



Assessing the impact of land use and land cover on river water quality using water quality index and remote sensing techniques

Md Ataul Gani · Abdul Majed Sajib · Md Abubakkor Siddik ·
Md Moniruzzaman

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Abstract The impact of land use on water quality is becoming a global concern due to the increasing demand for freshwater. This study aimed to assess the effects of land use and land cover (LULC) on the surface water quality of the Buriganga, Dhaleshwari, Meghna, and Padma river system in Bangladesh. To determine the state of water, water samples were collected from twelve locations in the Buriganga, Dhaleshwari, Meghna, and

Padma rivers during the winter season of 2015 and collected samples were analysed for seven water quality indicators: pH, temperature (Temp.), conductivity (Cond.), dissolved oxygen (DO), biological oxygen demand (BOD), nitrate nitrogen (NO₃-N), and soluble reactive phosphorus (SRP) for assessing water quality (WQ). Additionally, same-period satellite imagery (Landsat-8) was utilised to classify the LULC using the object-based image analysis (OBIA) technique. The overall accuracy assessment and kappa co-efficient value of post-classified images were 92% and 0.89, respectively. In this research, the root mean squared water quality index (RMS-WQI) model was used to determine the WQ status, and satellite imagery was utilised to classify LULC types. Most of the WQs were found within the ECR guideline level for surface water. The RMS-WQI result showed that the “fair” status of water quality found in all sampling sites ranges from 66.50 to 79.08, and the water quality is satisfactory. Four types of LULC were categorised in the study area mainly comprised of agricultural land (37.33%), followed by built-up area (24.76%), vegetation (9.5%), and water bodies (28.41%). Finally, the Principal component analysis (PCA) techniques were used to find out significant WQ indicators and the correlation matrix revealed that WQ had a substantial positive correlation with agricultural land ($r=0.68$, $P<0.01$) and a significant negative association with the built-up area ($r=-0.94$, $P<0.01$). To the best of the authors’ knowledge, this is the first attempt in Bangladesh to assess the impact of LULC on the water quality along the longitudinal gradient of a vast river

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M. Gani
Department of Botany, Jagannath University, Dhaka-1100,
Bangladesh
e-mail: gmdataul@bot.jnu.ac.bd

A. M. Sajib · Md Moniruzzaman (✉)
Department of Geography and Environment, Jagannath
University, Dhaka -1100, Bangladesh
e-mail: mdmoniruzzaman_bd@yahoo.com; m.zaman@
geography.jnu.ac.bd

A. M. Sajib
e-mail: majed.sajib@gmail.com; m140602039
@geography.jnu.ac.bd

M. Siddik
Department of Land Record and Transformation,
Patuakhali Science and Technology University,
Dumki Patuakhali-8602, Bangladesh
e-mail: masiddik@pstu.ac.bd
e-mail: masiddik@pstu.ac.bd

system. Hence, we believe that the findings of this study can support planners and environmentalists to plan and design landscapes and protect the river environment.

Keywords Unweighted Water Quality Index · RMS-WQI · Surface water · Land use and land cover · OBIA · Remote sensing · Bangladesh

Introduction

Surface water quality is an essential resource for humans, and aquatic life depends on it (Akter et al., 2018; Parween et al., 2022). Therefore, sustainable management of surface water quality has become a global priority (Asha et al., 2020; Uddin et al., 2018; Sultana et al., 2022). Rivers in the world are one of the primary sources of surface water, and they play pivotal roles in ensuring water for drinking, fisheries management, transportation, recreation, power generation, irrigation, and protecting ecosystems worldwide (Edokpayi et al., 2017; Ullah et al., 2018). However, anthropogenic activities, such as the discharge of massive volumes of ineffectively treated or untreated effluent into surface water, contaminate freshwater supplies and limit access to the world's finite water resources (Uddin et al., 2018; UNESCO, 2021). Researchers projected that climate change would decrease water quality (Cisneros et al., 2014; Delpla et al., 2009). Many developed countries, including Australia, Ireland, Canada, and the UK, have adopted various policies and guidelines to monitor surface water quality for effective water resource management. Still, they need help putting these frameworks in place due to limited resources (Uddin et al., 2020a; Uddin et al., 2020b). On the other hand, approximately three million people (90% of whom are children under the age of five) die every year from waterborne diseases in developing nations, according to the World Health Organization (WHO, 2018) (Dede et al., 2013). Recently, several researchers explained that there is a good relationship between land use and land cover (LULC) and surface water quality (Attua et al., 2014; Bonansea et al., 2021; Chen et al., 2016; Wilson, 2015; Wilson & Weng, 2010; Zhang et al., 2022). LULC results from human and natural activities directly impacting riparian ecosystem services (Tahiru et al., 2020). However, its association with the water quality may vary

depending on its spatial scales and patterns (Wu and Lu, 2021). LULC may affect the different physical, chemical, and biological processes of the watershed. As a result, the degradation of surface water quality is among the most severe effects of LULC change. Forest land cover, for example, plays a vital role in maintaining water purity, whereas urban and croplands (with high fertiliser use) degrade water quality (Liu et al., 2016; Mello et al., 2018; Wang & Zhang, 2018; Xiao et al., 2016). The availability of accessible freshwater in volume and quality has declined dramatically due to improper land management practices over the years (Li et al., 2008). Deteriorated water causes ecological imbalances in the surface water body and puts livelihoods and economic viability at risk (Liu et al., 2012). Researchers identified that agriculture, deforestation, and rapid urbanisation are the three main factors affecting surface water quality (Muhammaed et al., 2022). Therefore, monitoring and reporting surface water quality and identifying its relation to LULC have become crucial issues.

Generally, water quality analysis is mandatory for monitoring spatio-temporal variations in physical, biological, and chemical indicators of water (Fashae et al., 2019). Again, the management and monitoring of water quality require the collection and laboratory measurement of large water quality datasets, which are difficult to interpret and time-consuming (Uddin et al., 2022b; Uddin et al., 2022c; Singh et al., 2004). However, this kind of monitoring has some limitations regarding representing the overall scenario (Uddin et al., 2022a). Recently, the water quality index (WQI) models have been widely used for assessing water quality (surface and ground) because this technique is more straightforward to compare than the typical model (Aljanabi et al., 2021). The WQI models convert a series of water quality information into a unitless numerical form that illustrates the complete water quality scenario (Sutadian et al., 2016). Numerous WQI models have been developed by a variety of nations and organisations to achieve specific aims. But those techniques are criticised due to the model uncertainty, reliability, transparency, and sensitivity (Uddin et al., 2022d; Uddin et al., 2022e; Uddin et al., 2023a). Generally, the WQI models are a sum of four steps: (i) water quality indicators selection, (ii) sub-index process, (iii) weighting of water quality indicators; and (iv) aggregation function (Gupta & Gupta, 2021; Uddin et al., 2022a). A comprehensive

