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ORIGINAL ARTICLE

Land-Use and Land-Cover Change Detection in a North-Eastern Wetland Ecosystem of Bangladesh Using Remote Sensing and GIS Techniques

Shwarnali Bhattacharjee[1] · Md Tariqul Islam[1] · Mohammad Ehsanul Kabir[2] · Md Muhib Kabir[3]

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Abstract

Lakshmibaur-Nalair Haor, a freshwater wetland ecosystem is situated in the north-eastern region of Bangladesh. This place hosts the second largest freshwater swamp forest in Bangladesh. Containing rich biodiversity, this unique area experiences significant landscape changes. This study examines land-use and land-cover (LULC) changes between 1989 and 2019 in the Lakshmibaur-Nalair Haor area by operating Landsat multispectral imageries through remote sensing (RS) and geographic information system (GIS) techniques. The changing status of the haor was analyzed by initiating normalized difference vegetation index (NDVI) and modified normalized difference water index (MNDWI). The unsupervised classification technique was implemented to classify these images into five major classes (vegetation, cropland, bare soil, shallow water, and deep water bodies) using threshold values of NDVI and MNDWI. After accuracy assessment, the post-classification comparison method was performed to evaluate the change detection. This study demonstrates that this valuable area lost ~ 2208.6 ha (37.54%) of the deep water body and 489.6 ha (8.34%) of vegetation over the last 3 decades. However, it has gained about 1729 ha (29.39%) of cropland, 2673 ha (45.44%) of shallow water and 1124 ha (28%) of bare soil. Such changes indicate significant human interventions such as expansion of croplands with increased population pressure. Gradual change of deep water into shallow water over time is enabling local community to expand agricultural lands and activities during the dry season. This study's findings are useful in understanding and tracking changes in wetlands in Bangladesh and other similar settings.

Keywords LULC · NDVI · MNDWI · Haors · Bangladesh

✉ Md Tariqul Islam
islam-gee@sust.edu

Shwarnali Bhattacharjee
bhattacharjee.shwarnali@gmail.com

Mohammad Ehsanul Kabir
m.e.kabir@lancaster.ac.uk

Md Muhib Kabir
mdkab1@morgan.edu

[1] Department of Geography and Environment, Shahjalal University of Science and Technology (SUST), Sylhet 3114, Bangladesh

[2] Lancaster Environment Centre, Lancaster University, Lancaster LA1 4YQ, UK

[3] Department of Transportation and Urban Infrastructure Studies, Morgan State University, 1700 E. Cold Spring Lane, Baltimore, MD 21251, USA

1 Introduction

Wetlands play crucial role in global biodiversity and provide essential support to many species and people's livelihood across the world. These lands are among the most productive ecosystems which not only delivers larger degree of ecosystem services but also accommodating many endangered species in aquatic and terrestrial environment (Mitsch and Gosselink 1993; Ricaurte et al. 2017). Wetlands often seen as transitional lands between terrestrial and aquatic ecosystems, especially where shallow water covers the land, or the water table is generally at or near the land surface. Such wetlands are classified into seven landscape units, namely, estuarine, open coast, floodplains, freshwater marshes, lakes, peatlands and swamp forest (Cowardin and Golet 1995; Dugan 1990). Since 1990, about 64% of the wetlands have lost natural features worldwide. Over the last 40 years, almost 76% of freshwater animals and plants have also disappeared (UNEP

2015). Both natural and human-induced land-cover changes in the wetland areas impact the environment and society due to their inevitable interactions (Houghton 1994).

In Bangladesh, wetlands cover about 80,000 sq. km area, which is nearly half of the area of the entire country including streams, rivers, lakes, ponds, marshes, haors, baors,[1] beels,[2] and jheels[3] (Islam et al. 2018; Tatu and Anderson 2017). Among these, haors are large bowl-shaped depressions between the natural levees of rivers, which receives surface runoff water every year during monsoon and become huge water body for half of a year (Nishat 1993). Haors dry up after monsoon and become vast green lands during winter. These haors are found in the Haor basin, situated in the north-eastern part of Bangladesh (Rasheed 2008). In Bangladesh, total haor region consists of 373 haors covering about 859,000 ha lands, which cover 10% of the country's total wetland area (BHWDB 2012). About 50% population of the entire country are primarily dependent on wetland resources for their livelihood (Islam 2010). Nearly 70% of consumed animal protein comes from freshwater fishes and 6–8% of revenue comes from the country's marsh areas only (Kanan 2016).

Globally, tracking spatio-temporal variations in the wetlands along with adjacent uplands is essential to understand possible human interventions along with many natural changes (Ozesmi and Bauer 2002). Assessing LULC changes across the wetland ecosystems are commonly used by disciplines such as environmental management, land-use planning, resource management and climate studies (Chamling and Bera 2020). LULC changes detection commonly demonstrates spatio-temporal patterns of changes in wetlands, which can contribute to sustainable usage and management of wetland resources (Rahimi et al. 2020). To examine when, where or how LULC changes occurs, the change detection models usually examine empirically captured data about physical characteristics of an area with certain period of time to see any historical patterns of changes. These also help future projection of changes which are likely to occur. These data can be obtained more reliably through the uses of RS process (Alam et al. 2020).

Satellite remote sensing is cost-efficient method being widely used by contemporary researchers to gather spatial and temporal information on wetlands (Guo et al. 2017; Mahdavi et al. 2018). RS and GIS techniques are highly functional to develop LULC mapping to obtain spatial analysis (Barakat et al. 2019). These have the potentials to provide precise information associated with LULC changes (Alqurashi and Kumar 2013). Assessment of LULC changes in wetlands using RS continuously helps to detect and resist different environmental threats, which are prerequisite for conservation of natural habitats of wetlands (Sánchez-Espinosa and Schröder 2019). Thus, space-born satellite data have gained immense acceptability and being widely used in LULC change studies across the world (Ahmed 2011; Elagouz et al. 2020; Hassan 2017; Kaliraj et al. 2017; Kumar and Ghosh 2012; Rawat and Kumar 2015; and Sewnet 2016). Moreover, Landsat satellite imageries, amongst other satellite products, have become more popular in the scientific community due to broader coverage, free availability and acceptable resolution (Mao et al. 2020). Studies that have used such products for the mapping and monitoring of wetlands include Haque and Basak (2017) who involved satellite images such as Landsat multispectral scanner system (MSS), Landsat thematic mapper (TM) and Landsat enhanced thematic mapper (ETM) to determine spatio-temporal land-cover changes in Tanguar Haor, located in northern Sylhet region in Bangladesh. Cong et al. (2019) used satellite imageries of Landsat MSS, TM and operational land imager–thermal infrared sensor (OLI-TIRS) to analyze the dynamic changes in the wetland landscape pattern of the Yellow River Delta in China from 1976 to 2016.

Despite haor's influential role in its surrounding terrestrial environment, only a few prominent haors in Bangladesh have been studied so far. Though the Lakshmibaur-Nalair Haor could draw attention for being the second largest freshwater swamp forest in Bangladesh (Deshwara and Eagle 2017), no research work has yet been conducted involving this haor. Therefore, this study is principally comprised of the Lakshmibaur-Nalair Haor, situated in the north-eastern haor basin of Bangladesh. The aim of this study is to detect spatio-temporal LULC changes between 1989 and 2019 in Lakshmibaur-Nalair Haor. The main objective of the study is to apply NDVI and MNDWI indices to assess the nature, rate and magnitude of changes in this haor. Using satellite imageries of Landsat TM and Landsat OLI-TIRS through RS and GIS techniques, this study examines an unexplored wetland area in the country. The findings of this study will help to identify the past and present land scenarios in this haor area, which can potentially guide policy makers and managers with scientific evidence for improved haor management.

[1] Ox-bow lakes are known as baors in southwestern Bangladesh, formed due to the separation of a meander from the main river (Rasheed 2008).

[2] Lake like wetlands but filled with static water locally known as 'Beel' are commonly found in the haor areas of Bangladesh (Akter 2011).

[3] Freshwater marshes are usually referred to jheels—often the term is used to determine permanent water bodies of different sizes (Rasheed 2008).

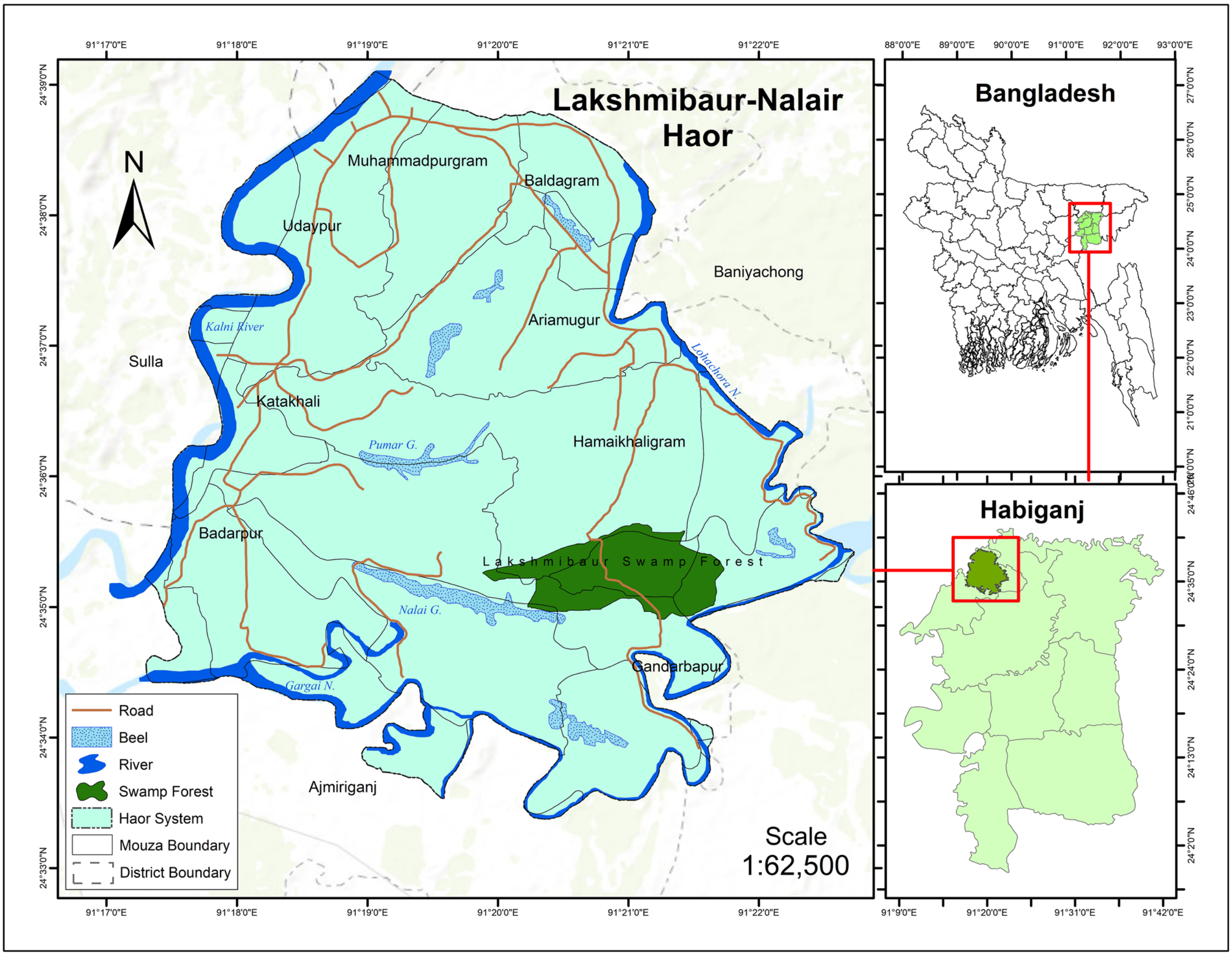

Fig. 1 Geographical location of Lakshmibaur-Nalair Haor in Habiganj district of Bangladesh. Base map source: Department of Bangladesh Haor and Wetlands Development (2016)

