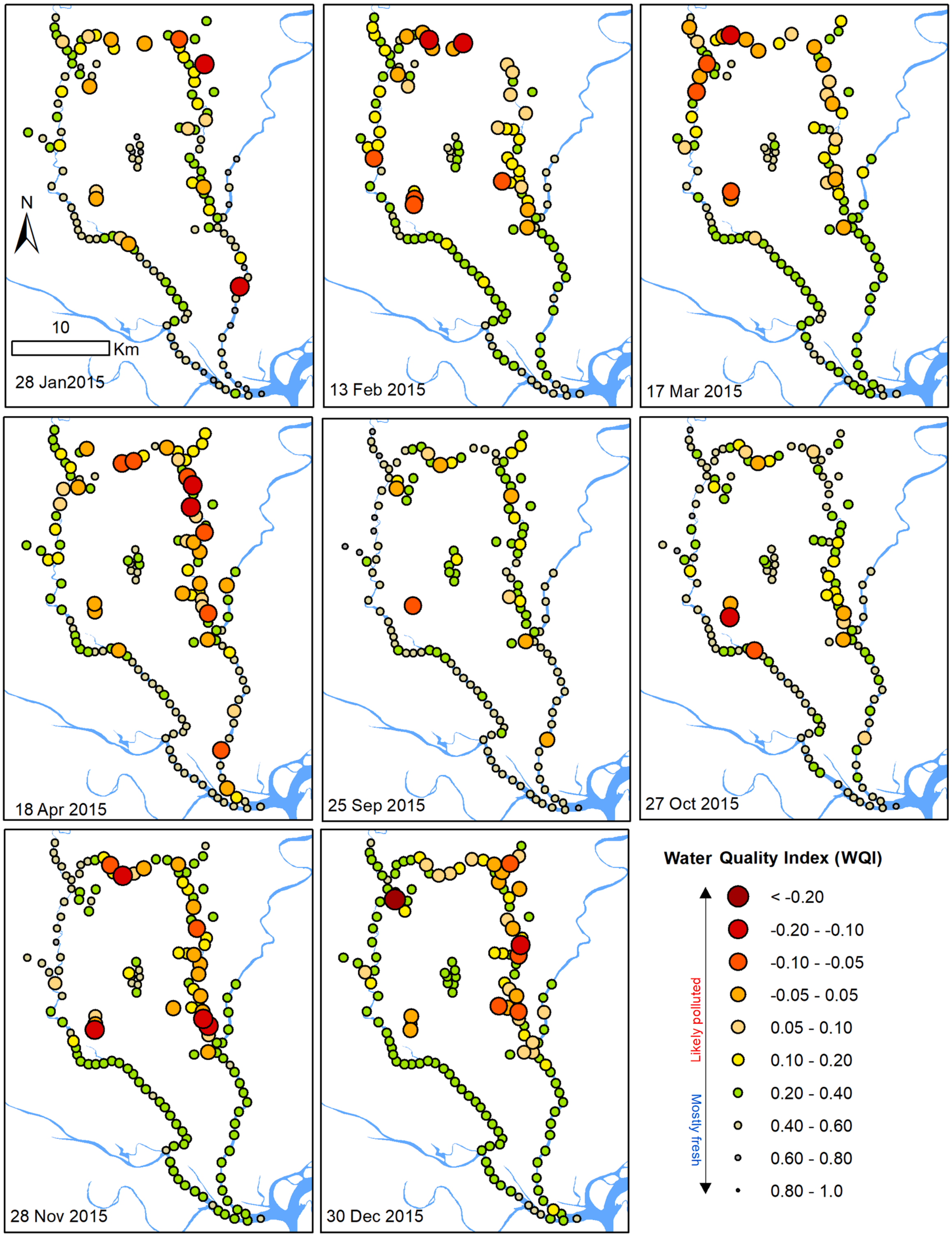

Fig. 5. Spatial and temporal characteristic of WQI, 2015.

using a classical regression model. The use of their algorithm in this work is proved problematic because the algorithm was developed using reflectance data derived from Level 1 product but not Level 2, which are used in this study. However, Landsat 5 image of 02 Feb 2011 (L2) was used to get surface reflectance for the measured TSS sample locations to generate a similar algorithm. A 5 × 2 window of the area of interest (AOI) was defined, following an approach of Griffin et al. (2011), at each sampling location and used to extract average reflectance values from visible and near-infrared bands (SI, S.3: reflectance data). The number of pixels across the river channel was limited to two pixels, to avoid non-water and shallow water reflectance. This reflectance dataset was then used for establishing the relationship of TSS to various spectral band combinations using linear regression (section S.2 in SI) and in developing a water quality index (see below). The use of a regression model, based on one year of observed data may not be suitable for assessing inter-annual variability because seasonality and inter-annual differences are likely to affect empirical constants. Besides, all empirical linear models estimate observed TSS data, but most models also