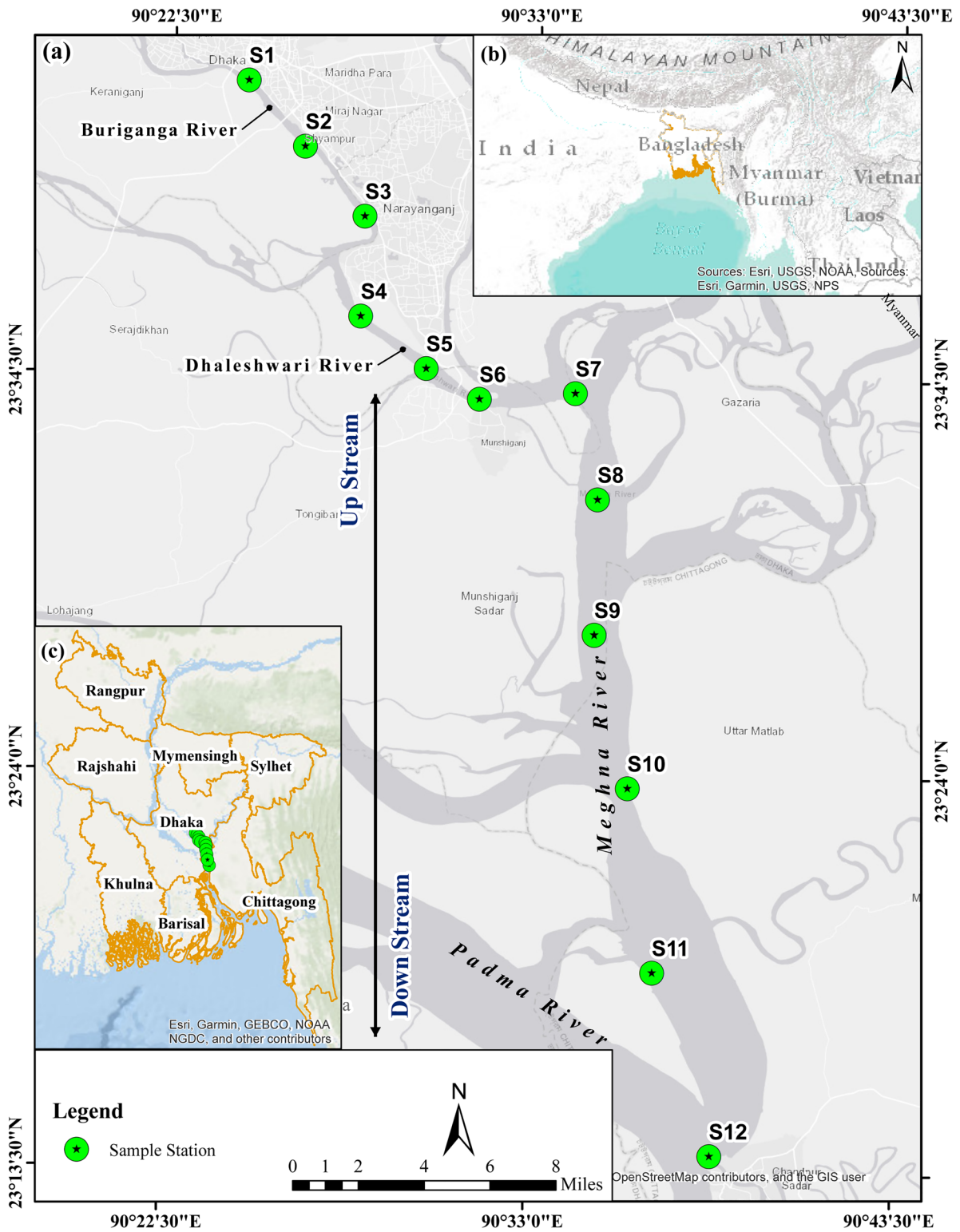
review of different WQI models, including their pros and cons, can be found in Uddin et al., 2021. Since the last few decades, tools and approaches based on Geographical Information Science (GIS) have been widely utilised to visualise the spatio-temporal distribution of water quality status (Uddin et al., 2022e; Uddin et al., 2023b; Uddin et al., 2023c; Kumar et al., 2019; Ram et al., 2021; Sultana & Dewan, 2021; Chai et al., 2021). In addition, multivariate statistical techniques such as principal component analysis (PCA) are employed to identify the crucial WQ indicators. PCA is widely used in water quality research for selecting significant WQ indicators (Akhtar et al., 2021; Fu et al., 2022; Yang et al., 2020).

LULC change monitoring is essential for socio-economic development and ecosystem change (Kimwatu et al., 2021; Talukdar et al., 2022). The traditional way of doing a LULC survey is difficult and takes a long time. However, remote sensing incorporating GIS technology makes the process simpler for the researcher (Tewabe & Fentahun, 2020). Numerous free satellite images, such as Landsat, Sentinel, etc., are routinely utilised for LULC monitoring. Although, varying resolutions of satellite images, classification methods, diverse computer software, and human error during the selection of training samples made the LULC classification system complex (Mohan et al., 2021). In addition, classification systems, e.g., sub-pixel, knowledge-based, contextual-based, supervised, unsupervised, object-based image analysis (OBIA), and hybrid-based methods still need to be fully computerised and have certain limitations (Quader, 2019). Again, one of the significant tasks for LULC classification is accuracy assessment (Das et al., 2021; Makinde & Oyelade, 2020). The error matrix, confusion matrix, and kappa-coefficient are frequently utilised for image classification accuracy assessment (Petropoulos et al., 2015).

Many studies have been conducted globally to investigate the impact of various LULC types on the quality of surface water, including urban, cropland, forest, and other forms of land use/cover (Tahiru et al., 2020; Pana et al., 2022; Bonansea et al., 2021; Zhang et al., 2022; Chen et al., 2016; Wilson, 2015; Kumar et al., 2019; Sultana & Dewan, 2021; Chotpantararat and Boonkaewwan, 2018; Petropoulos et al., 2015; Attua et al., 2014; Wilson & Weng 2010). Pana et al. (2022) identified land use impact on surface water quality in the Suquia river basin in Argentina. Again, Kang et al.

(2010) found a positive association between surface water pollution (nitrogen, phosphorus, and ammonia) and the urban area in the Yeongsan river basin, South Korea. They found a negative association between water pollution, forest land, and grassland cover. Tong and Chen (2002) discovered a significantly positive connection between different indicators (phosphorus, nitrogen, and faecal coliform) of surface water and land use. According to Liu et al. (2016), urban development increases the amount of built-up land and impermeable coatings, which disrupts the drainage process and contributes to higher water contamination. Similarly, Bullard (1966) determined that urban surface water contamination results from urban stream loads containing a lot of sand, dust, soot particles, and oil-washed off buildings, roads, footpaths, and other pavements.

In the context of Bangladesh, particularly in Dhaka city and peripheral areas, rapid unplanned urbanisation and industrial development and their associated activities, i.e., untreated sewage, domestic waste, and industrial waste, have been deteriorating the surface water quality (Hasan et al., 2019; Nahar et al., 2021; Tania et al., 2021). Again, climate change and natural and artificial disasters are increasing the pressure on surface water (Malak et al., 2020; Quader et al., 2021). Several studies were carried out to assess the water quality of the urban rivers in the country and their spatio-temporal distribution, such as the Buriganga River (Islam et al., 2019; Kamal et al., 1999; Pramanik & Sarker, 2013; Zerín et al., 2017), Dhaleshwari River (Hasan et al., 2020; Real et al., 2017), Shitalakhya River (Kabir et al., 2020), Turag River (Rahman et al., 2021a), and Meghna River (Bhuyan et al., 2017; Rima et al., 2020). But, none of them focuses on the impact of LULC on water quality. Therefore, this study aimed to assess the impact of LULC on the quality of surface water in the Buriganga, Dhaleshwari, Meghna, and Padma river system in Bangladesh. The specific objectives were (i) to identify the water quality status in a longitudinal gradient of the Buriganga, Dhaleshwari, Meghna, and Padma rivers system; and (ii) to explore the relationship between LULC and water quality of the studied river system. Thus, the association between LULC and surface water quality seems to have significant conceptual and managerial implications. It provides several thoughts regarding the safeguarding of surface water bodies. Subsequently,



◀**Fig. 1** The inserted map (a) illustrates the water sample location (denoted in green colour point) overlain in grey canvas base world map. There are a total of twelve (12) sampling locations. The water sample was collected from the Buriganga, Dhaleshwari, Meghna, and Padma rivers; the inserted map (b) shows the location of Bangladesh (denoted in orange colour) three sides, east, west, and north bordered by India, a short border with Myanmar in the southeast, and the south bordered by the Bay of Bengal. Finally, the insert map (c) shows the water sample locations in the divisional boundary of Bangladesh

it helps supply water in many sectors, including potable water, agricultural, industrial, municipal, and recreational uses. It will help policymakers and watershed managers to take proactive steps in future land use development.