2 Study Area

Lakshmibaur-Nalair Haor is located between 24°37′9.01″N and 24°36′27.29″N latitudes and between 91°17′54.47″E and 91°21′31.14″E longitudes, which is in the northwestern side of Habiganj district in Bangladesh (see Fig. 1). Within the entire extent of Lakshmibaur-Nalair Haor, there are two sub-districts (upazilas) within Habiganj district, namely, Ajmiriganj and Baniyachong. This haor covers about 5365 ha (BHWDB 2012) area, adjacent to Kalni River in the west and Kushiyara River both in the south and the east. This haor area accommodates 17 villages where the villagers are largely dependent on locally available natural resources. This study area includes multiple Beels; Nalair G. and Pumar G. are the two largest beels located within Lakshmibaur-Nalair Haor. Lakshmibaur freshwater swamp forest is also a unique ecosystem in the study area, located in the southeastern part of this haor. About 520 acre forest lands are submerged under seven-eight feet of water during monsoon, starting from May to October every year (Deshwara and Eagle 2017). Locally, this swamp forest is known as "Khorotir Jungle".

In the context of physiography of Bangladesh (Brammer 2012), Lakshmibaur-Nalair Haor is part of the Surma-Kushiyara floodplain, which is further divided into two sub-units: Sylhet basin and Eastern Surma-Kushiyara floodplain. Sylhet Basin covers larger portion of this haor, whereas a smaller part is covered by Eastern Surma-Kushiyara floodplain (see Fig. 2). Geological characteristics include alluvial silt and clay, marsh clay and peat surface sediments long deposited in the Holocene epoch of Lakshmibaur-Nalair Haor (see Fig. 2) (Alam et al. 1990). Alluvial silt and clay surface sediments deposited in the northern region while marsh clay and peat sediment deposited in the southern part of the study area. According to the soil classification in Bangladesh (Brammer

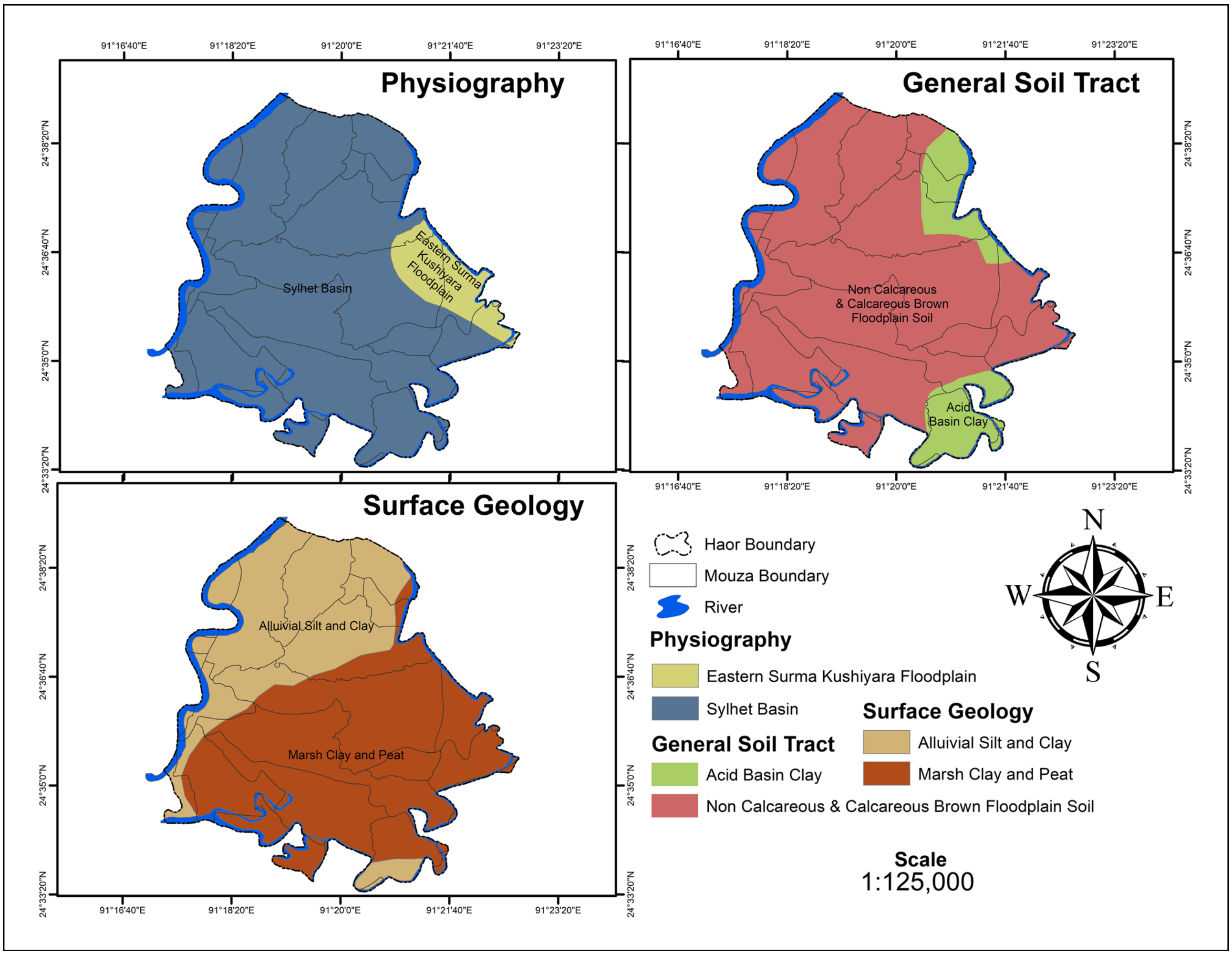

Fig. 2 Physiography, general soil tract and surface geology of Lakshmibaur-Nalair Haor

1996), the entire haor consists of two units: acid basin clay and non-calcareous calcareous brown floodplain soil (see Fig. 2).

The study area has a tropical monsoon climatic condition, which is identified by the bi-annual inversion of air movement. Air flows from the north-east between December and March, then it flows from the south-west between June and September (Ali 2014). Monsoon season appears from June to October and supplies over 80% of the annual rainfall. Air temperature usually fluctuates between 26 °C and 31 °C during pre-monsoon season (March to May), between 28 °C and 31 °C during rainy season and between 26 °C and 27 °C during dry season (Bennett et al. 1995). A map of temporal RGB Landsat satellite imageries of the Lakshmibaur-Nalair Haor dated 1989, 1999, 2009 and 2019 is shown in Fig. 3 with true-color composite 321 for Landsat TM and 432 for Landsat OLI-TIRS.

3 Materials and Methods

3.1 Data Sources

This study has exploited two different sensors of Landsat Level-1 satellite products, where processing levels of the both include terrain precision correction. Landsat-5 TM satellite imageries of 1989, 1999 and 2009 and Landsat-8 OLI-TIRS satellite image of 2019, were obtained from the USGS (United States Geological Survey) official website. Landsat-5 TM imageries comprise seven spectral bands of which the spatial resolution for bands 1–5 and 7 is 30 m and band 6 comes with 120 m spatial resolution (resampled to 30 m pixels). Landsat 8 OLI-TIRS include eleven spectral bands and 30 m spatial resolution for bands 1–8. Spatial resolution for bands 10 and 11 are 100 m each (resampled to 30 m). Landsat 8 has 16-bit radiometric