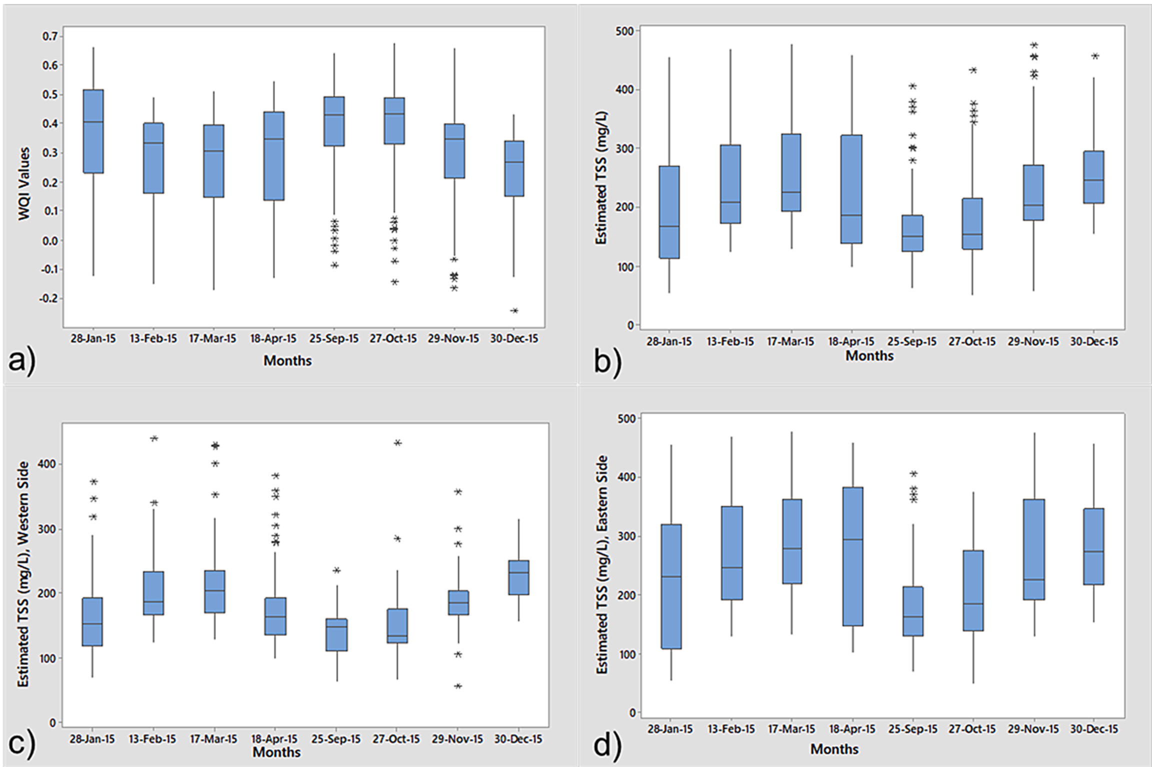

Fig. 6. Boxplots showing estimated TSS data as retrieved for the pre-specified 147 locations (see figure-1) for 2015. (a) WQI values, (b) Estimated TSS values for all points, (c) Estimated TSS values only for the 46 points located in the western side, (d) Estimated TSS values only for 53 points located in the eastern side.

produced some (practically impossible) negative TSS when applied to images. Thus, it was essential to develop a theoretical index.

Development of a spectral-based water quality index

Water features are highly discernible in infrared channels compared to other land cover categories. Water indices, which are calculated from two or more bands, are a simple and effective approach to distinguishing between water and non-water features. McFeeters (1996) introduced Normalised Difference Water Index (NDWI) to identify water surfaces using Landsat Multispectral Scanner (MSS) bands 2 (0.52-0.60 μm) and 4 (0.77-0.90 μm), which may be used with other sensors as long as similar wavelengths are recorded. Xu (2006) discovered that shortwave infrared (SWIR) band may reflect some minor water features, and suggested mNDWI (modified Normalised Difference Water Index) by replacing band 4, NIR (0.77-0.90 μm) in McFeeters (1996), with band 5, SWIR (1.55-1.75 μm). Landsat satellite sensors capture data over the electromagnetic spectrum in several ranges (bands); however, because band names (e.g., Bands 1, 2, 3, and so on) might be confusing, we used spectral wavelength in brackets to facilitate comparison amongst sensors.

The equation related to mNDWI is as follow:

$$mNDWI = \frac{B_2 - B_5}{B_2 + B_5} \tag{1}$$

This mNDWI not only identifies water bodies but also allows insight into variation within water bodies in terms of the index values, where negative values represent a non-water category. A careful examination of the variations within waterbody in accordance with reflectance characteristics could signpost the differences in the water clarity related quality parameters (e.g., TSS, turbidity, and even organic content) as clean water has the highest reflectance in band 2 (0.52-0.60 μm), but it shifts towards band 3 (0.63-0.69 μm), even to band 4 (0.76-0.90 μm) (Figure 2) (Schowengerdt, 2007), and thereby, indirectly indicates the level of water quality. Previously, these changes were utilised to examine bathymetry (Jupp et al., 1985). However, the variation most likely reflects the effect of water depth on reflectance, as well as the effect of water quality (Gao, 2009; Lafon et al., 2002).

Laboratory and field studies on water quality show that water reflectance peaks shift toward band 3 where absorption of energy is lowest as opposed to band 1 in the presence of dissolved organic matters and/or other colour influencing additives (TSS, Sediments, Chlorophyll) in water (Kutser et al., 2005). However, for water depths between 1.5 m and 10 m the reflectance variation is within 5% (Lafon et al., 2002), while water quality may contribute up to 20% of the reflectance difference (Han, 1997) in the electromagnetic region of 0.51-0.60 μm, which corresponds to TM band 2. Furthermore, bands 1 and 3 have varied reflectance for the same water depth, but the difference in reflectance is negligible for water depths of around 1.5 to 10 m within these bands (Lafon et al., 2002). Therefore, the reflectance difference between bands 1 and 3 was added to band 2 to amplify the influence of water quality. Then the added total was normalised against band 5 where reflectance is hardly influenced by any water quality variation or water content in general (Eq. 2). This proposed algorithm is called Water Quality Index (WQI) which takes the following form:

$$WQI = \frac{\{B_2 + (B_1 - B_3)\} - B_5}{\{B_2 + (B_1 - B_3)\} + B_5} \tag{2}$$

The WQI amplifies the difference between clean and polluted water, which normally gives an index value between 0 and +1. However, in the case of heavily polluted water, lower values could cross the 0 line and be slightly negative (Figure 3). In this index, lower and near negative values could indicate polluted water, while higher positive values can point to cleaner unpolluted water at the centre of the river where the water column is over 1.5 m i.e., the influence of depth on reflectance would be minimum.