Materials and methods

Overview of the research area

Over the last forty years, extreme pollution incidents have happened in the rivers surrounding Dhaka (Uddin & Jeong, 2021). Dhaka is known globally as a metropolis with chaotic land use and urban development, as well as one of the most vulnerable cities due to the increasing impact of natural disasters (Rahman et al., 2018; Malak et al., 2022). In Dhaka's outlying waterways, water quality deteriorates rapidly due to widespread pollution-related growth, i.e., urbanisation and industrialisation (Nargis et al., 2021). The study area comprises four main urban rivers in Dhaka city and its peripheries: the Buriganga, Dhaleshwari, Meghna, and Padma rivers (Fig. 2). Among them, the Buriganga identifies primary pollution sources in Dhaka (Bashar & Fung, 2020) and main receptors of industrial effluent (Hossain et al., 2021), ranked top among the world's most contaminated waterways (Uddin et al., 2016; Hossain et al., 2021; Kamal et al., 1999). In 2009, the Bangladesh government declared the river an ecologically critical area (ECA) (DoE, 2015). Other peripheral rivers in the city, such as the Dhaleshwari and Padma rivers, also receive pollutants from industrial discharges and domestic sewage (UNDP, 2010), although these rivers contribute to the socioeconomic growth of the region (Hasan et al., 2020). In a more downstream part,

the Meghna river merged with the Padma River in the Chandpur district (one of the largest rivers in the north-western part of Bangladesh). The Meghna river, Bangladesh's most significant and broadest river, is vital to (e.g., navigation, irrigation, fish spawning and shelter, industrial usage, and drinking water sources) millions of people living nearby (Rahman et al., 2021b). The river basin area is dominated by agricultural and industrial activities, which may impact the river water quality.

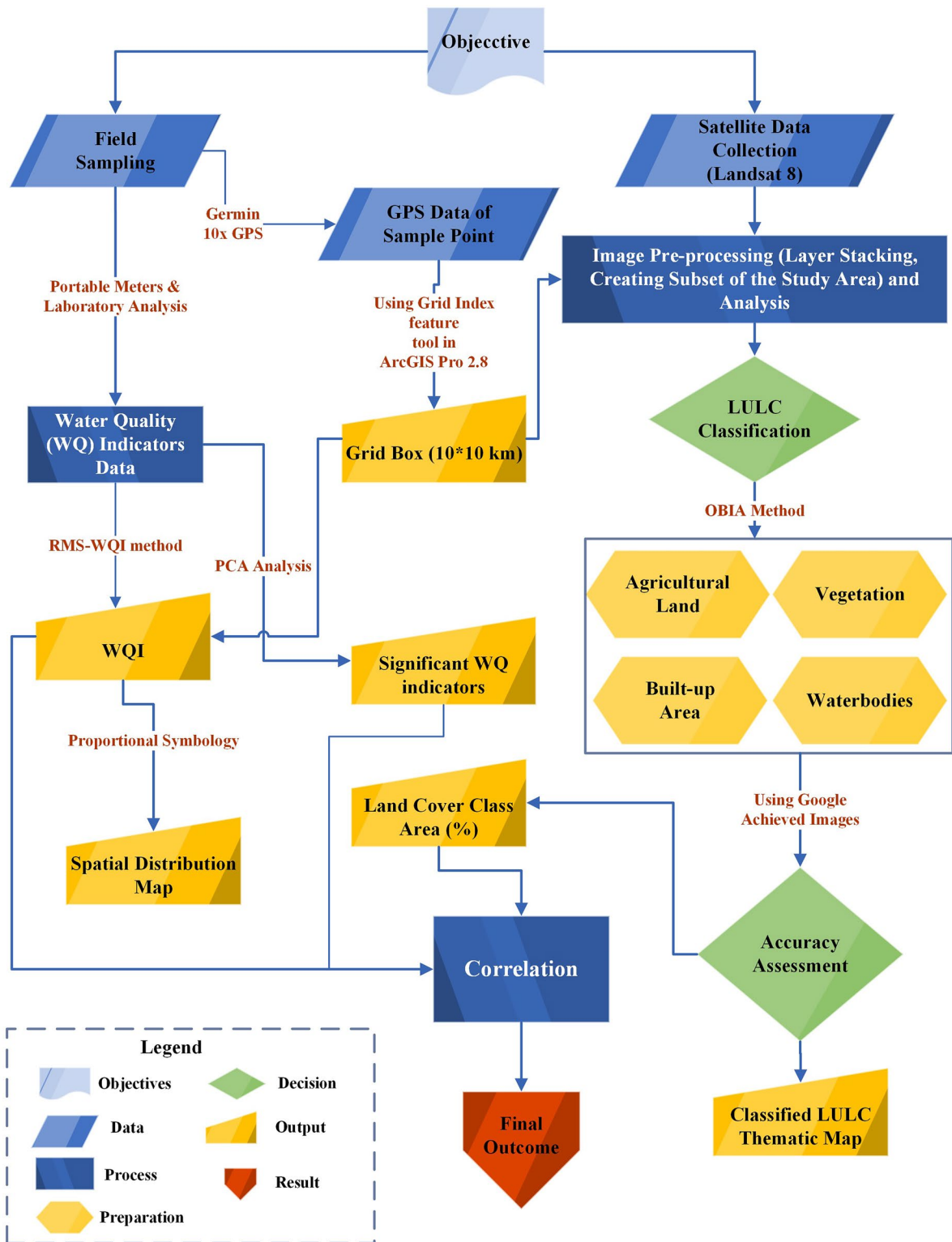
Research design

The methodology used to conduct this research includes field data collection, laboratory analysis, and satellite imagery analysis. Finally, a correlation matrix was developed to show the influence of the LULC on WQI (Fig. 2).

Water sample collection and laboratory analysis

A total of 12 water samples were collected from twelve sampling locations during the winter season (Fig. 1). The sampling sites are located from upstream to downstream, representing the longitudinal gradient of the rivers and the diversity of LULC types and pollution pressures. The sampling sites were marked as S1 to S12 along the longitudinal gradient of the rivers (Fig. 1). Sampling sites, their local correspondence names, and coordinates are presented in Table 1.

Water samples were directly collected from the middle of the river using a rented launch (water vehicle). A Schindler sampler (5-L capacity, 50 cm long) was used to collect integrated surface water samples. After collection, samples were kept cool in an ice box and later transported to the research laboratory in the department of Botany and the department of Geography and Environment, Jagannath University. In situ, measurements of water temperature (mercury thermometer), pH (HI-96107, Hanna), dissolved oxygen (DO, DO200A-YSI, USA), and conductivity (EC 300-YSI, USA) were done using portable meters. Biochemical oxygen demand (BOD) was measured using BOD bottles and kept in the dark for five days. After reaching the laboratory, all the samples were filtered through Whatman GF/F filter paper for total suspended solids (TSS) and chemical analysis. The concentrations of NO₃-N and soluble reactive phosphorus (SRP) in the filtered water sample were



◀**Fig. 2** Flowchart of applied methods. Different shapes are used in this figure to denote objective, data, process, preparation, decision, output, and result. (LULC, land use/land cover; RMS-WQI, Root Mean Squared-Water Quality Index; OBIA, object-based image analysis)

determined following the methods of Müller and Wiederman (1995), and Murphy and Riley (1962), respectively. Analytical methods for seven investigated water quality indicators are summarised in Table 2, and a flow chart of the research methodology is presented in Fig. 2.

Assessing water quality using the RMS-WQI model

The water quality index is a popular method for assessing surface water quality and employs aggregation techniques to convert extensive water quality data into a single index or value (Uddin et al., 2023c; Yan et al., 2022). The root mean squared water quality index (RMS-WQI) model was utilised to assess the water quality of the Buriganga, Dhaleshwari,

Meghna, and Padma rivers in this research. One of the advantages of this method is that it produces lower uncertainties (Uddin et al., 2023a). Details of the RMS-WQI model can be found in Uddin et al., 2022c. The RMS-WQI model was calculated in four steps, which are detailed below.

Selecting water quality indicators

The first step of WQI model development is water quality indicator selection. Indicator selection considers expert opinions, data availability, and environmental significance (Uddin et al., 2017; Abed et al., 2022). During the present study, water temperature, pH, DO, conductivity, BOD, TSS, NO₃-N, and SRP were included in a mathematical equation to determine the water quality. The physicochemical indicators were selected based on the inland surface water regulation of the Environmental Conservative Rules (ECR), (1997). Additionally, NO₃-N and SRP were selected, which are essential indicators for assessing the water quality of the rivers in Bangladesh (Zerin et al., 2017).