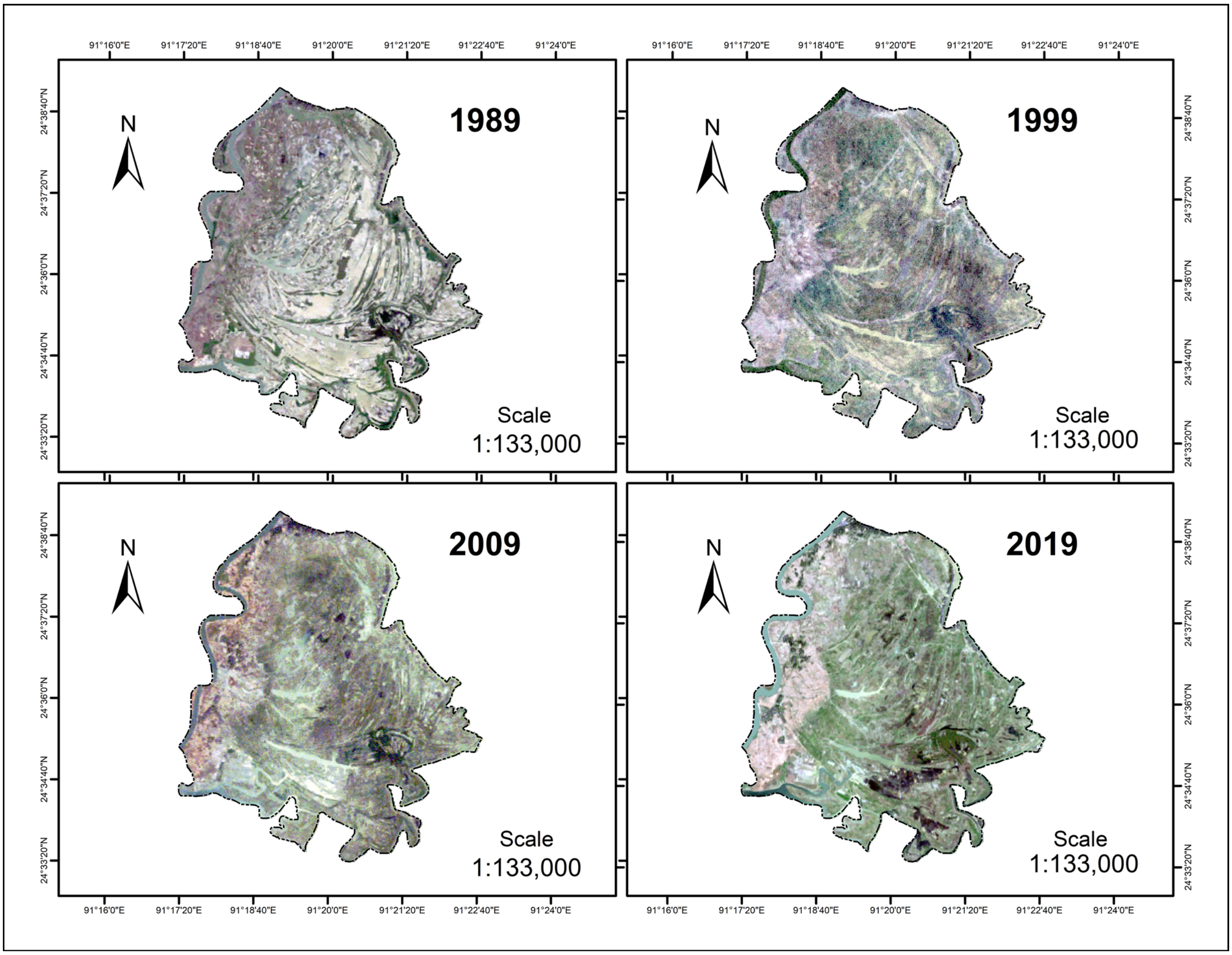

Fig. 3 Temporal RGB Landsat satellite imageries of Lakshmibaur-Nalair Haor

Table 1 Properties of acquired satellite images

Satellite ID	Sensor name	Path/raw	Acquisition date	Spatial resolution (m)	Quality
Landsat 5	TM	137/43	04-01-1989	30	9
Landsat 5	TM	137/43	16-01-1999	30	7
Landsat 5	TM	137/43	11-01-2009	30	9
Landsat 8	OLI/TIRS	137/43	07-01-2019	30	9

resolution while Landsat 5 has 8-bit radiometric resolution. Landsat 8 has a greater spectral resolution (more spectral bands) than Landsat 5. Both Landsat 5 and Landsat 8 have the 16 day temporal resolution. We obtained all of these satellite images from the same season of the year, which is basically dry time in January to reduce the influence of cloud coverage and seasonal changes on the classification procedure that could otherwise distress the eminence of the resulting imageries. In the haor area, winter is the main season for rice cultivation, particularly Boro (a local variety) rice (Alam et al. 1970). The month January has been chosen for analyzing this study also because from December to January is the sowing time for Boro rice farming (Kalpoma et al. 2019). Four satellite images were selected with 10 years of the time interval starting from 1989 to 2019 to analyze 30 years' LULC changes within the haor (see Table 1).

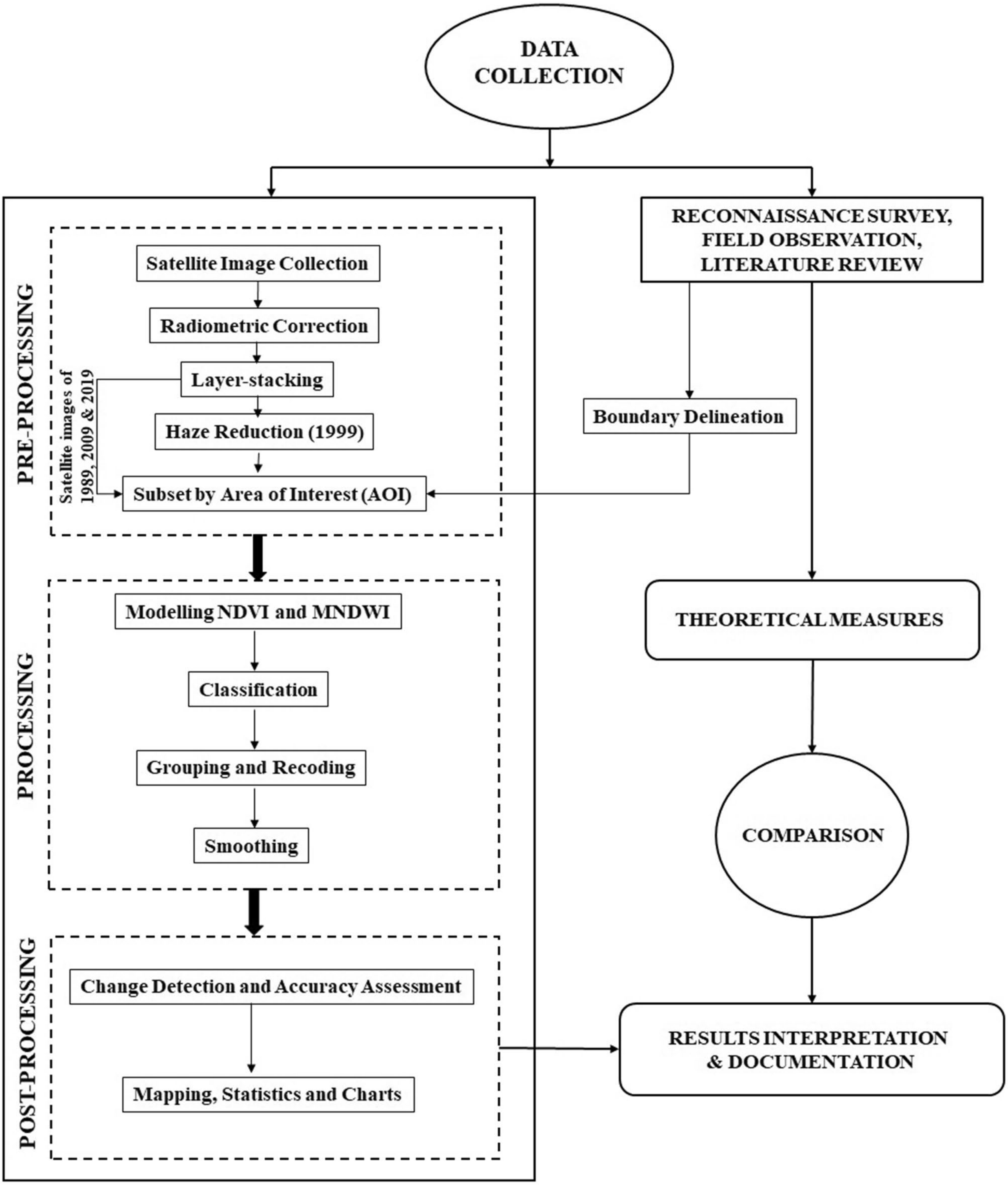

Fig. 4 Methodology flowchart

3.2 Base Map Collection

This study's base maps include Lakshmibaur-Nalair Haor boundary map, union[4] map, upazila map, mouza[5] map and Topographical Sheet (No. 78 p/6). Lakshmibaur-Nalair Haor boundary map was collected from the Master Plan of Haor Area developed by Bangladesh Government's Wetland and Haor Development Board through digitization. Mouza, union, and upazila shapefiles were accumulated from an open-source of GIS inventory named Geo Planning for Advanced Development in Bangladesh (GPADBD).

3.3 Processing and Analysis of Satellite Image

Image pre-processing, processing and post-processing are three categories of the present study's procedure, as displayed in Fig. 4. RS and GIS techniques using few software namely, ArcGIS 10.6, ERDAS imagine 2014 and ENVI 5.3 were applied to accomplish the methods of this research.

3.3.1 Image Pre-processing

After acquiring Landsat-5 TM (1989, 1999, and 2009) and Landsat OLI–TIRS (2019) images of the study site, conversion of Digital Number (DN) values to Top of Atmosphere (ToA) reflectance was conducted following standard procedures provided by the USGS (2018). Geometrically and radiometrically corrected satellite images of years 1989, 1999, 2009 and 2019 of the study site were imported to the ERDAS Imagine software after the discrete spectral bands were stacked into a layer. Using ERDAS Imagine haze reduction tool, haze reduction was implicated on the satellite image of 1999 to reduce visual haze and improve the image's visualization. Figure 5 shows the pre-haze reduction and post-haze reduction satellite images of 1999. All satellite images were geo-rectified during analysis and projected to GCS WGS 1984 UTM Zone 43 N (datum) to confirm uniformity between datasets. Additionally, subsetting of images was prepared to extricate the area of interest (AOI), applying a vector shapefile of each dataset's haor boundary.

3.3.2 Image Processing

In this study, NDVI and MNDWI indices have been analyzed respectably to calculate and visualize the vegetation cover and water cover feature of Lakshmibaur-Nalair Haor.

3.3.2.1 NDVI and MNDWI NDVI is a widely used, well-known index to determine and anticipate the biomass and the greenness in a specific region (Alphan and Derse 2013; Tan et al. 2012). MNDWI is a more suitable index to enhance and extract information from the water surface area dominated by build-up land and mixed with vegetation (Singh et al. 2015; Xu 2006). NDVI and MNDWI are enumerated employing Eqs. (1) and (2) as illustrated below, respectively.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}. \tag{1}$$

$$MNDWI = \frac{(GREEN - MIR)}{(GREEN + MIR)}. \tag{2}$$

According to USGS, satellite images of Landsat 5 and Landsat 8 have different spectral bands for calculating NDVI and MNDWI values. Landsat-5 (TM) has assigned spectral bands 2, 3, 4, and 5 for green, red, near infrared (NIR) and middle infrared (MIR), respectively. Whereas, Landsat-8 (OLI-TIRS) has allotted spectral bands 3, 4, 5 and 6 for green, red, near infrared (NIR) and middle infrared (MIR), respectively (USGS 2017).