A spatial model was built and combined in an image processing system to generate the WQI. It should be noted that this index is a semi-

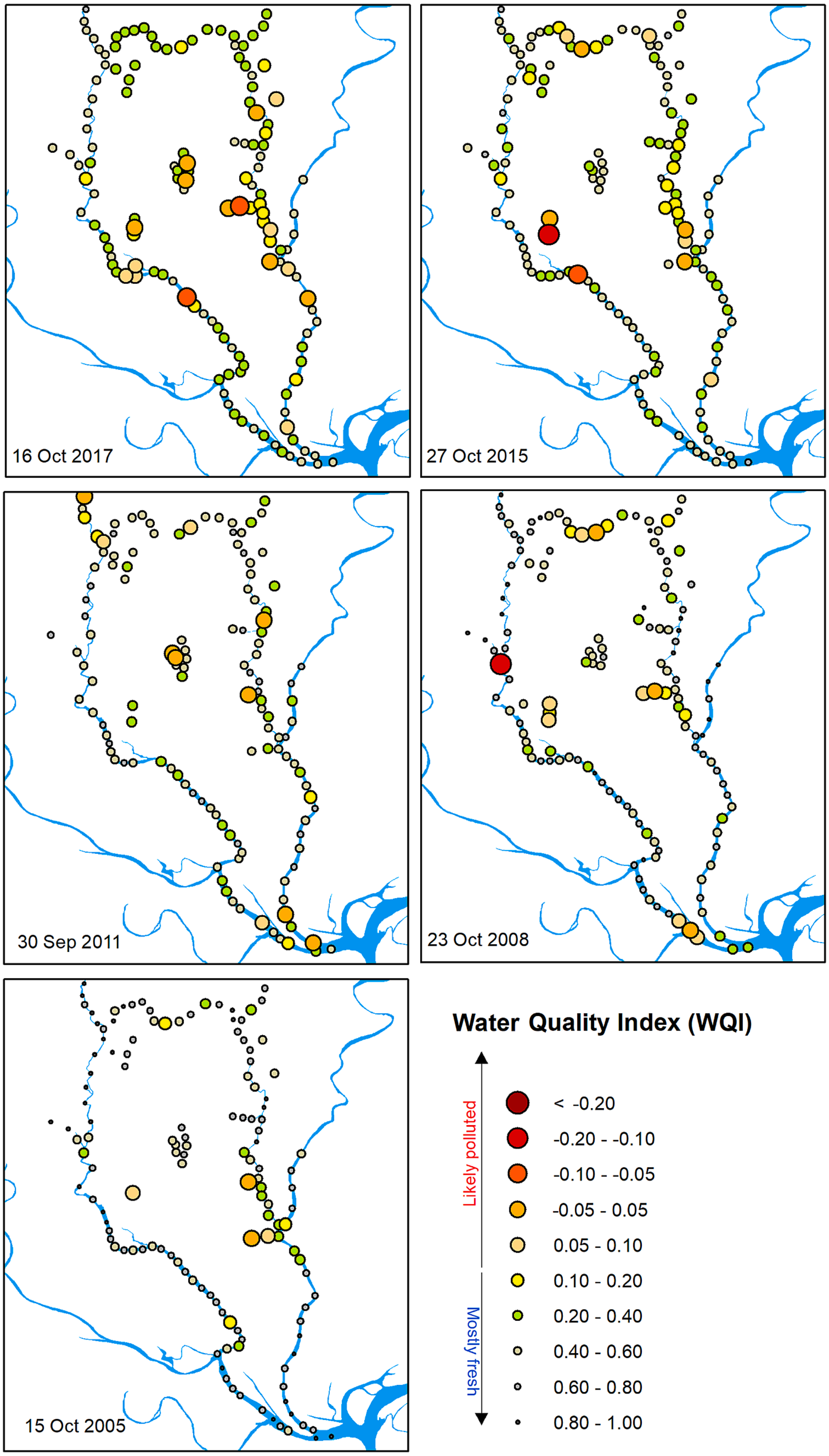

Fig. 7. Variation in WQI values over the rainy season between 2005 and 2017.

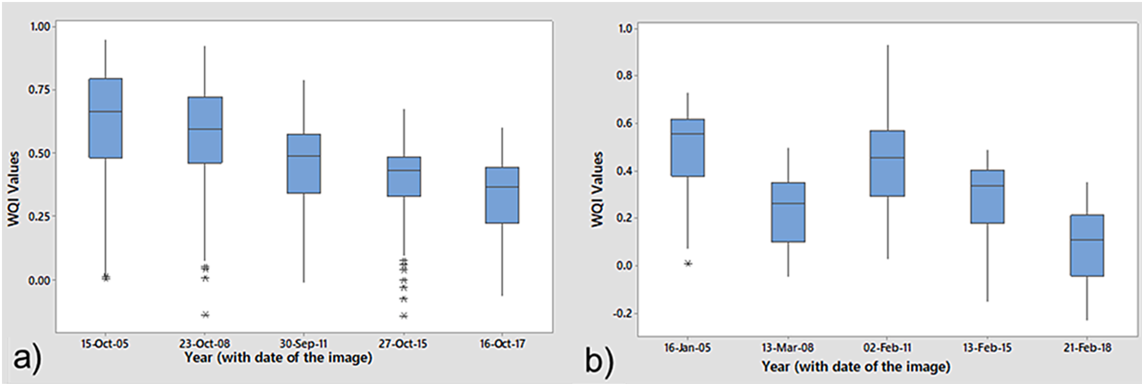

Fig. 8. Boxplots showing estimated WQI as retrieved for the pre-specified 147 locations for the year 2005 to 2017: a) Rainy seasons and b) Dry season both showing a downward trend indicating a deterioration of water quality in both seasons. Note that there was not cloud free data for Jan or Feb in 2008.