Table 1 Sampling sites, location name, and coordinates of the study area of the Buriganga, Dhaleshwari, Meghna, and Padma river system in Bangladesh

Sampling site	Location name	Latitude (N)	Longitude (E)	Name of the river
S1	Sadarghat	23° 42' 15.5"	90° 24' 36.3"	Buriganga
S2	Postogola ecopark	23° 40' 57.4"	90° 25' 53.8"	Buriganga
S3	Fotullah	23° 38' 01.3"	90° 27' 54.2"	Buriganga
S4	Nabinagar bazar	23° 36' 44.5"	90° 27' 25.1"	Dhaleshwari
S5	Muktarpur	23° 35' 36.0"	90° 28' 32.8"	Dhaleshwari
S6	Ismanirar char	23° 33' 53.3"	90° 31' 24.9"	Dhaleshwari
S7	Gazaria	23° 33' 59.4"	90° 33' 04.7"	Meghna
S8	Daulatpur	23° 33' 39.0"	90° 34' 32.0"	Meghna
S9	Shatnol	23° 30' 32.1"	90° 34' 38.9"	Meghna
S10	Mohonpur	23° 23' 40.6"	90° 35' 49.1"	Meghna
S11	Ekhlaspur	23° 18' 49.0"	90° 30' 57.5"	Meghna
S12	Chandpur	23° 13' 58.5"	90° 38' 19.5"	Padma

Table 2 Physico-chemical indicators of river water and analytical methods

Water quality indicators	Abbreviation	Unit	Analytical instruments/method
pH		–	HI-96107, Hanna
Dissolve oxygen	DO	mg/l	DO, DO200A-YSI, USA
Biological oxygen demand	BOD ₅	mg/l	Laboratory Analysis
Conductivity	Cond	µS/cm	EC 300-YSI, USA
Soluble reactive phosphorus	SRP	mg/l	Murphy and Riley (1962)
Nitrate-nitrogen	NO ₃ -N	mg/l	Müller and Wiederman (1995)
Water temperature	Temp	°C	Mercury thermometer

Table 3 Sub-indexing equations for the WQ indicators used in this study

WQ indicator	Conditions	Sub-index equation
pH	(i) If, pH < 6.5	$SI = (SI_u - SI_l) - \frac{(WQ_m - STD_l)}{(STD_u - STD_l)} \times SI_{u(1)}$ where SI_u and SI_l are the lower and upper limits of SI values (0 and 100, respectively), STD_l and STD_u are the lower and upper reference values, and WQ_m is the measured water quality indicator value
	(ii) If pH ≥ 6.5	0.0
DO	(i) If, DO < 6.0	Equation (1)
	(ii) If, DO ≥ 6.0	0.0
BOD ₅	(i) If, BOD ₅ < 2.0	Equation (1)
	(ii) If, BOD ₅ ≥ 2.0	0.0
Cond	(i) If, Cond. < 2250	Equation (1)
	(ii) If, Cond. ≥ 2250	0.0
SRP	(i) If, SRP < 6.0	Equation (1)
	(ii) If, SRP ≥ 6.0	0.0
NO ₃ -N	(i) If, NO ₃ -N < 10.0	Equation (1)
	(ii) If, NO ₃ -N ≥ 10.0	0.0
Temp	(i) Temp. ≤ 25	100
	(ii) Temp. > 25	0.0

Sub-index (SI) generation

Sub-indexing transforms all WQ indicators into a common number to calculate the WQI calculation, which ranges from 0 (poor water quality) to 100 (excellent water quality) (Uddin et al., 2023a; 2023d). The sub-index (SI) value will score 100 if the WQ indicator falls between guideline values; otherwise, it will score 0. In this regard, ECR surface water quality regulation values (ECR, 1997) were used to calculate the SI. The utilised sub-index equations are summarised in Table 3.

Obtaining indicators weight values

Typically, an indicator weight value is calculated based on the significance of an indicator or reference regulation of water quality (Uddin et al., 2023b). Nonetheless, the RMS-WQI model is an unweighted WQI model. Therefore, this index does not require a weight value for assessing the final value (Uddin et al., 2023c).

Aggregation formula

The present study applied the following equation to calculate the index scores of the Buriganga,

Dhaleshwari, Meghna, and Padma rivers. The RMS-WQI calculation process details are attached in Supplementary Tables 1a and 1b. The aggregation formula is as follows:

$$RMS - WQI = \sqrt{\frac{1}{n} \sum_{i=1}^n SI^2} \tag{2}$$

where n denotes the number of water quality indicators and SI is the sub-index value of the i th indicator. The final score was evaluated based on the classification scheme provided in Table 4. More information on the classification scheme can be found in Uddin et al., 2023b).

Geospatial data analysis

In the geospatial data analysis part, we established LULC and spatial distribution maps of RMS-WQI of the study area. The grid box method was used for each sample location to develop AOI (Area of Interest). Using the Grid index feature tool in ArcGIS Pro 2.8, we created a 10*10 km grid box because it was enough to cover the investigated river channel/s. The grid index method is a pre-set division index in which a region is divided into rectangular grids to reflect a predefined spatial area (ESRI, 2023a). The grid

Table 4 Classification scheme of the RMS-WQI index (According to Uddin et al., 2022a)

No. of class	WQI class	WQI class value range
1	Good	80–100
2	Fair	50–79
3	Marginal	30–49
4	Poor	0–29

object’s position encompasses a portion of the area within the grid’s limits, and this item is part of the grid. The size of the grids is determined by the object being examined (Nigmatov et al., 2022). Total eight grid box is created which named as A1, B1, B2, C1, D1, E1, F1, and F2 (Fig. 6).

Land use and land cover (LULC) classification

Remotely sensed, multi-temporal satellite data from Landsat series 8 (Thermal Infra-Scanner (TIRS)/ Operational Land Imager (OLI)) were used as primary inputs to quantify the 2015 land cover area. The satellite image was obtained on 28 January 2015 from the United States Geological Survey, Earth Observation and Science Center (USGS-EROS) website (<https://earthexplorer.usgs.gov/>). The raster image was processed through ArcGIS Pro 2.8 software (image pre-processing including geometric and radiometric correction, grid-box clipping, mapping, and analysis). For the LULC classification, we used the object-based image analysis (OBIA) method in Trimble eCognition software (Developer version 9.0). The OBIA method is applied due to the advantages over the classification (Ahmed et al., 2020) and the recognition of good classification results (Quader, 2019). Details of OBIA techniques can be found in Zaki et al. (2022). The image was spatially referenced

in the Universal Transverse Mercator (UTM) projection system (zone 46 north) with the World Geodetic System (WGS) 1984 as the datum. The details of the satellite image are summarised in Table 5.

LULC classification accuracy assessment

Accuracy assessment methods are utilised to validate the classification accuracy of classified maps. A wide variety of accuracy assessment techniques are described in remote sensing literature; among them, the error matrix is widely used to calculate the accuracy of LULC classification (Nasir et al., 2022). Error matrixes define errors in LULC map classification caused by image pixels in one class being allocated to another (Foody, 2008). The error matrix computes the user, producer, overall accuracy, and the kappa statistics, which helps to rate the classification. Details of user, producer, overall accuracy, and kappa coefficient can be found in Chughtai et al., 2021. Over 100 reference pixels were chosen for the error matrix development using stratified random sampling in ArcGIS Pro 2.8. Stratified random sampling is a widely used tool for accuracy assessment sampling (Sajib & Moniruzzaman, 2021). Details of stratified random sampling can be found in Stehman and Foody (2019) and kappa value interpretation classification (rating criteria) can be found in Islami et al. (2022). The following equations are utilised for the calculated user (Eq. 3), producer (Eq. 4), overall accuracy (Eq. 5), and kappa coefficient (Eq. 6).

$$UA = \frac{X_{ii}}{X_{irow}} \tag{3}$$

$$PA = \frac{X_{ii}}{X_{icol}} \tag{4}$$

Table 5 Details of satellite data used for land cover map preparation

Satellite/sensor	Date acquired	Path/row	Cloud cover (%)	Spatial resolution (m)	Band considered with spectral resolution (µm)
LANDSAT-8 OLI/TIRS	28 January 2015	137/44	.01	30	0.45–0.51 (blue)
				30	0.53–0.59 (green)
				30	0.64–0.67 (red)
				30	0.85–0.88 (NIR)

$$OA = \frac{\sum_{i=1}^r X_{ii}}{N} \tag{5}$$

$$K_c = \frac{N \sum_{i=1}^r (X_{ii}) - \sum_{i=1}^r (X_{icol} * X_{irow})}{N^2 - \sum_{i=1}^r (X_{icol} * X_{irow})} \tag{6}$$

where r is the number of rows in the matrix, N is the total number of observations, X_{ii} is the correctly classified pixel numbers, and X_{icol} and X_{irow} are the column and row total, respectively.