The NDVI and MNDWI values range from -1 to $+1$. The accurate NDVI and MNDWI values for classification are attained by examining various threshold values and visually scrutinizing the tested images of the satellite (Jawak and Luis 2013). Authors synthesized the most common values of NDVI and MNDWI and the corresponding classes (illustrated in Table 2) from Mozumder et al. (2014), Gandhi et al. (2015), Haque and Basak (2017) and Eid et al. (2020). ERDAS Imagine spatial model maker tool was used to get the NDVI and MNDWI values from four Landsat satellite images. Figures 6 and 7 display the temporal NDVI and MNDWI images of Landsat satellite for the years 1989, 1999, 2009 and 2019 respectively, prepared in ArcGIS software by utilizing NDVI and MNDWI values.

3.3.2.2 Unsupervised Classification This study applied the NDVI and MNDWI indices for demonstrating the scenario of the haor area. NDVI and MNDWI values were classified using the unsupervised classification method. Then, using the threshold values shown in Table 3, we reclassified the NDVI values into four classes: vegetation, cropland, bare soil and no-vegetation. Similarly, the MNDWI values are classified into three categories: deep water, shallow water and non-water surface. We used the model maker tool of the ERDAS Imagine software for such reclassification.

3.3.3 Image Post-processing

3.3.3.1 Accuracy Assessment The accuracy assessment is a verifying process conducted to validate the generated image classifications' authenticity. Accuracy of classifications must

[4] Unions are the lowest local government and rural administrative units in Bangladesh (Khan 2008).

[5] A Mouza is a specific land area with settlements that is used as a revenue collection unit (Islam 2003).

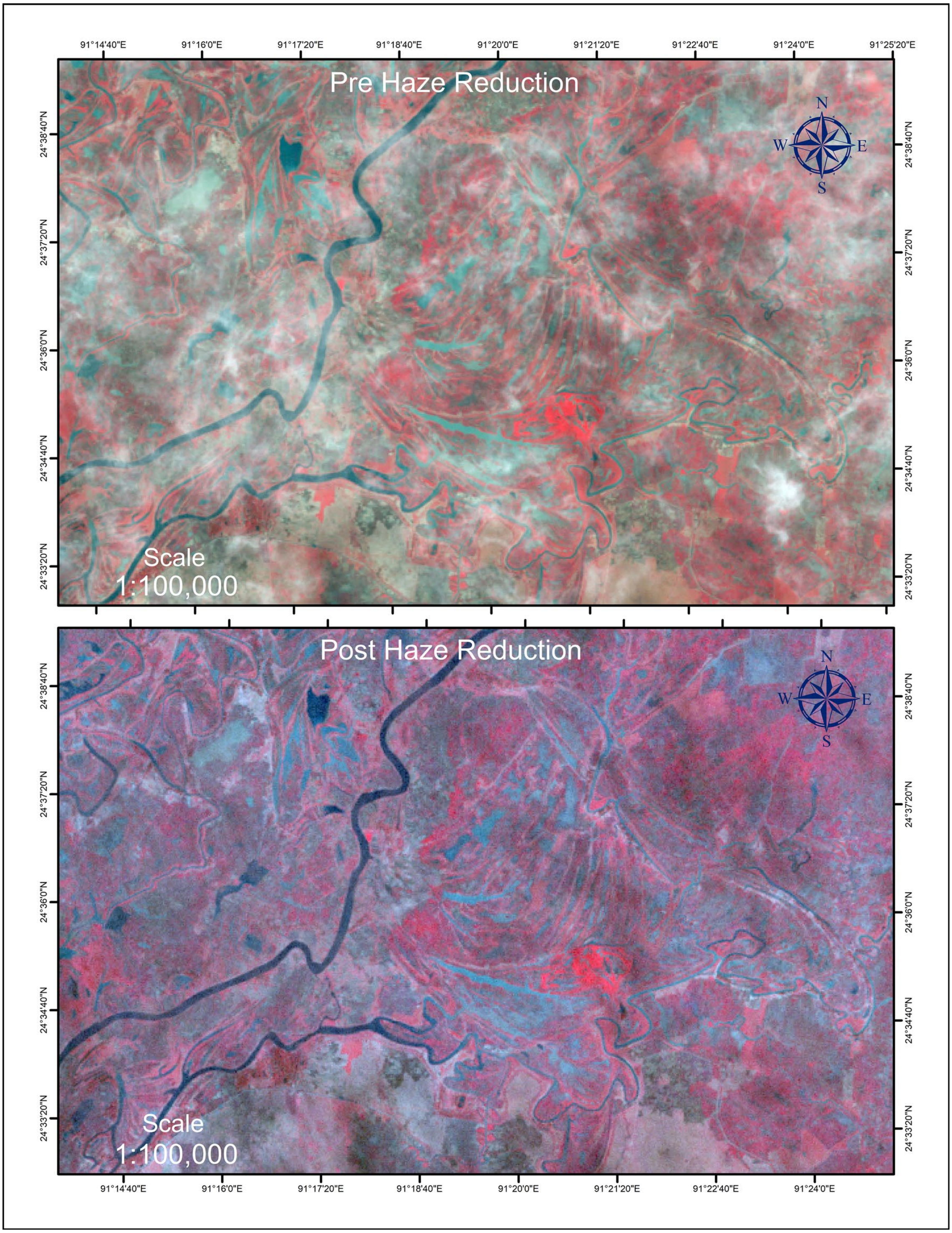

Fig. 5 Pre and post haze reduction of the 1999 satellite image

be done through ground-truthing in the study site. Thus, 50 ground control points (GCPs) collected from the field were applied on the NDVI and MNDWI classified images of the year 2019 in a random manner. One of the most frequently used—Kappa accuracy assessment technique was chosen to assess the accuracy of these images. Accuracy assessments of 1989, 1999 and 2009 images were not possible due to the vivid google earth images' unavailability. The overall accuracy of NDVI and MNDWI classified images of 2019 were 86% and 90%, with overall Kappa statistics of 80.38% and

Table 2 NDVI and MNDWI values, and corresponding classes

NDVI intervals	Classes	MNDWI intervals	Classes
0.1 or less	Barren areas of rock, sand, or snow	− 1 to 0	Non-water surface
0.2 to 0.3	Grass and shrubland	0 to 0.3	Shallow water (semi inundated land filled with marshy vegetation)
0.6 to 0.8	Tropical and temperate rainforests	0.3 to 1	Deep water (river, permanent open water, perennial lakes and reservoirs)
Close to zero	Bare soil		
Negative values	Water bodies		

86.03%, respectively. Individual user accuracy and producer accuracy of all the classes of NDVI and MNDWI images are presented in Table 4.

3.3.3.2 Change Detection Change detection refers to the procedure of determining transformations of a phenomenon or condition by examining it at different periods (Singh 1989). Change detection processes can be categorized under three major headings: (1) multi-date data classification, (2) post-classification comparison, and (3) image enhancement on the basis of data variations processes and the analysis method (Mas 1999). The post-classification comparison technique was applied to assimilate three change scenes for the years 1989, 1999 and 2009 dependent on 2019 in this study. It contains the classification of each of the temporal (before and after) images autonomously to ascertain areas where changes have happened by discriminating the corresponding pixel (thematic) labels (Alsalman 2012). ENVI 5.3 Thematic Change Workflow tool was generated to determine change detection in NDVI and MNDWI maps of the study area. This tool examines the conversion dynamics of a specific land-cover class to a different class at a particular range. Classified images of NDVI and MNDWI for the years 1989, 1999 and 2009 were imported as time 1 images independently, while the image of 2019 was imported as time 2 images for getting the changing scene of the previous three dates based on the 2019 image. The post-classification technique is the most apparent change detection process that is important for comparing classified images (Abd El-Kawy et al. 2011).

4 Result and Discussion

4.1 LULC Scenario of the Lakshmibaur-Nalair Haor

This study has analyzed LULC in Lakshmibaur-Nalair Haor to observe the changing pattern over the past three decades. Figures 8 and 9 display the classified NDVI and MNDWI maps for Lakshmibaur-Nalair Haor for the years 1989, 1999, 2009 and 2019. Additionally, areas in hectares (ha) and percentage of NDVI and MNDWI classes of the study site are exhibited on Tables 5 and 6, sequentially. The outcome of satellite image processing shows that the NDVI classifies this area into four classes: bare soil, cropland, vegetation (that indicates swamp forest and village vegetation) and no-vegetation which includes deep water and shallow water class of the MNDWI class. The MNDWI classifies the region into three classes: shallow water, deep water and non-water surface (which comprises vegetation, cropland and bare soil of the NDVI together). We plotted charts to display the areas in hectares of numerous NDVI and MNDWI classes over the three decades presented in the Figs. 10 and 11.

The detailed LULC scenario of the Lakshmibaur-Nalair Haor is introduced as follows:

Vegetation: During the study period, vegetation, including swamp forest and village vegetation, found as concentrated in the smallest portion of the study area. Land covered by vegetation was 695.79 ha (11.83%) in 1989. However, its covered area has reduced by 206.19 ha (3.49%) in 2019. This land cover type has decreased by 8.34% at an average of 16.32 ha/year between 1989 and 2019. During the field visit, the local villagers reported that expansion of agricultural land is the main cause for the decrease of vegetation coverage in this research site. Cutting trees from the swamp forest is another reason for reducing vegetation (Deshwara and Eagle 2017).

Cropland: It is one of the land-use classes which displays the dramatic expansion over the 30 years. The cropland area increased from 1391.58 ha (23.65%) in 1989 to 3120.32 ha (53.04%) in 2019. This class has increased by 1728.74 ha (29.39%) with a mean rate of 57.62 ha/year from 1989 to 2019. However, this growth was not consistant during all the years studied. Though growing initially, cropland area reduced from 2889.18 ha (49.11%) in 1999 to 1135.08 ha (19.29%) in 2009. Once again, from 2009 to 2019, it expanded from 1135.08 ha to 3120.32 ha.