quantitative measure of water quality, indicating the relative change in overall water quality from one location to another and/or over time. Water clarity is seen as a measure of water quality, and a poorer clarity of water is considered to signal water pollution, particularly in an urban context. However, the index values can be converted to a water quality parameter using the field measured data, ideally coupled with bathymetry data to correct the influence of depth variation. Here, TSS is used as an example by deploying the aforementioned dataset (Figure 3). There is a linear relationship but TSS in water follows an 'S' shape, i.e., at lower concentration TSS will increase slowly and at higher concertation, it may plateau while in the middle concertation would rise sharply (Han, 1997). Therefore, a simple exponential relationship is used, however, the linear relationship is maintained to accord with observed data. In the case of larger datasets, this may follow the theoretical 'S' curve. This exponential model would always produce positive TSS values. This relationship may not hold in other years or seasons because the index to TSS conversion only used data from February 2011. Here, this should assist to demonstrate the index's ability to convey water quality state in a more perceptible manner.

Because we lack field data to test the WQI to TSS conversion, we produced a TSS data set 100 m downstream of the each sample location and expected it to be equivalent to the observed TSS value. When we compared this to modelled TSS, we identified a reasonable relationship with some overestimation (Figure S.3).

Data retrieval and visualisation

There are 147 extraction points at the mid-location of the channels, at 1 km spacing, were created because reflectance values away from the middle of the channel are likely to be influenced by shallow depths. Among those 147 points, some are inside the city on the lakes and internal stream channels and some are set on the tributaries (Figure 1). These data were also portrayed on maps for interpretation and TSS values were used for a statistical summary in terms of seasonal and interannual comparison.

Results

Water Quality Index (WQI) vs observed TSS

The water quality Index (WQI) provides values for February 2011, for which observed TSS data were available, that ranged from -0.05 to 0.8, and varies spatially with lower values in the northern and eastern side of the city (Figure 4). These values range from near zero to negative compared to the rivers in the southern and western part of the city, indicating potential variation of polluted waters in the rivers.

Converting WQI values to TSS using the model (Figure 3) indicates that the values are mostly comparable to the observed data in those areas where water quality information is available. The TSS values indicate the northern and eastern parts are more polluted than the southwestern part of Dhaka.

Monthly variation

Satellite images of 2015 were transformed to index values, which were retrieved at the predetermined 147 locations (Figure 5) to understand the level of pollution during the various months. It is clear that the degree of pollution mapped by index values vary, spatially and temporally, from around -0.2 to +0.6. However, the changes are conspicuous throughout the year. It decreases from September to December. This decreasing pattern appears to continue until April (driest month of a year) (Figure 5). The continuous data were not available to show the pattern in 2016 due to presence of cloud. By contrast, January and February of 2015 images show relatively higher index values compared to December 2015 (Figure 6).

The converted index values to TSS show a clear seasonal pattern (Figure 6). The boxplot shows that the median of TSS values varies between 150 and 260 mg/L, with lower values occuring in September and October while higher values can be found in December to February (Figure 6).

The flow regime of the rivers is different in the eastern and western sides of the study area. On the western side, flow is higher and the rivers are deeper and wider. To ascertain the associated differences between these two areas, data were grouped into eastern and western segments which generally show higher TSS values in the eastern side (median is around 250 mg/L) of the city compared to the western (median is around 150 mg/L) side (Figure 6). However, on both sides, seasonality remains similar i.e., low TSS can be found between Sept and Oct while higher TSS values occur in December till February.

Long-term variation

From monthly analysis, it is clear that pollution levels in the rivers are high in the dry season (February) and low at the end of the rainy season (October). This implies that long-term variation could be analysed by considering images from these two seasons.

Rainy season: satellite images were picked for the month of Octobers except for the year 2011 when cloud-free image was found for 30th September. Long-term analysis shows that there are more negative index values in recent years (Figures 7, 8). A recurrent and remarkable decline is observed in 2011, 2015 and 2017. The pattern is similar in the western and eastern sides of the city, but the magnitude of change is greater in the eastern side.

An increasing overall trend in TSS values is also noticeable (Figure S.4). The median TSS values in 2005 were around 50 mg/L. Since 2011, the TSS values increased to around 200 mg/L from 135 mg/