Spatial distribution mapping

The spatial variation of water quality indicators and the RMS-WQI index was visualised using proportional symbology through ArcGIS Pro computer software (version 2.8). It illustrates the relative differences among the features based on quantities (ESRI, 2023b). Details about proportional symbol mapping can be found in Tanimura et al. (2006) and Gao et al. (2019).

Statistical analysis

Statistical analysis was applied to determine the impact of LULC types on water quality. First, for screening significant physicochemical factors in the study area, PCA was performed using Primer v6 (Clarke & Gorley, 2006). After that, R version 4.2.1 (R core Team, 2021) was used to correlate the selected physicochemical factors, WQI value, and land use types (%). Prior to PCA, all the indicators were transformed $\log(x + 1)$ except water temperature and pH, which were standardised.

Table 6 Statistical summary of water quality indicators in Buriganga, Dhaleshwari, Meghna, and Padma rivers

WQ indicators	Mean	Max	Min	SD	Reference value (ECR, 1997)
pH	7.917	8.4	6.1	0.592	6.5
Temp	24.25	26	22	1.055	25
Cond	655.5	1518	265	354.8	2250
DO	4.955	6.69	2.77	1.026	6
BOD ₅	0.828	1.64	0.34	0.391	2
SRP	0.314	0.94	0	0.376	6
NO ₃ -N	0.374	0.715	0.179	0.156	10

Results

Descriptive statistics of water indicators

General statistical calculations such as mean, maximum, minimum, and standard deviation for studied water quality indicators, along with reference values, are provided in Table 6, while Fig. 3 illustrates the variation of water quality indicators in different sampling sites. In the sampling site, the highest (8.40) pH value was recorded at sampling site S6 and the lowest (6.10) value at sampling site S1. Additionally, 80% of sampling sites (10 out of 12) are found alkaline (8.00–8.40), which surpasses the guideline value and indicates the presence of CO₃²⁻, Ca²⁺, and Mg²⁺ in the river system (Billah et al., 2016). Again, 90% of the sampling sites’ surface water temperature was found within guideline values, whereas conductivity was found in the range of the guideline limit.

In the study area, dissolved oxygen (DO) levels range between 2.77 and 6.69 mg/L with a mean value of 4.86 ± 1.11 mg/L, and the majority are within the reference value, except sampling site S9. DO play an active role in the river water quality system and its influence by the photosynthesis process (Dordoni et al., 2022). According to ECR (1997), the threshold value for BOD₅ is 2.00 mg/L for river ecosystems, and in this study, BOD₅ is within the threshold limit. Both NO₃-N and SRP concentrations were found in the reference value limit range.

Assessment of water quality using RMS-WQI

The water quality status of Buriganga, Dhaleshwari, Meghna, and Padma rivers were classified using the RMS-WQI model, and the calculated score of this model for each sampling site was visualised in Fig. 4. In the present study, the “fair” status of water quality found in all sampling sites which ranges from 66.50 to 79.08. This result indicated that a few indicators exceed the reference value. The highest WQI score (79.08) was found for sampling station S12, where the river system flows downward, and the lowest WQI score (66.50) was calculated for sampling station S11. Additionally, Fig. 5 presents the spatial–temporal distribution of the calculated RMS-WQI score at each monitoring site of the study area. This distribution revealed that the WQ score is high in the downstream and low in the upstream. RMS-WQI followed the

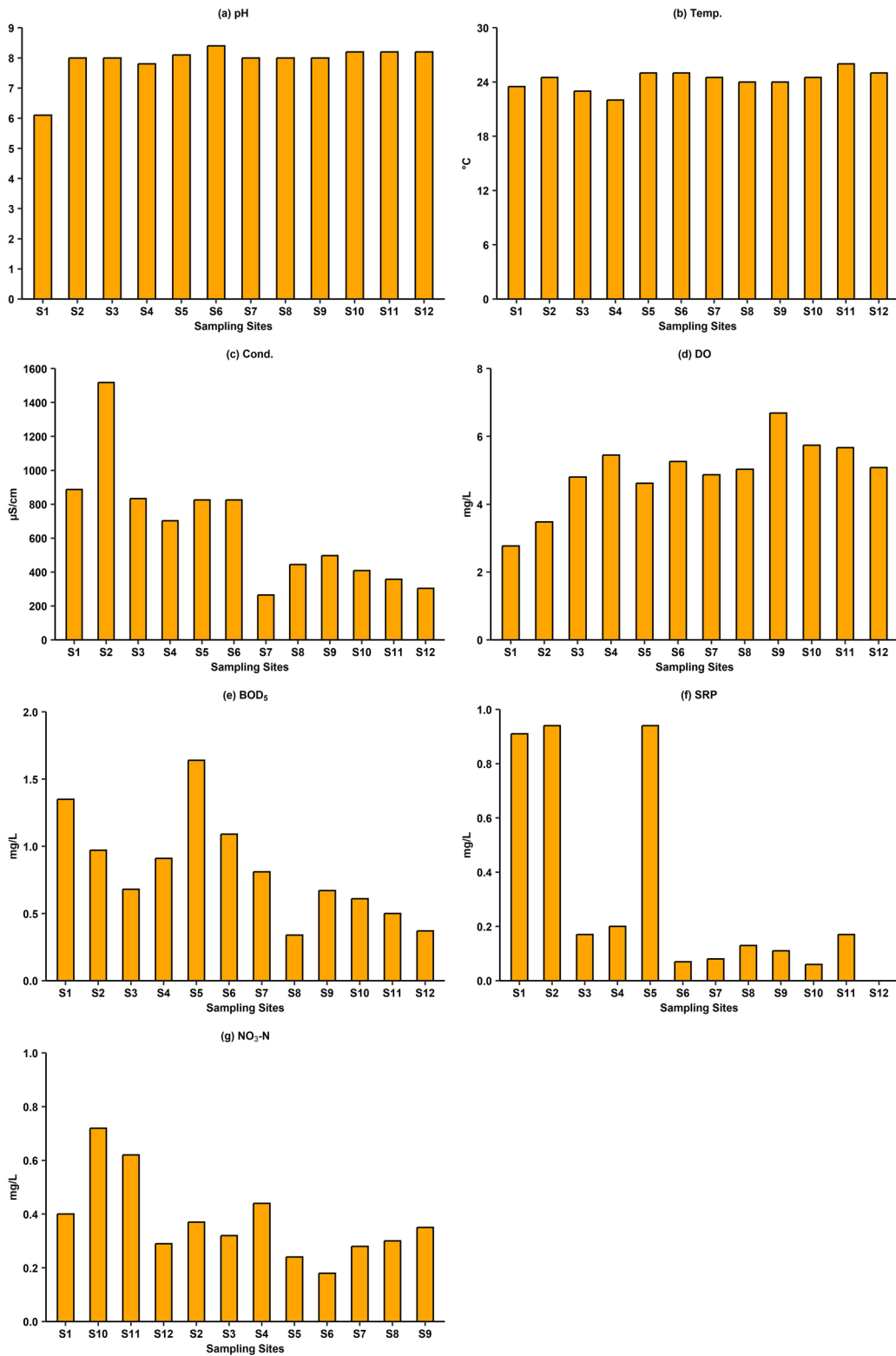


Fig. 3 Variation of water quality indicators in different sampling sites of Buriganga-Dhaleshwari-Meghna-Padma rivers