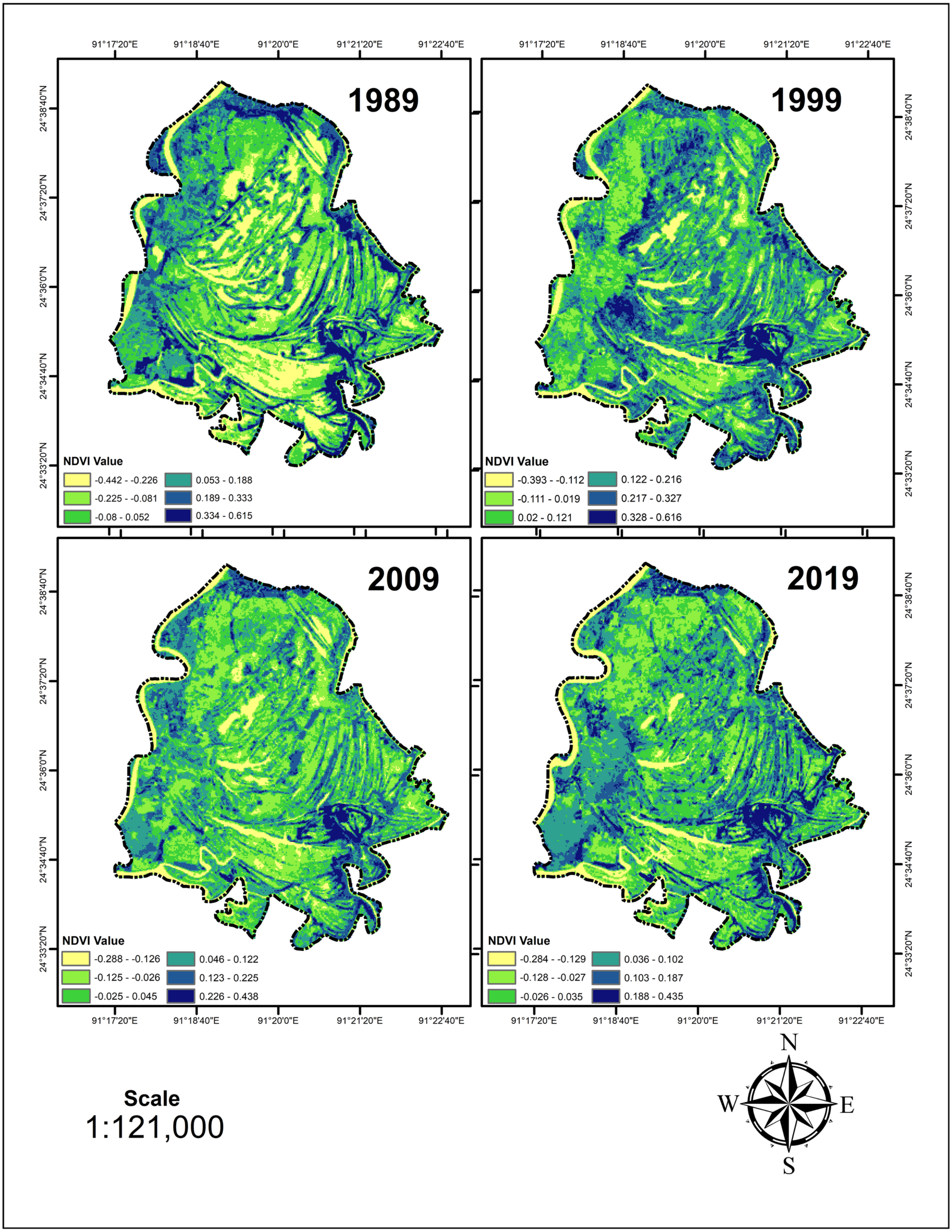

Fig. 6 Temporal NDVI images of Lakshmibaur-Nalair Haor for the year of 1989, 1999, 2009 and 2019

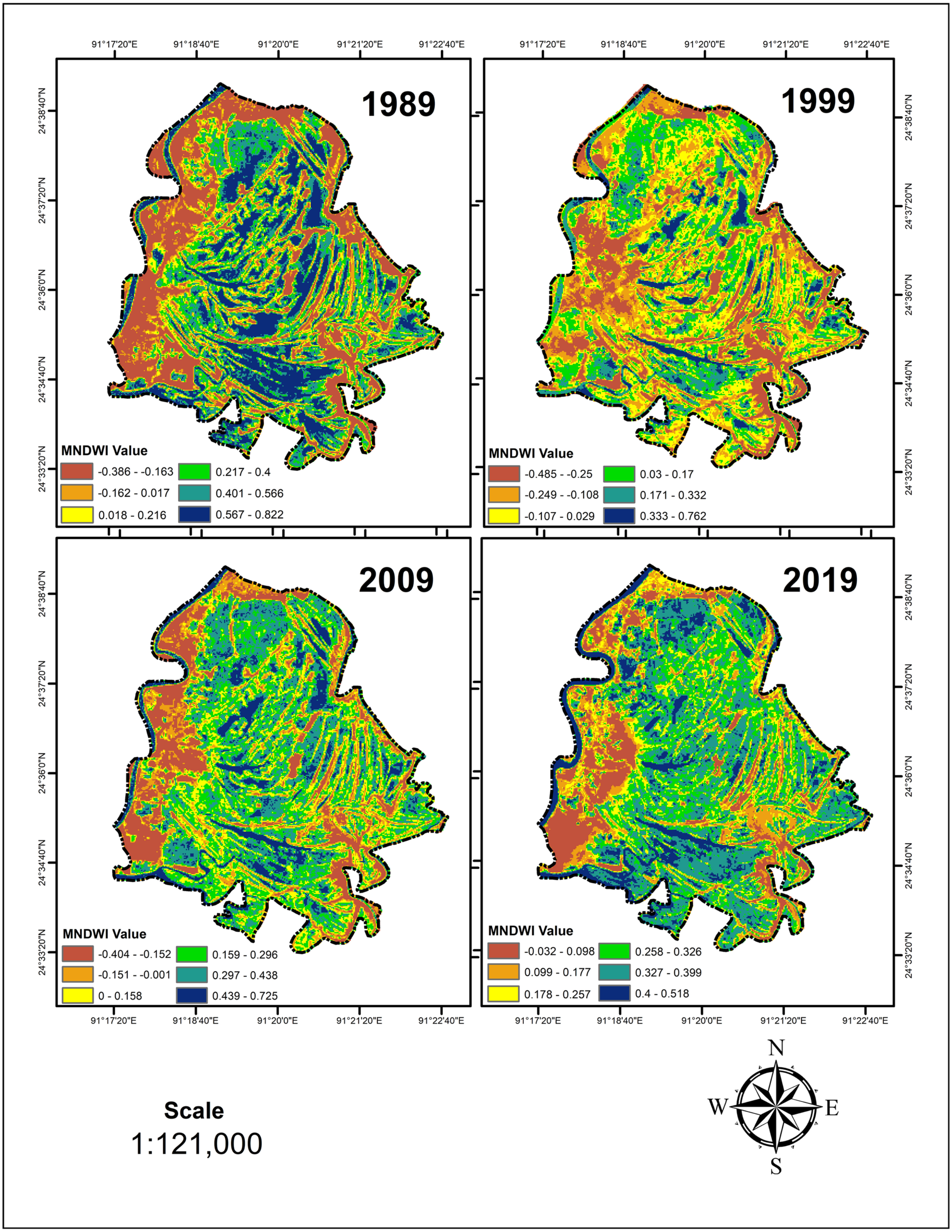

Fig. 7 Temporal MNDWI images of Lakshmibaur-Nalair Haor for the year of 1989, 1999, 2009 and 2019

Table 3 NDVI and MNDWI classes for Lakshmibaur-Nalair Haor

Values of NDVI	Classes	Values of MNDWI	Classes
− 1 to 0	No-vegetation	− 1 to 0	Non-water surface
0 to 0.1	Bare soil	0 to 0.3	Shallow water
0.1 to 0.3	Crop land	0.3 to 1	Deep water
0.3 to 1	Vegetation		

Bare soil: It is another land type that shows an upward trend over the three decades. The entire area of bare soil was incremented from 831.24 ha (14.13%) in 1989 to 1955.62 ha (33.24%) in 2019. However, in 2009, it has displayed the highest cover of 2005.38 ha compared to the other three years (1989, 1999 and 2019). It has increased by 1124.38 ha (27.99%) with an average rate of 37.48 ha/year between 1989 and 2019.

Deep water*:* Deep water was the primary land cover type in 1989 which comprised 2673.54 ha (45.44%) of the study area. This indicates that approximately half of the study area was covered by deep water about 30 years ago. However, deep water exhibits noticeable shrinkage over the last 30 years. The total extent of deep water decreased from 2673.54 ha (45.44%) in 1989 to 464.94 ha (7.9%) in 2019. The studied haor area has lost 2208.6 ha (37.54%) deep water body at a mean rate of 73.62 ha/year from 1989 to 2019. We noticed a rapid decrease in the deep water from 2673.54 ha (45.44%) in 1989 to 774.63 ha (13.17%) in 1999. Then the deep water body decreased gradually from 774.63 ha (13.17%) in 1999 to 464.94 ha (7.9%) in 2019.

Shallow water*:* This waterbody type has shown a gradual increasing trend from 1989 to 2019. About 1113.12 ha (18.92%) area comprised the overall amount of shallow water body in 1989. It increased from 1113.12 ha (18.92%) in 1989 to 3786.3 ha (64.36%) in 2019. In 2009, the extent of shallow water was 3534.12 ha (60.08%), which continued to increase up to 2019, covering 3786.3 ha (64.36%) area. The study area has gained 2673.18 ha (45.44%) shallow water body with an average value of 89.106 ha/year over the last 3 decades.

4.2 Change Detection

Change detection was performed to indicate the changes that are identified for the temporal dates 1989, 1999 and 2009 of the NDVI and MNDWI classes with respect to the year 2019 (shown in Figs. 12, 13). Tables 7 and 8 display the statistics of change detection of the NDVI and MNDWI, respectively. The changing area has been stated in hectare unit and the percentage of change has been measured based on the total land area of the study site. We have plotted graphs of the change detection to display the variations in the three change sights, 1989–2019, 1999–2019 and 2009–2019 of the NDVI and MNDWI classes (presented in Figs. 14, 15). Results obtained from these change detection show significant LULC changes in Lakshmibaur-Nalair Haor over the last three decades.

For the period 1989–2019, significant changes were observed from no-vegetation to bare soil, where no-vegetation indicates water surface area (deep water and shallow water). About 1531.97 ha of no-vegetation area has been converted to bare soil, while only 19.26 ha of the bare soil was converted to water surface area. Another major conversion occurred over the last 30 years is that about 1137.45 ha of the haor area converted from no-vegetation to crop land. About 2349.65 ha area shifted from deep water to shallow water. From the total vegetation, about 520.47 ha area changed to cropland, 121.41 ha area remained unchanged and 60.22 ha area changed to bare soil. From the total crop land area, 238.05 ha area converted to bare soil and 1098.94 ha area remained unchanged. About 180.74 ha areas of deep water altered to non-water surface area and 320.59 ha area stayed unchanged. However, 143.64 ha area shifted to non-water surface area from the total shallow water, 719.53 ha area remained unchanged and 13.78 ha area converted to deep water.