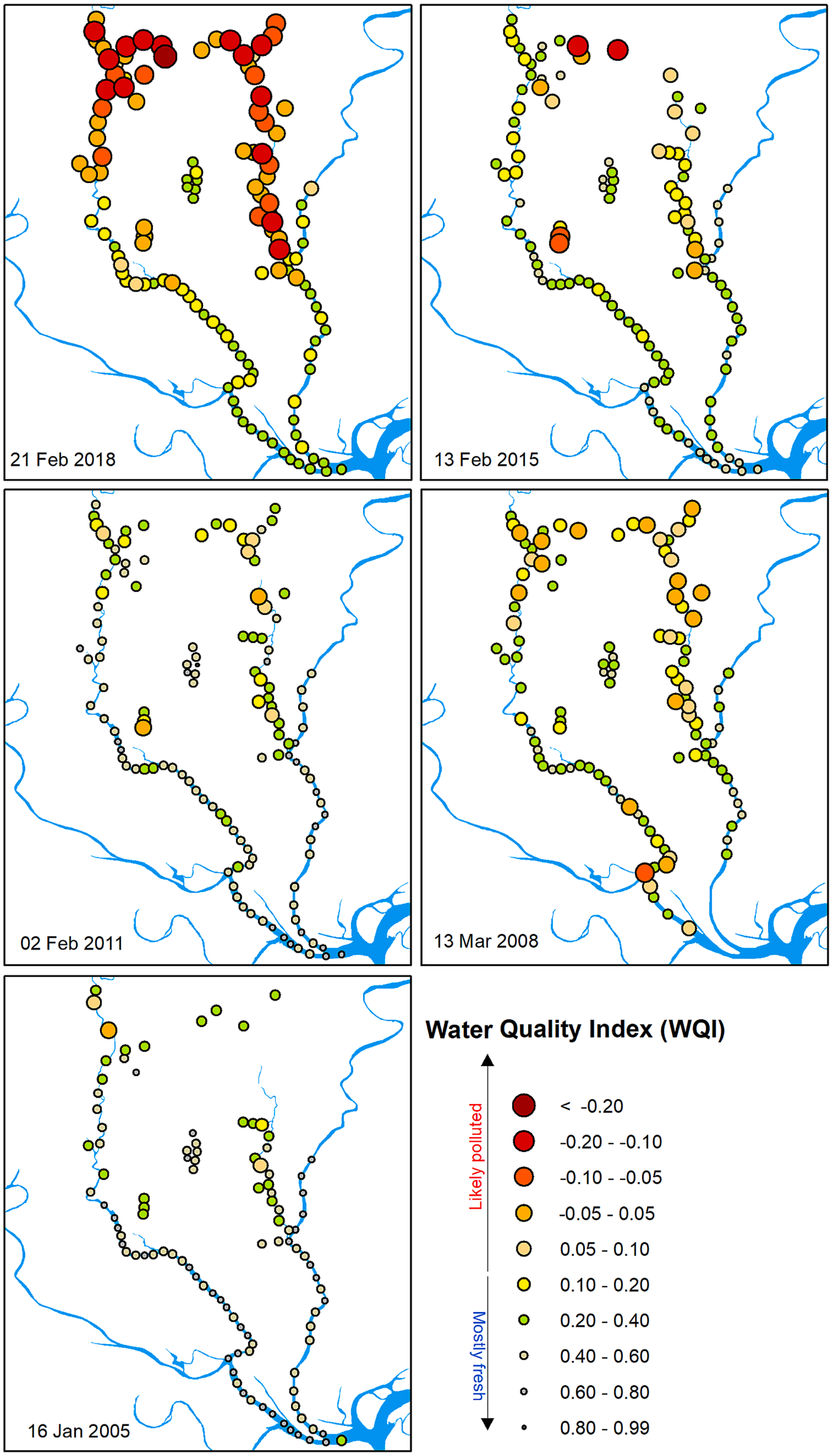

Fig. 9. Variations in WQI values over the dry season from 2005 to 2018.

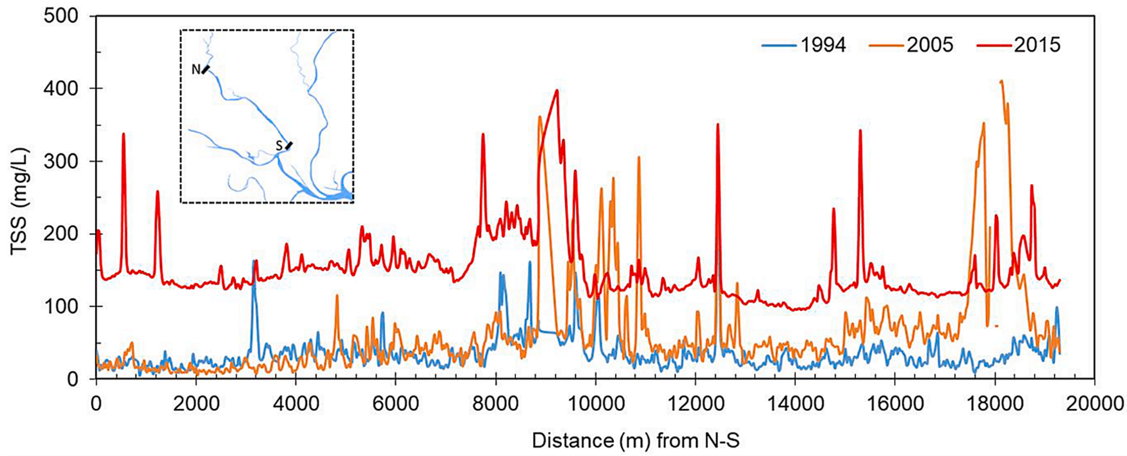

Fig. 10. Decadal variations of TSS in 1994, 2005 and 2015 along the Buriganga River. Inset map shows the river reach with respect to other rivers.

L, which is almost a one-third increase over six years. The variations in TSS values in the eastern and western sides do not differ significantly if the medians are considered, but variability is high in the eastern side (Figure S.4).

Dry season: Near negative to negative values were observed more frequently during the dry season. Figures 8 and 9 show that negative index values have become more common in recent years, particularly since 2011. The years 2005 and 2008 do not follow the previously described trend as closely, but please note that the data is from January and March of the relevant years, rather than February, when water pollution fluctuates significantly. During the rainy season, the pattern is similar in the western and eastern sides but the magnitude of change is significantly high in the eastern side.

Conversion of index values to TSS values and the boxplot (Figure S.5) indicates an increasing trend of the TSS values except for the year 2008. It also shows that the median TSS value around 140 mg/L and rose to around 330 mg/L in 2018. A similar pattern of change can be observed on the eastern and western sides but the magnitude of change is higher on western side though pollution concentration is high on eastern side.