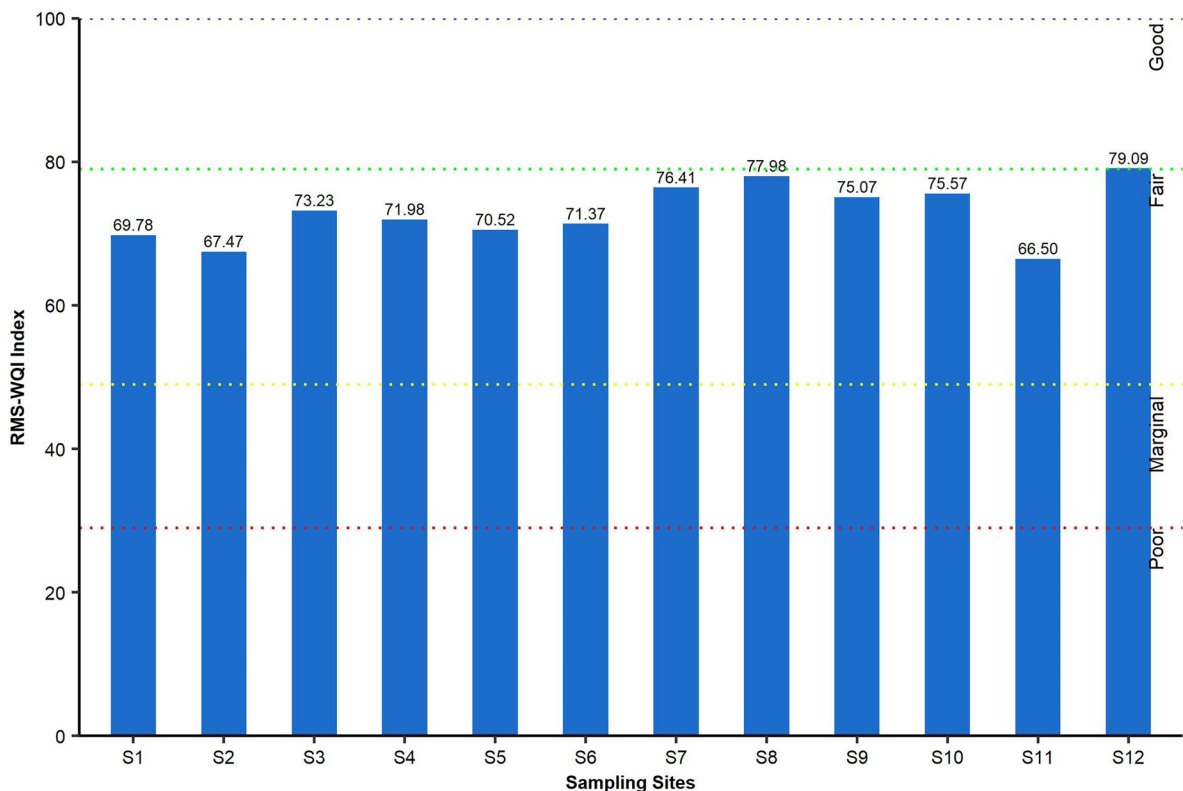


Fig. 4 Calculated RMS-WQI score in different sampling sites in the Buriganga-Dhaleshwari-Meghna-Padma rivers

sequence in order of S11 > S5 > S2 > S1 > S6 > S4 > S3 > S9 > S10 > S7 > S8 > S12 based on their calculated value. The order also indicates that the RMS-WQI index score is higher upstream and lower downstream (except sampling site S11).

States of LULC and classification accuracy

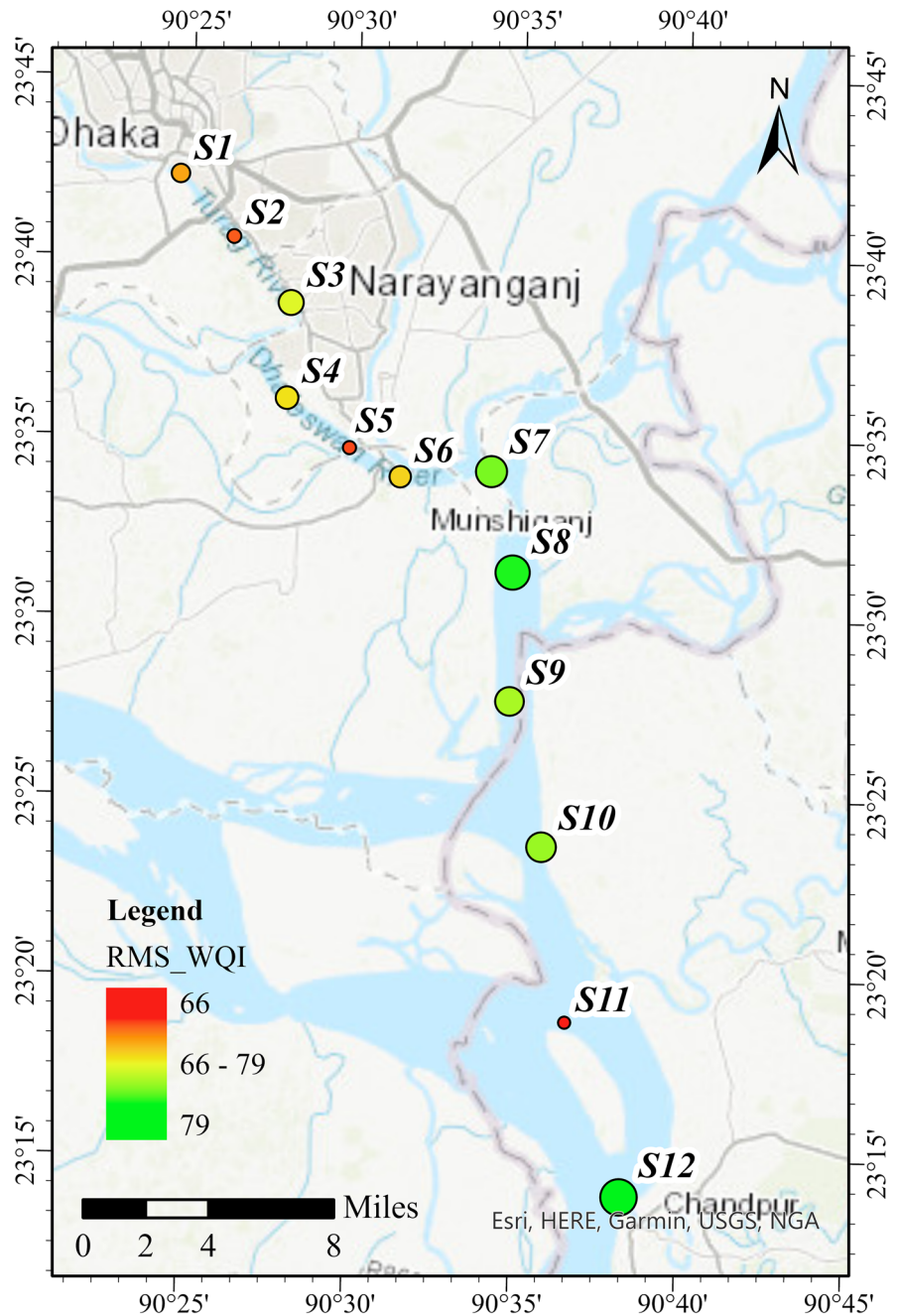
Based on the field observations, a total of four major land cover types were present in the Map (Fig. 6), which include (1) agricultural land (AL), (2) built-up areas (BA), (3) vegetation (Veg), and (4) water bodies (WB). The area of the 2015 land cover was calculated in square kilometres (Table 7). In the 2015 classified image, agricultural land was the dominant LULC type, making up 37.33% of the study landscape, followed by built-up area (24.76%), vegetation (9.5%), and water bodies (28.41%).

In terms of agricultural land, grid box D1 (sample site-S9), E1 (sample site-S10), F1 (sample site-

S11) have more than 16% agricultural land, and A1 (sample site-S1), B1 (Sample site (S2, S3, S4), C1 (sample site-S5), C2 (sample site-S6, S7, and S8), F2 (sample site-S12) have less than 16% agricultural land, respectively. A1 block occupied the highest (29.90%) built-up area land cover, and the E1 block had the lowest (0.72%) built-up area. Only two grids (F2 and C1) had more than 20% vegetation cover, whereas grids A1, B1, C2, D1, E1, and F1 only occupied more than 5% of vegetation cover. The area percentage of water bodies from grids C2-F2 is more than 14%, and A1-C1 ranges from 3 to 7%. The LULC classified map (Fig. 6) indicates that upstream grids (A1, B1, C1) were densely urbanised areas, whereas downstream grids (D1, E1, F1, F2) were agriculture-dominant areas. Lastly, the C2 grid box is a mixture of urban and agricultural land areas.

The overall accuracy assessment and kappa coefficient value of post-classified images were 92% and 0.89, respectively. The accuracy of agricultural

Fig. 5 Proportional distribution of RMS-WQI in sampling sites



land, built-up area, vegetation, and waterbodies area was 90.70%, 100%, 95.24%, and 85%, respectively. On the other hand, the user accuracy of all LULC classes ranges from 84 to 100%. The statistical summary of the accuracy assessment can be found in Supplementary Table 2.