Table 4 User and producer accuracy assessment of NDVI and MNDWI classified maps of 2019

Classification	Class name	Reference total	Classified total	Number correct	User accuracy (%)	Producer accuracy (%)
NDVI	No-vegetation	17	16	16	100	94.12
	Bare soil	11	9	7	78.98	65.67
	Cropland	17	17	14	82.35	82.35
	Vegetation	7	8	6	75	85.71
MNDWI	Non-water surface	24	23	22	95.65	91.67
	Shallow water	14	15	12	80.00	85.71
	Deep water	13	12	11	91.67	84.62

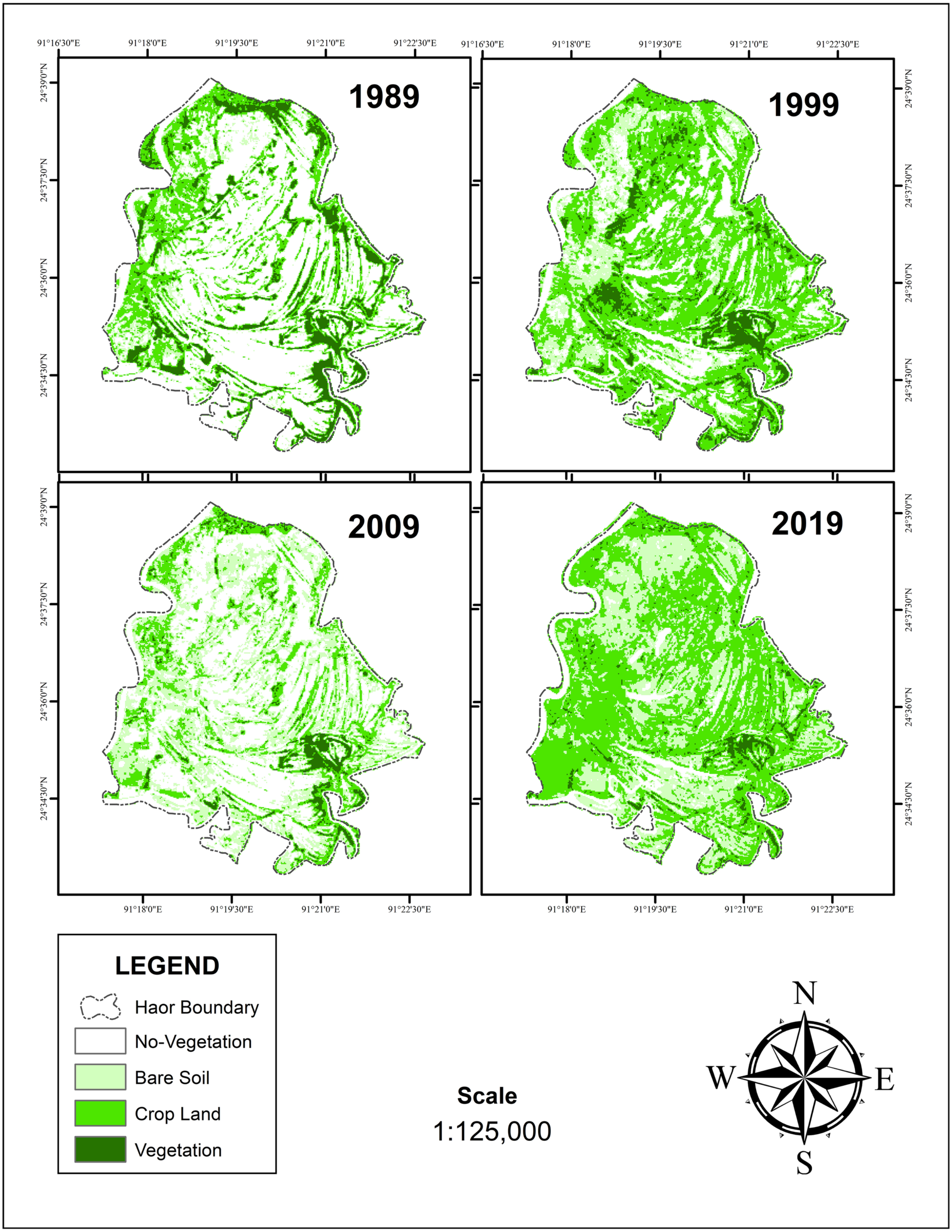

Fig. 8 Classified NDVI Map of Lakshmibaur-Nalair Haor (1989, 1999, 2009 and 2019)

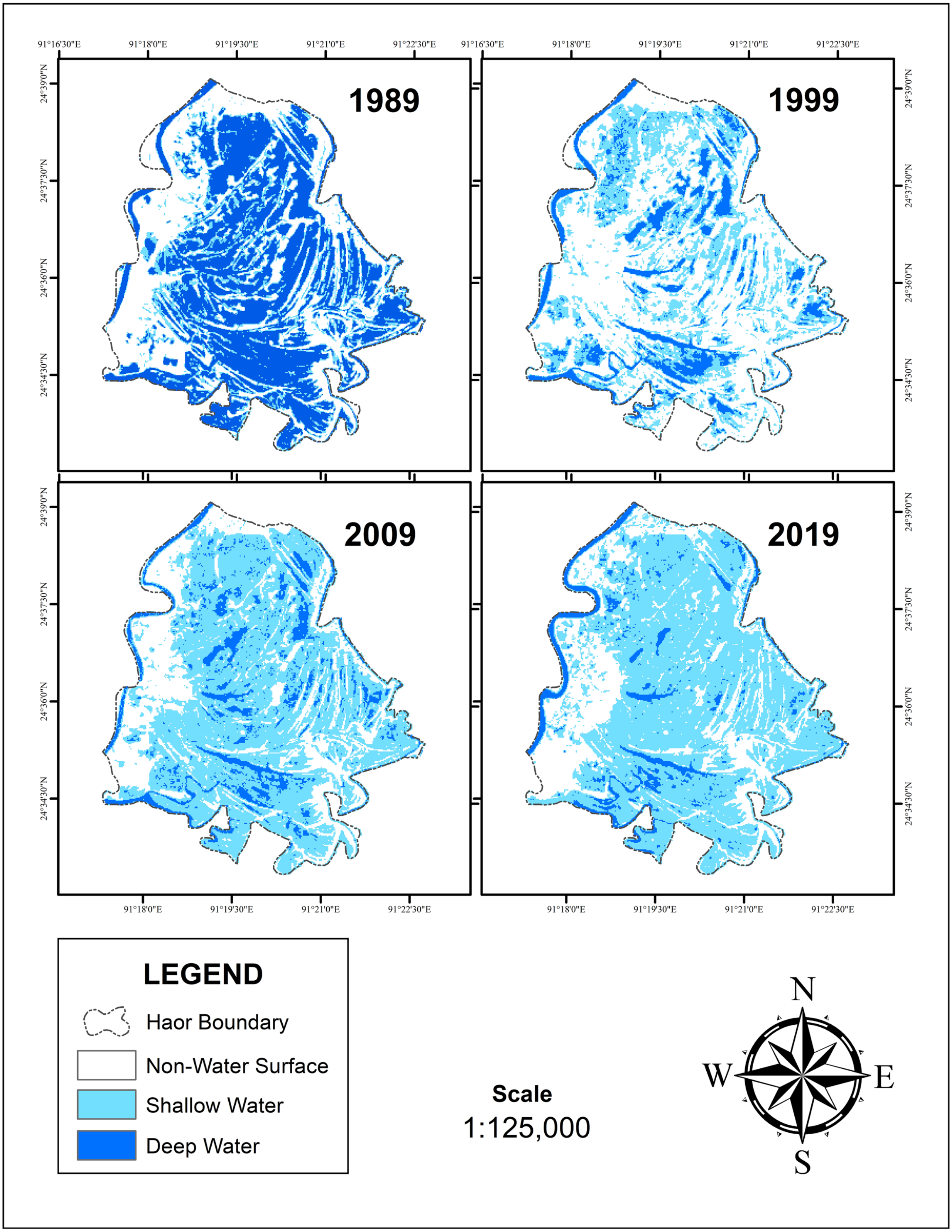

Fig. 9 Classified MNDWI Map of Lakshmibaur-Nalair Haor (1989, 1999, 2009 and 2019)

Table 5 Area (ha) and percent of each NDVI classes of Lakshmibaur-Nalair Haor

Class Name	1989		1999		2009		2019	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
No-vegetation	2964.33	50.39	1163.97	19.78	2517.3	42.79	600.41	10.21
Bare soil	831.24	14.13	1315.26	22.36	2005.38	34.09	1955.62	33.24
Crop land	1391.58	23.65	2889.18	49.11	1135.08	19.29	3120.32	53.04
Vegetation	695.79	11.83	514.53	8.75	225.18	3.83	206.59	3.51
Total	5882.94	100	5882.94	100	5882.94	100	5882.94	100

Table 6 Area (ha) and percent of each MNDWI classes of Lakshmibaur-Nalair Haor

Class Name	1989		1999		2009		2019	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Non-water surface	2096.28	35.64	3314.25	56.34	1681.92	28.58	1631.7	27.74
Shallow water	1113.12	18.92	1794.06	30.49	3534.12	60.08	3786.3	64.36
Deep water	2673.54	45.44	774.63	13.17	666.9	11.34	464.94	7.9
Total	5882.94	100	5882.94	100	5882.94	100	5882.94	100