Decadal variation

Water quality appears to change over time in all rivers surrounding Dhaka, and images from October 1994, 2005, and 2015 were chosen to study decadal trends. For decadal change, a sub-area consisting of a 20-km reach in south-west corner of the city, along the Buriganga River, is chosen, where the river is wide and deep. It was assumed that this should provide a clearer estimate of water quality than any other parts. The profiles in Figure 10 clearly shows a shift in the baseline from <50 mg/L to >150 mg/L in the TSS content between 2005 and 2015. This change, in fact, becomes apparent since 2011 and worsens over time.

Discussion

Water quality index (WQI)

Water quality from various aquatic settings have been studied extensively using satellite-derived multispectral data through mathematical models, based on band ratioing and regression models (Bonansea et al., 2015; Chowdhury et al., 2014; Griffin et al., 2018; Kutser, 2012). This requires in-situ data to develop the empirical models. On the contrary, index-based approach where theoretical understanding of the reflectance against land features is used to have qualitative to semi-quantitative insights, and often the index values are linked to observed field values to have deeper understanding (Prabhakara et al., 2015). Although there are a number of indices for waterbody delineation, none exists for water quality, particularly for inland waterbodies. In this study, a water quality index was implemented by augmenting an existing water index (Xu, 2006) in identifying temporal change in water quality in the rivers, encircling Dhaka megacity. The new, water quality index (WQI), integrated reflectance variability of Landsat-5 bands 1 to 3 (and equivalent wavelength of Landsat-8) and utilised the index value variation between near 0 and +1 where values close to 0 (both negative and positive) indicated polluted water, particularly when the depth of water is 1.5 m or more where reflectance difference for water depth between Landsat bands 1 and 3 is minimum (Lafon et al., 2002). Most of the river reaches in Dhaka are significantly wider and appear on Landsat images and the middle of the river is few meters deep even in the dry season. The values, in relation to observed data, converted to TSS provided a complying scenarios to understand spatio-temporal variation of water quality in Dhaka.

The proposed index will have application in most water quality attributes but empirical relationship will vary depending on the types of pollutants (e.g., turbidity, DOM, TSS), and the constants may also vary seasonally. However, the application of this index may not be suitable for mapping water quality in wetlands because the depth of water in most of the wetlands around Dhaka is less than a couple of meters.

Long term water quality trends

Analysis of Landsat data clearly showed a temporal change in the index values, which were frequently becoming smaller in the dry season (Figures 8 and 10). The pollution was very severe in the northeast corner, from which it spreaded to other sides of the river. Seasonal variation in water pollution was found year-round, with higher concentration in the northeast corner; however, in October and November, when the rivers receive a significant amount of water flow, TSS concentration become smaller. The spatial and temporal patterns of pollution levels occurred consistently, which had not been observed previously using field-based point measurements (Whitehead et al., 2018). All the analyses consistently found relatively higher levels of pollution in the rivers of northern and north-eastern (N & NE) sides of the city where rivers are relatively narrower and shallower. However, it is unlikely to be an artefact of the digital image processing as the extensive field-based measurements over few seasons in the same river reach by Whitehead et al. (2018) and spot sampling by Hoque et al. (2014) observed similar pollution patterns. Also, the retention time of pollutants in the N & NE reaches would be higher as the discharge rate are slower compared to the Buriganga (Hafiz et al., 2017).

The city's chronic deterioration of river water quality was noticeable on a decadal scale (e.g., Figure 10) and coincided with the city's rapid growth (Choe and Roberts, 2011). Most rivers, on an annual time scale, used to return to the background level by the end of the rainy season, when river flows were at their peak (Hafiz et al., 2017; Islam et al., 2015). Since 2011, the rivers remained highly polluted even in the rainy season, which is now occurring at every location of the rivers.

Rapid population growth, unplanned urbanisation, lack of sanitation infrastructures are leading to poor management of faecal sludge in Dhaka, causing 90% of it effectively ending up in the surrounding rivers (Peal et al., 2020). The capability and capacity of natural purification of anthropogenic pollution has been extensively studied since the birth of public health engineering (e.g., Cooper et al., 1919; Hipsey et al., 2008) but in the rapidly growing cities of global south, this capacity is exceeded (Subrata et al., 2014) and increasingly dwindling wetland and rivers around Dhaka (e.g., Sultana et al., 2009) may have reached to this level. This means limiting the input of pollutants and untreated industrial effluents and/or sewage to the rivers in Dhaka would be the most important approach to improving river water quality.

Conclusion

This study, though exploratory in nature, provided an approach for identifying water quality situation over space and time. Therefore, the outcome of the work would provide important insight for the restoration of river health and water quality in Dhaka. Previous studies addressing the water quality of rivers in Dhaka focused on the segment of a river but this study mapped significant spatial variability that may be used to guide execution and direction of future research. Also, the approach proposed in this work can be applied to any water quality investigation, particularly in an urban setting, as this is based on the theory of reflectance. Combining the approach developed here with a large amount of field data collected over several seasons would undoubtedly improve its utility. Given that the field data collected in 2011, results of this study should be interpreted with caution. The findings, on the other hand, revealed that the spatiotemporal pattern of water quality in Dhaka's rivers is deteriorating rapidly, which is consistent with how various stakeholders perceive it.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

We would like to thank Drs Faith Taylor, Harold Lovell and Mo Hoque for a discussion which help improve the study design and interpretation of the results. The USGS is sincerely acknowledged for making the Landsat data freely available. The authors are also grateful to Razia A. Chowdhury for in-situ TSS data, used to validate the WQI developed in this work.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envadv.2021.100097.

References

Bonansea, M., Ledesma, C., Rodríguez, C., Pinotti, L., Antunes, M.H., 2015. Effects of atmospheric correction of Landsat imagery on lake water clarity assessment. Adv. Sp. Res. 56, 2345–2355. https://doi.org/10.1016/J.ASR.2015.09.018.