Multivariate statistical analysis

Selection of WQ indicators using PCA analysis

PCA of different physicochemical factors among 12 sampling sites resulted in three axes. The first two axes

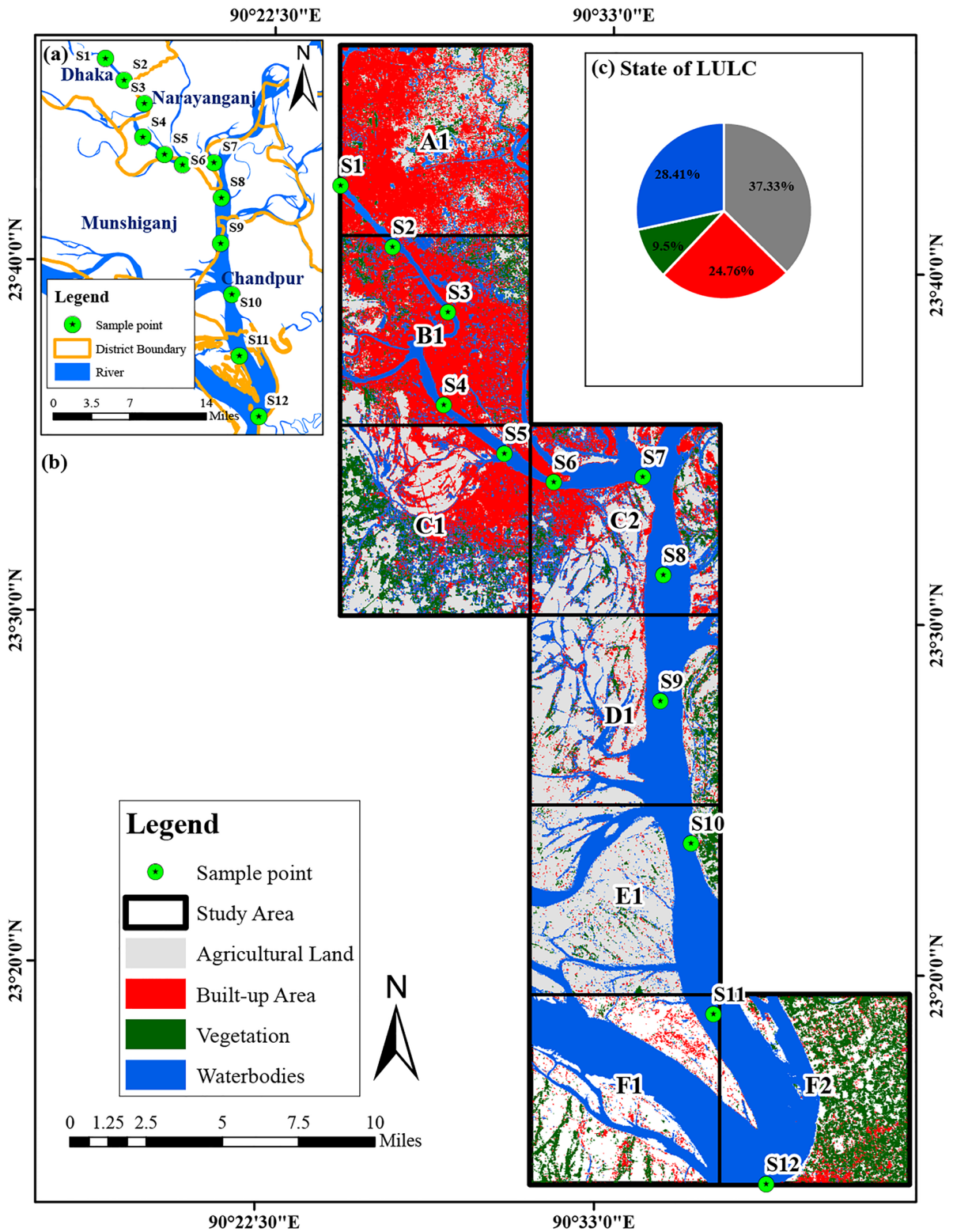


Fig. 6 LULC types (agricultural land, built-up areas, vegetation, and water bodies) of the Buriganga-Dhaleshwari-Meghna-Padma river system in Bangladesh

Table 7 Land-use type of the study area of the Buriganga, Dhaleshwari, Meghna, and Padma river system in Bangladesh

Grid box/sampling site	Agricultural land		Built-up area		Vegetation		Waterbodies	
	km ²	%	km ²	%	km ²	%	km ²	%
A1/S1	28.99	9.71	59.23	29.90	4.13	5.43	7.65	3.37
B1/S2-S3-S4	11.89	3.98	63.70	32.16	7.67	10.09	16.74	7.36
C1/S5	35.57	11.91	32.41	16.36	16.51	21.72	15.51	6.82
C2/S6-S7-S8	31.94	10.69	24.54	12.39	5.49	7.22	38.03	16.73
D1/S9	53.35	17.87	5.73	2.89	5.96	7.84	34.95	15.38
E1/S10	60.58	20.29	1.42	0.72	4.05	5.33	33.95	14.94
F1/S11	49.53	16.58	4.19	2.12	5.16	6.79	41.12	18.09
F2/S2	26.78	8.97	6.84	3.45	27.04	35.57	39.34	17.31
Total	298.63	100.00	198.06	100.00	76.03	99.99	227.28	100.00

explained 86% variance of physiochemical factors in sampling sites. The eigenvalue of PC1 and PC2 were 1.59 and 0.68, respectively. Out of 7 variables, only three were selected based on the eigenvectors. pH ($r=0.677$) and SRP ($r=-0.389$) correlated with PC1 while water temperature ($r=0.778$) correlated positively with PC2 (Fig. 7).

Relationship between WQ indicators, RMS-WQI and LULC

The statistically valid association between the PCA-based selected WQ indicators, calculated RMS-WQI value, and LULC classes revealed multiple significant positive and

Fig. 7 PCA ordination plot of different physicochemical variables of the study area

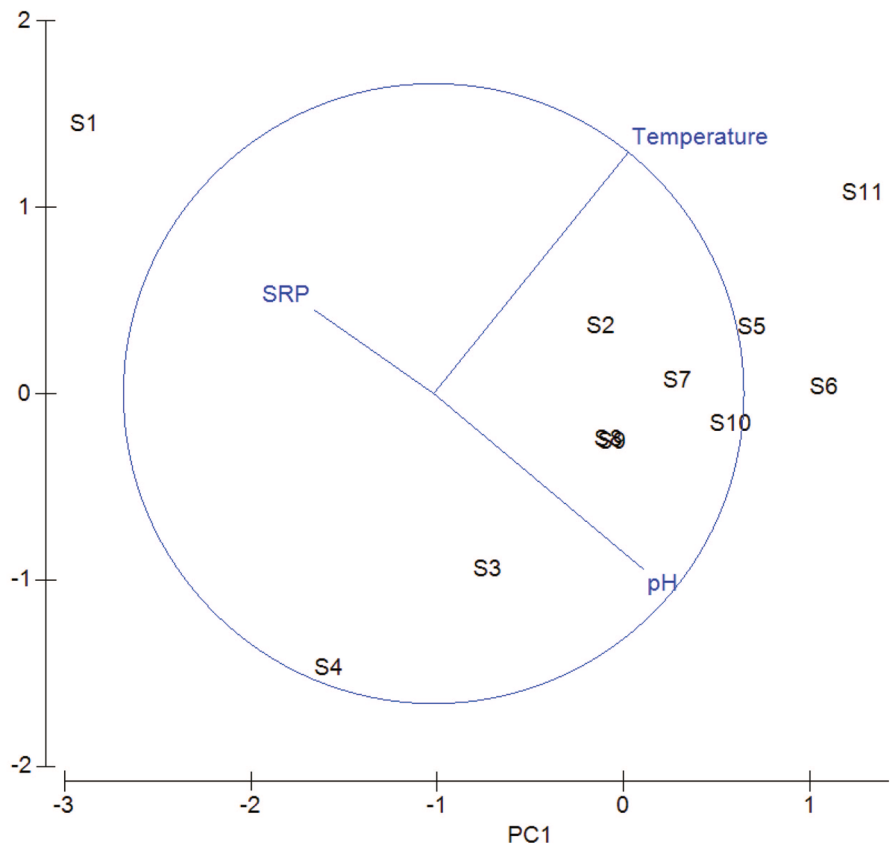
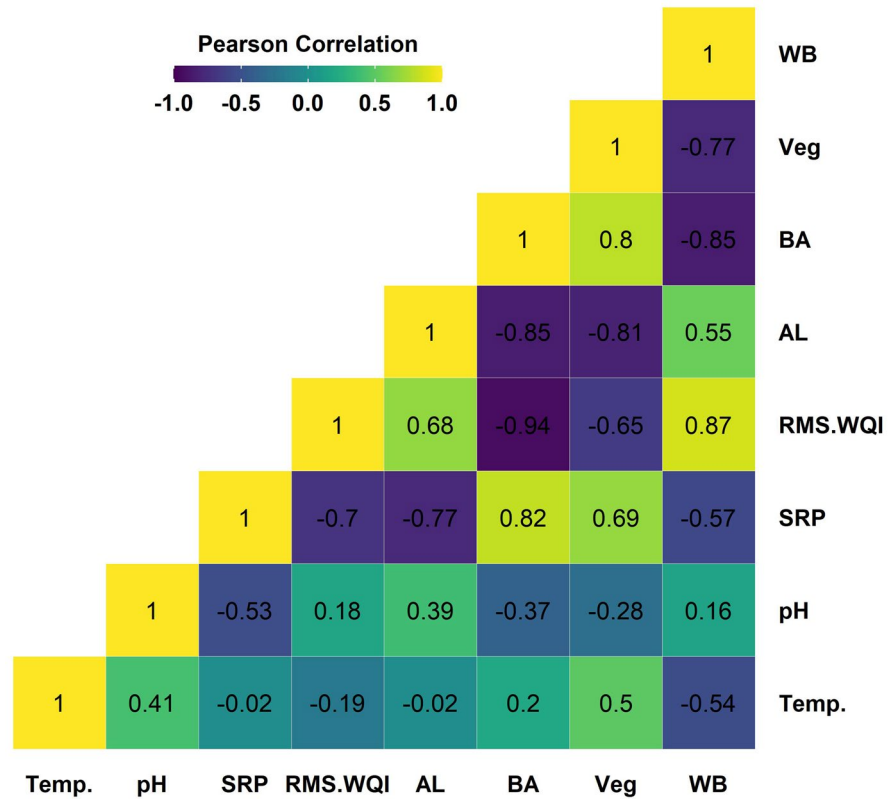