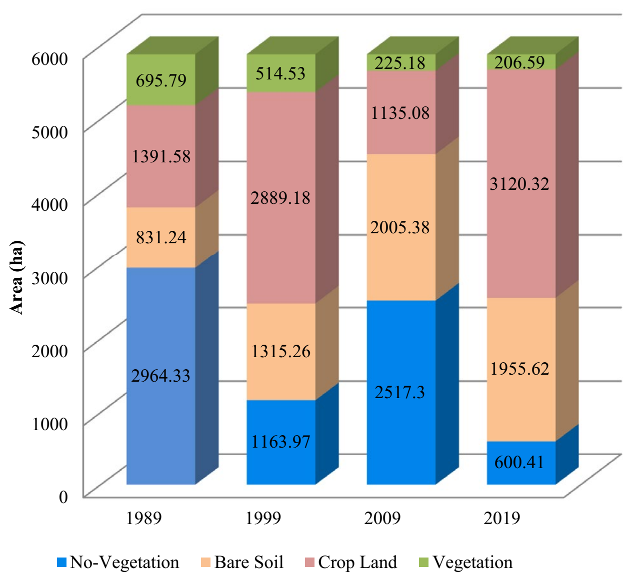

Fig. 10 Area (ha) of NDVI classes

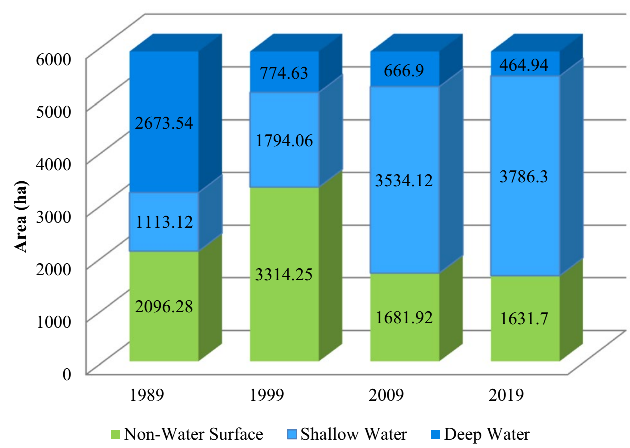

Fig. 11 Area (ha) of MNDWI classes

This study outcomes exhibit that the water surface area of Lakshmibaur-Nalair Haor has been changed during the period examined. Mainly, deep water area has been decreased dramatically and converted to shallow water area. The reason behind this conversion, claimed by the local villagers during the field visit, is the dam construction on the upstream which is one of the influential factors of the increment of siltation rate and the reduction of the navigability in the surrounding river system. The change statistics also show that shallow water area has augmented by around 45% over 30 years period, which is more amiable for agricultural activities. Consequently, the cropland of the study area has incremented by approximately 30% over the last three decades due to increased population and food demand. Moreover, swamp forest and village vegetation stated as vegetation class in this study has been declined gradually. During the field visit, local community also reported that fishing activity allow them to gain more profit than agriculture because fish value is higher than rice whereas haor area allow them to pursue single cropping within a year. Fish diversity in the haor area was also declined for degradation of the deep water area, the local residence reported. The vegetation of the study area was also decreased because of increasing population pressure. It would be worth mentioning that similar trend of LULC changes has also been found in two other hoars in Bangladesh, namely Tanguar haor and Hakaluki haor—situated in the same haor basin. Tanguar haor and Hakaluki haor have also experienced reduced water bodies and increased agricultural lands over the last thirty years

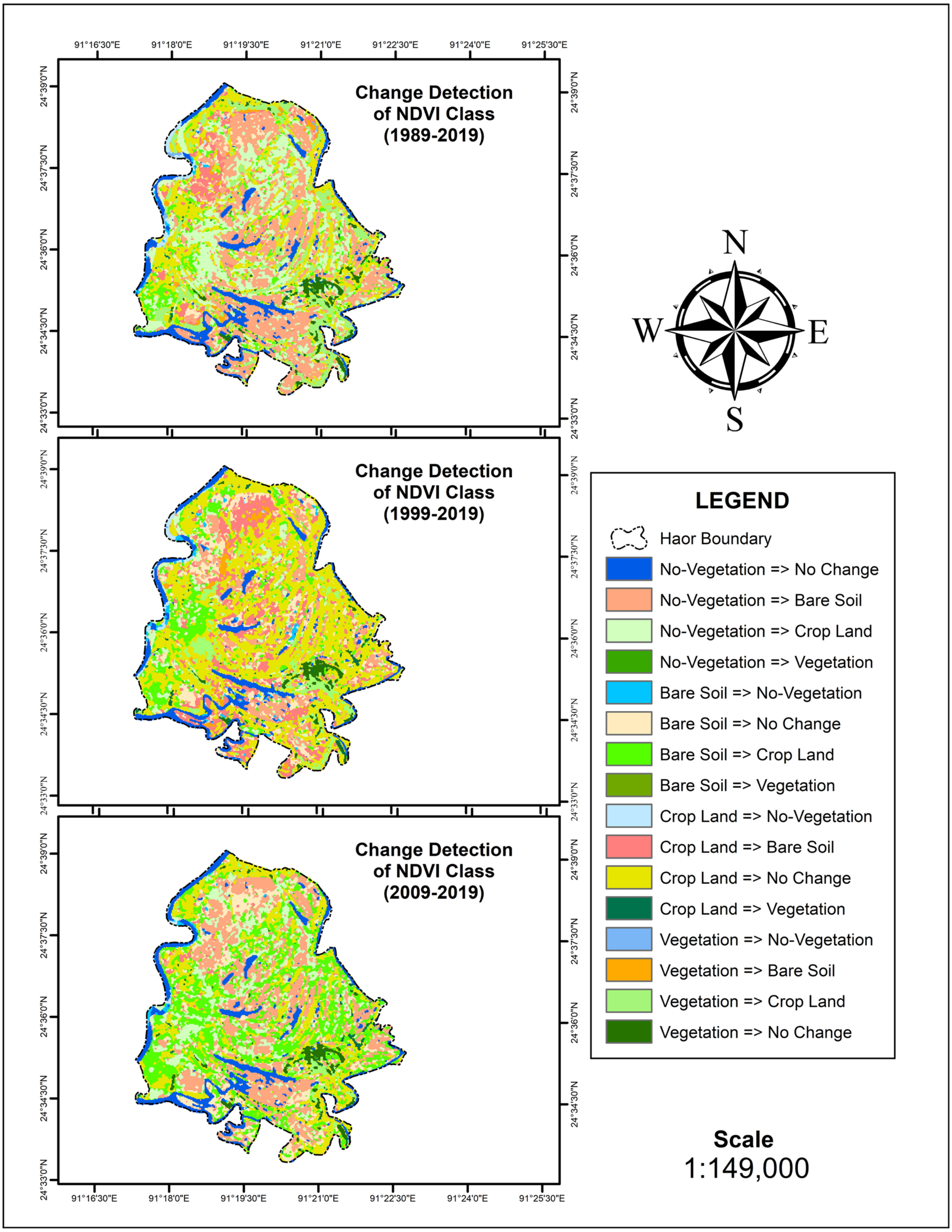

Fig. 12 NDVI change detection map of Lakshmibaur-Nalair Haor on the year of 1989, 1999 and 2009 with reference to the year of 2019

(Haque and Basak 2017; Uddin et al. 2013). These studies clearly indicate that the land cover of haor regions has been changed dramatically with an increased demographic pressure. Haor ecosystems are being impacted due to lack of proper monitoring and management. This current study contributes to understand such changes by comparing past and present scenarios. So, accurate and up-to-date information is significantly important for continuous monitoring of the haor region and more sustainable management of haor resources.

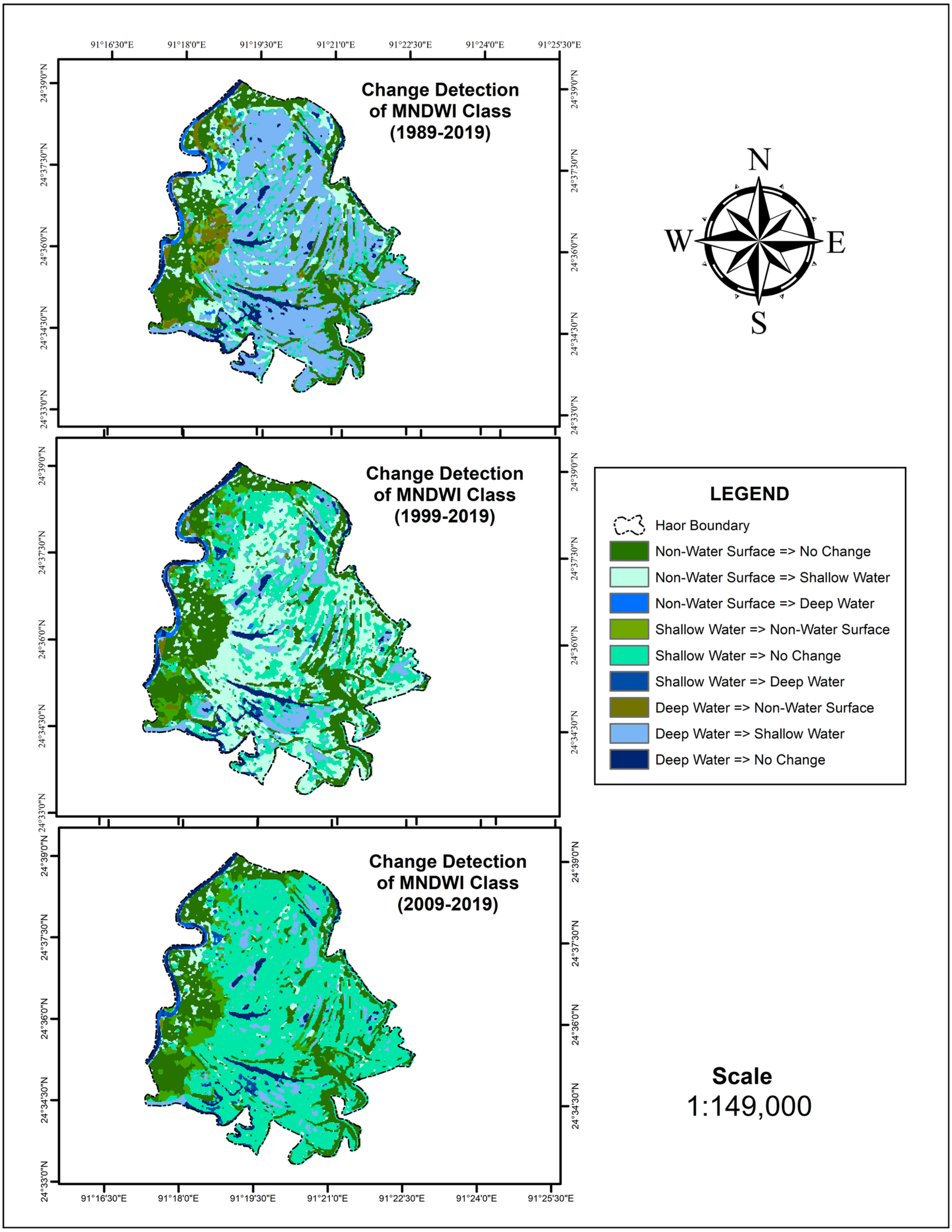

Fig. 13 MNDWI change detection map of Lakshmibaur-Nalair Haor on the year of 1989, 1999 and 2009 based on 2019, from top to bottom, sequentially

Table 7 Change detection of NDVI classes for the years of 1989, 1999 and 2009 with respect to 2019