Bonansea, M., Rodriguez, M.C., Pinotti, L., Ferrero, S., 2015. Using multi-temporal Landsat imagery and linear mixed models for assessing water quality parameters in Río Tercero reservoir (Argentina). Remote Sens. Environ. 158, 28–41. https://doi.org/10.1016/J.RSE.2014.10.032.

Campos, J.C., Sillero, N., Brito, J.C., 2012. Normalized difference water indexes have dissimilar performances in detecting seasonal and permanent water in the Sahara–Sahel transition zone. J. Hydrol. 438–446. https://doi.org/10.1016/J.JHYDROL.2012.07.042, 464–465.

Choe, K., Roberts, B., 2011. Competitive cities in the 21st century: Cluster-based local economic development. Mandaluyong City, Philippines.

Chowdhury, R.A., Rashid, T., Hoque, S., 2014. Assessing Surface Water Quality Using Landsat TM and In Situ Data: An Exploratory Analysis, pp. 301–318 in: Dewan, A., Corner, R. (Eds.), Dhaka Megacity: Geospatial Perspectives on Urbanisation, Environment and Health. Springer Netherlands, Dordrecht doi:10.1007/978-94-007-6735-5_16.

Cooper, A.E., Cooper, E.A., Heward, J.A., 1919. On the Self-Purification of Rivers and Streams. Biochem. J. 13, 345–367. https://doi.org/10.1042/bj0130345.

Corner, R.J., Dewan, A.M., Chakma, S., 2014. Monitoring and Prediction of Land-Use and Land-Cover (LULC) Change. In: Dewan, A., Corner, R. (Eds.). Springer Geography, Springer, Dordrecht, pp. 75–97.

Dewan, A.M., Corner, R., Hashizume, M., Ongee, E.T., 2013. Typhoid Fever and Its Association with Environmental Factors in the Dhaka Metropolitan Area of Bangladesh: A Spatial and Time-Series Approach. PLoS Negl. Trop. Dis. 7, e1998. https://doi.org/10.1371/journal.pntd.0001998.

Dewan, A.M., Yamaguchi, Y., 2009. Land use and land cover change in Greater Dhaka, Bangladesh: Using remote sensing to promote sustainable urbanization. Appl. Geogr. 29, 390–401. https://doi.org/10.1016/j.apgeog.2008.12.005.

Gao, J., 2009. Bathymetric mapping by means of remote sensing: Methods, accuracy and limitations. Prog. Phys. Geogr. 33, 103–116. https://doi.org/10.1177/0309133309105657.

Gholizadeh, M.H., Melesse, A.M., Reddi, L., 2016. A Comprehensive Review on Water Quality Parameters Estimation Using Remote Sensing Techniques. Sensors 16.

Goodin, D.G., Han, Luoheng, Fraser, R.N., Rundquist, D.C., Stebbins, W.A., Schalles, J.F., 1993. Analysis of suspended solids in water using remotely sensed high resolution derivative spectra. Photogramm. Eng. Remote Sens. 59, 505–510.

Griffin, C.G., Frey, K.E., Rogan, J., Holmes, R.M., 2011. Spatial and interannual variability of dissolved organic matter in the Kolyma River, East Siberia, observed using satellite imagery. J. Geophys. Res. Biogeosci. 116 https://doi.org/10.1029/2010JG001634.

Griffin, C.G., McClelland, J.W., Frey, K.E., Fiske, G., Holmes, R.M., 2018. Quantifying CDOM and DOC in major Arctic rivers during ice-free conditions using Landsat TM and ETM+ data. Remote Sens. Environ. 209, 395–409. https://doi.org/10.1016/j.rse.2018.02.060.

Hafiz, R.B., Rahman, A., Yunus, A., 2017. Simulation of Hydrodynamic Parameters of Dhaka Peripheral River System of Bangladesh.

Han, L., 1997. Spectral reflectance with varying suspended sediment concentrations in clear and algae-laden waters. Photogram. Eng. Remote Sens. 63, 701–705.

Hassan, M.M., Southworth, J., 2018. Analyzing Land Cover Change and Urban Growth Trajectories of the Mega-Urban Region of Dhaka Using Remotely Sensed Data and an Ensemble Classifier. Sustainability 10.

Geospatial, Hexagon, 2016. ERDAS IMAGINE, 2016.

Hipsey, M.R., Antenucci, J.P., Brookes, J.D., 2008. A generic, process-based model of microbial pollution in aquatic systems. Water Resour. Res. 44 https://doi.org/10.1029/2007WR006395.

Hoque, M.A., McArthur, J.M., Sikdar, P.K., Ball, J.D., Molla, T.N., 2014. Tracing recharge to aquifers beneath an Asian megacity with Cl/Br and stable isotopes: the example of Dhaka, Bangladesh. Hydrogeol. J. 22, 1549–1560. https://doi.org/10.1007/s10040-014-1155-8.

Islam, M.S., Uddin, M.K., Tareq, S.M., Shammi, M., Kamal, A.K.I., Sugano, T., Kurasaki, M., Saito, T., Tanaka, S., Kuramitz, H., 2015. Alteration of Water Pollution Level with the Seasonal Changes in Mean Daily Discharge in Three Main Rivers around Dhaka City, Bangladesh. Environments 2, 280–294. https://doi.org/10.3390/environments2030280.

Jupp, D.L.B., Mayo, K.K., Kuchler, D.A., Claasen, D.V.R., Kenchington, R.A., Guerin, P.R., 1985. Remote sensing for planning and managing the great barrier reef of Australia. Photogrammetria 40, 21–42. https://doi.org/10.1016/0031-8663(85)90043-2.

Karn, S.K., Harada, H., 2001. Surface Water Pollution in Three Urban Territories of Nepal, India, and Bangladesh. Environ. Manage. 28, 483–496. https://doi.org/10.1007/s002670010238.