Fig. 8 Correlation matrix between different physico-chemical variables, WQI value, and LULC types (AL, agricultural land, BA, built-up areas, Veg, vegetation, and WB, water bodies)



negative correlations through Pearson’s correlation test at a 99% confidence level (Fig. 8). Results of the Pearson correlation showed that RMS-WQI displayed a significant positive correlation with agricultural land ($r=0.68$) while the negative association with the built-up area ($r=-0.94$) and vegetation ($r=-0.65$). This indicates that water quality value decreased with increased urbanisation, and in our study (except sampling station S11), we observed lower RMS-WQI values in the grids (A1, B1, B2, C1) which occupied the highest percentage (more than 90%) of the built-up area. Among physiochemical parameters, SRP showed significant correlation with RMS-WQI ($r=-0.7$) and all LULC types (AL: $r=-0.77$, BA: $r=0.82$, Veg: $r=0.69$, WB: $r=-0.57$).

Discussion

During the present study, PCA showed that except for S3 and S4, all the sampling sites coincide between pH and water temperature. Significant positive and negative associations of these factors with PC’s axes

were observed (Fig. 7). So, an increase or decrease in these factors can impact the WQI value resulting in an alteration in water quality.

In the present study, the downstream area is larger than the upstream, so it was expected that the water quality tends to improve as the river system flows downward. The WQI value did not gradually decrease from S1 to S12, which urges other factors responsible for the water quality. Sometimes, this can be explained by the water quality indicators or WQI. Surprisingly, the lowest WQI value was calculated in sampling site S11. The sampling site S11 is located downstream of the rivers, and agricultural activities surround the area. The degradation of water quality may be caused by agricultural runoff, which required future investigation. Again, the second and third lowest RMS-WQI in S2 and S1 sampling sites are located in the country’s most polluted urban river (Buriganga river) and receive a tremendous amount of untreated human waste beyond its limit (Kibria et al., 2015). Moreover, urban runoff could significantly impact the physicochemical properties of surface water (Diganta

et al., 2020). The correlation between RMS-WQI and the built-up area (BL) supported the result (Fig. 8).

On the other hand, the highest RMS-WQI value was found in the sampling site S12, located in the Padma River; fair water quality was found due to less built-up area and an expansion of the surface area of the main channel (Figs. 4 and 6). Ding et al. (2015) and Liu et al. (2016) found similar results in China. Ding et al. (2015) found that urban areas significantly influenced water quality in the Dongjiang River basin, Southeastern China. They performed the variance analysis and found that basins with the less built-up area have better water quality. Likewise, Liu et al. (2016) stated that the negative impact of the urban areas was amplified by the rise in urban impervious surfaces, which worsened the degradation of natural water quality. Therefore, the association between stream water quality and urban areas negatively correlates. Conversely, they found negative consequences of agricultural land on natural stream water quality because urban infrastructure masked arable land. Similarly, Mello et al. (2018), Rather and Dar (2020), Kim et al. (2020), and Cheah and Hamid (2016) found comparable results in Brazil, India, South Korea, and Malaysia, respectively. Mello et al. (2018) observed a positive correlation between water quality and total suspended solids, total nitrogen, and total phosphorus at a 0.01 significant level, as well as organic suspended solids and faecal coliforms at a 0.05 significant level in low-order natural streams in Southeastern Brazil. Instead, Rather and Dar (2020) found that a rise in the built-up area has been strongly associated with an increase in the average COD, nitrate-nitrogen, and total phosphorus of Dal Lake, India, since 1980. Kim et al. (2020) concluded that urban area is the dominant land cover class that deteriorates the stream water quality indicators, i.e., microbiological and nitrogen. Cheah and Hamid (2016) found that the rivers with built-up areas recorded the highest level of pollution in the river water of Kedah, Penang, and Perak states of Malaysia. In the present study, we found a significant correlation between SRP and LULC (Fig. 8). But among the LULC types the correlation coefficient was maximum in built-up areas which indicated that the major source of SRP was from the urban area affecting the water quality and thus correlation of SRP with RMS-WQI supported the result.

Conclusion

This research aimed to assess the impacts of LULC on the water quality of the Buriganga, Dhaleshwari, Meghna, and Padma rivers in Bangladesh. The major conclusions from the study are as follows:

1. Most WQ indicators were found within the reference value except pH.
2. The RMS-WQI result showed that the water quality of Buriganga, Dhaleshwari, Meghna, and Padma rivers belongs to the “fair” category group, indicating that few WQ indicators deviate from their reference value.
3. Four major LULC types were identified in the study where agricultural land was the dominant LULC type, making up 37.33% of the study landscape, followed by built-up area (24.76%), vegetation (9.5%), and water bodies (28.41%).
4. The PCA identified pH, Temperature, and SRP as significant WQ indicators that support the evaluation of the relation between WQ indicators, RMS-WQI and LULC.
5. The correlation study showed that WQ had a significant positive correlation with agricultural land and a negative association with the built-up area. It indicates that increasing urbanisation has a significant impact on water quality.

Degradation of river water quality is among the most severe effects of LULC change, influencing the watershed's different physical, chemical, and biological processes. Therefore, proper monitoring and land use planning are required to protect surface water quality. To combat future water pollution, the authors believe that the findings of this study can support land use planners and environmentalists in the planning and design of landscapes as well as protect the river environments, which may gradually improve the WQ. The primary drawback of the present study is that water quality was analysed utilising just seven WQ indicators and WQ indicator data from one year. Time series data of WQ and LULC may aid in a more comprehensive understanding of the relationship between WQ and LULC. Despite its limitation, the present study assesses the relationship between LULC and WQ in Buriganga, Dhaleshwari, Meghna, and Padma rivers. The current research established that LULC could be used as a proxy of

anthropogenic pollution measures to assess river water quality. Thus, identifying LULC can provide an indirect estimate for the river management authorities to implement restoration programmes.

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Data availability The datasets generated during and analysed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication All authors consent to the publication of this article.

Conflict of interest The authors declare no competing interests.

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