Class name	1989		1999		2009	
	Area (ha)	%	Area (ha)	%	Area(ha)	%
No-vegetation ⇒ no change	514.74	8.75	473.52	8.05	558.44	9.49
No-vegetation ⇒ bare soil	1531.97	26.04	464.14	7.89	1326.78	22.55
No-vegetation ⇒ crop land	1137.45	19.34	231.46	3.93	664.85	11.3
No-vegetation ⇒ vegetation	5.13	0.09	2.63	0.04	1.88	0.03
Bare soil ⇒ no-vegetation	19.26	0.33	70.6	1.2	38.08	0.65
Bare soil ⇒ no change	145.89	2.48	531.27	9.03	538.59	9.16
Bare soil ⇒ crop land	388.47	6.6	528.86	8.99	1395.54	23.72
Bare soil ⇒ vegetation	4.24	0.07	3.47	0.06	4.05	0.07
Crop land ⇒ no-vegetation	54.38	0.92	49.15	0.84	10.55	0.18
Crop land ⇒ bare soil	238.05	4.05	776.89	13.22	58.68	0.99
Crop land ⇒ no change	1098.94	18.68	2266.84	38.53	1023.93	17.41
Crop land ⇒ vegetation	31.7	0.57	52.75	0.89	51.53	0.88
Vegetation ⇒ no-vegetation	10.62	0.18	4.99	0.08	3.45	0.06
Vegetation ⇒ bare soil	60.22	1.02	68.94	1.17	9.18	0.16
Vegetation ⇒ crop land	520.47	8.82	261.65	4.45	88.33	1.5
Vegetation ⇒ no change	121.41	2.06	95.78	1.63	109.08	1.85
Total	5882.94	100	5882.94	100	5882.94	100

Table 8 Change detection of MNDWI classes for the years of 1989, 1999 and 2009 with respect to 2019

Class name	1989		1999		2009	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Non-water surface ⇒ no change	1338.4	22.75	1406.34	23.91	1287.09	21.88
Non-water surface ⇒ shallow water	721.75	12.27	1919.84	32.63	239.1	4.07
Non-water surface ⇒ deep water	94.86	1.61	57.69	0.98	33.3	0.57
Shallow water ⇒ non-water surface	143.64	2.44	192.54	3.27	315.81	5.38
Shallow water ⇒ no change	719.53	12.23	1468.89	24.97	3327.3	56.56
Shallow water ⇒ deep water	13.78	0.23	84.36	1.43	109.08	1.82
Deep water ⇒ non-surface water	180.74	3.08	47.76	0.82	19.23	0.33
Deep water ⇒ shallow water	2349.65	39.94	439.66	7.47	295.04	5.02
Deep water ⇒ no change	320.59	5.45	265.86	4.52	256.99	4.37
Total	5882.94	100	5882.94	100	5882.94	100

5 Conclusion

Vegetation and water body are the regular features of wetlands. NDVI and MNDWI analysis took place to examine the similar variation among the variables of vegetation and water body. The unsupervised classification technique has been generated to produce classified maps of NDVI and MNDWI. The change detection process has been applied to determine variations in coverage of the area of all the resultant classes. This study demonstrated that the study location's deep water surface area declined at an alarming rate (~ 74 ha/year) over the last 30 years. Indeed, comparing with 1989, the current deep water area decreased by 37.54% of which about 40% also transformed into shallow water area. Thus, shallow water displayed an increasing trend during the study period. Vegetation showed a downward trend between 1989 and 2019; it decreased by 8.34% over the study period. On the other hand, cropland appeared as a land-use class showing significant expansion. Croplands increased by 29.39% over the three decades due to rising shallow water (which is favorable for agriculture activities in the dry season) and increased population pressure (which

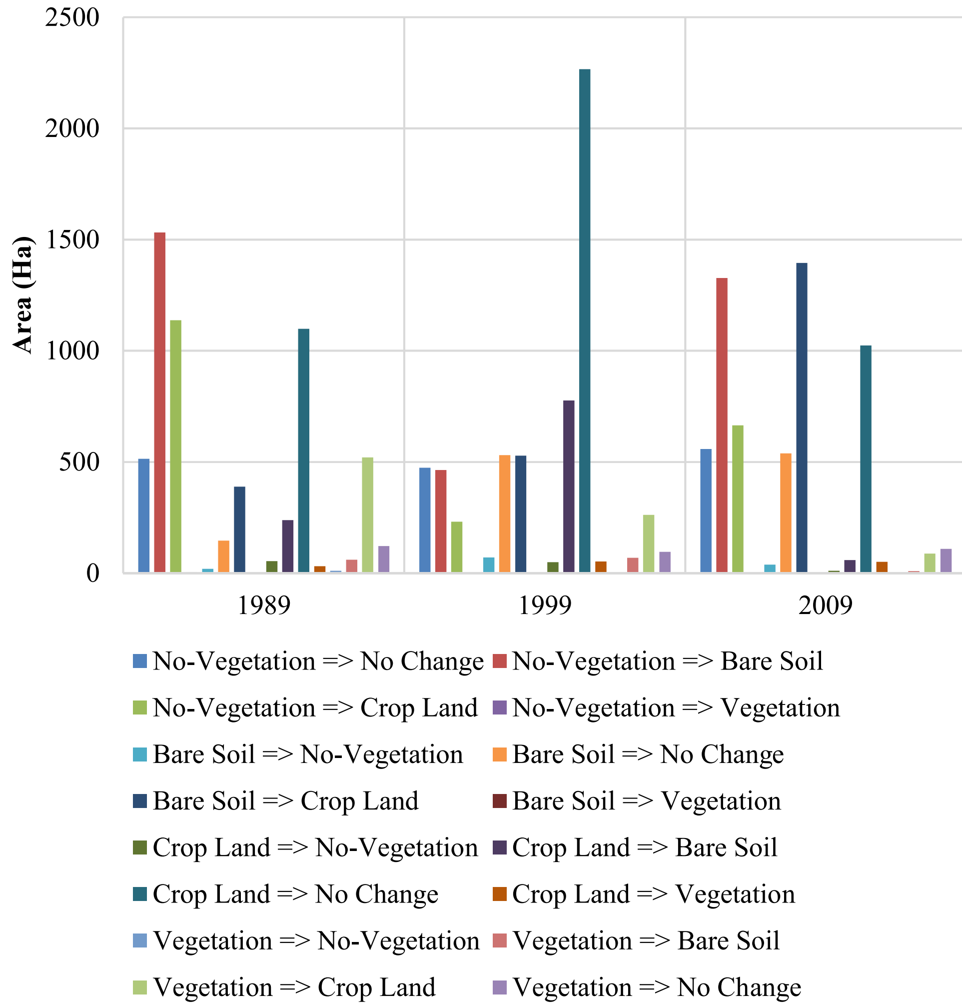

Fig. 14 Area (ha) of NDVI change detection classes for the years of 1989, 1999 and 2009 with reference to 2019

attracts more agriculture activities). Bare soil also displayed an upward trend between 1989 and 2019. Studies including Chakraborty et al. (2018) and Pal and Saha (2018) claimed that construction of dams curtailed discharge below the dam and squeezed wetland areas in some other locations in Bangladesh and neighbouring India. Though no scientific evidence available to establish such a connection as the main reason for changes in water depths in the current study area, as mentioned before, local villagers during this fieldwork claimed that dam construction on the upstream is changing water depth in the studied haor area. Both haor managers and future researchers will have the responsibility to undertake actions to examine and mitigate the potential impacts of such drivers altering hydrological feature in the study area. However, this baseline study illustrates LULC change of a freshwater wetland using spatio-temporal analysis of the Lakshmibaur-Nalair Haor area. Future studies can continue monitoring trends in LULC dynamics through LULC

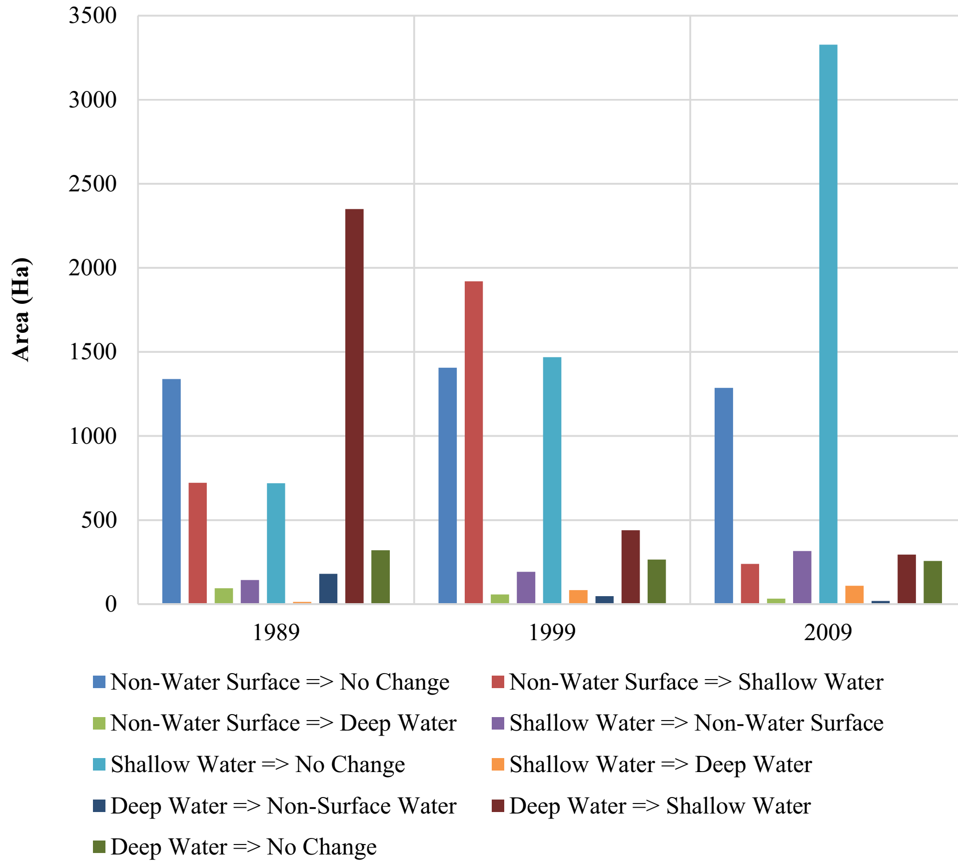

Fig. 15 Area (ha) of MNDWI change detection classes for the years of 1989, 1999 and 2009 with reference to 2019

modeling which is an essential tool for improved haor management. The findings of this study would be significant for biodiversity conservation and environmental decision making in the context of Lakshmibaur-Nalair Haor and other similar settings.

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Compliance with ethicalstandards

Conflict of interest The authors declare that they have no conflict of interest.

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