Kloiber, S.M., Brezonik, P.L., Olmanson, L.G., Bauer, M.E., 2002. A procedure for regional lake water clarity assessment using Landsat multispectral data. Remote Sens. Environ. 82, 38–47. https://doi.org/10.1016/S0034-4257(02)00022-6.

Kutser, T., 2012. The possibility of using the Landsat image archive for monitoring long time trends in coloured dissolved organic matter concentration in lake waters. Remote Sens. Environ. 123, 334–338. https://doi.org/10.1016/J.RSE.2012.04.004.

Kutser, T., Pierson, D.C., Tranvik, L., Reinart, A., Sobek, S., Kallio, K., 2005. Using Satellite Remote Sensing to Estimate the Colored Dissolved Organic Matter Absorption Coefficient in Lakes. Ecosystems 8, 709–720.

Lafon, V., Froidefond, J., Lahet, F., Castaing, P., 2002. SPOT shallow water bathymetry of a moderately turbid tidal inlet based on field measurements. Remote Sens. Environ. 81 (1), 36–148. https://doi.org/10.1016/S0034-4257(01)00340-6.

Lathrop, R.G., 1992. Landsat Thematic Mapper monitoring of turbid inland water quality. Photogramm. Eng. Remote Sensing 58, 465–470.

Masek, J.G., Vermote, E.F., Saleous, N.E., Wolfe, R., Hall, F.G., Huemmrich, K.F., Gao, F., Kutler, J., Lim, T.-K., 2006. A Landsat surface reflectance dataset for North America, 1990-2000 IEEE Geosci. Remote Sens. Lett. 3, 68–72. https://doi.org/10.1109/LGRS.2005.857030.

Mitsch, W.J., Gosselink, J.G., 2000. The value of wetlands: importance of scale and landscape setting. Ecol. Econ. 35, 25–33. https://doi.org/10.1016/S0921-8009(00)00165-8.

Peal, A., Evans, B., Ahilan, S., Ban, R., Blackett, I., Hawkins, P., Schoebitz, L., Scott, R., Sleigh, A., Strande, L., Veses, O., 2020. Estimating Safely Managed Sanitation in

Urban Areas; Lessons Learned From a Global Implementation of Excreta-Flow Diagrams. Front. Environ. Sci. 8 (1) https://doi.org/10.3389/fenvs.2020.00001.
Prabhakara, K., Hively, W.D., McCarty, G.W., 2015. Evaluating the relationship between biomass, percent groundcover and remote sensing indices across six winter cover crop fields in Maryland, United States. Int. J. Appl. Earth Obs. Geoinf. 39, 88–102. https://doi.org/10.1016/J.JAG.2015.03.002.
Pramanik, B.K., Sarker, D.C., 2013. Evaluation of surface water quality of the Buriganga River. J. Water Reuse Desalin. 3, 160–168. https://doi.org/10.2166/wrd.2013.059.
Rahman, S., Hossain, F., 2008. Spatial assessment of water quality in Peripheral Rivers of Dhaka City for optimal relocation of water intake point. Water Resour. Manag. 22, 377–391. https://doi.org/10.1007/s11269-007-9167-y.
Sakamoto, M., Ahmed, T., Begum, S., Huq, H., 2019. Water Pollution and the Textile Industry in Bangladesh: Flawed Corporate Practices or Restrictive Opportunities? Sustainability 11. https://doi.org/10.3390/su11071951.
Schowengerdt, R.A., 2007. Remote sensing, models, and methods for image processing, 3rd ed. Academic Press, Amsterdam.
Subrata, P., Delwar, H., MNH, M., PLC, P., MK, S., 2014. water quality degradation Buriganga. Bangladesh J. Progress. Sci. Technol. 11, 85–88.
Sultana, M.S., Islam, G.M.T., Islam, Z., 2009. Pre- and Post-Urban Wetland Area in Dhaka City,Bangladesh: A Remote Sensing and GIS Analysis. J. Water Resour. Prot. 1, 414–421. https://doi.org/10.4236/jwarp.2009.16050.
Swain, R., Sahoo, B., 2017. Mapping of heavy metal pollution in river water at daily time-scale using spatio-temporal fusion of MODIS-aqua and Landsat satellite imageries. J. Environ. Manage. 192, 1–14. https://doi.org/10.1016/J.JENVMAN.2017.01.034.
Swapan, M.S.H., Zaman, A.U., Ahsan, T., Ahmed, F., 2017. Transforming Urban Dichotomies and Challenges of South Asian Megacities: Rethinking Sustainable Growth of Dhaka, Bangladesh. Urban Sci. 1.
UN, 2015. World Urbanization Prospects: The 2014 Revision. New York, USA.
Vermote, E., Justice, C., Claverie, M., Franch, B., 2016. Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. Remote Sens. Environ. 185, 46–56. https://doi.org/10.1016/J.RSE.2016.04.008.
Whitehead, P., Bussi, G., Hossain, M.A., Dolk, M., Das, P., Comber, S., Peters, R., Charles, K.J., Hope, R., Hossain, M.S., 2018. Restoring water quality in the polluted Turag-Tongi-Balu river system, Dhaka: Modelling nutrient and total coliform intervention strategies. Sci. Total Environ. 223–232. https://doi.org/10.1016/J.SCITOTENV.2018.03.038, 631–632.
Xu, H., 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int. J. Remote Sens. 27, 3025–3033. https://doi.org/10.1080/01431160600589179.
Bright, E. A., Rose, A. N., Urban, M. L., & McKee, J. J. (2017). *LandScan 2016* (2016 RI-). Oak Ridge National Laboratory SE - July 1, 2017. https://landscan.ornl.gov/.