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Modelling agricultural transformation: A remote sensing-based analysis of wetlands changes in Rajshahi, Bangladesh

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ABSTRACT

Agricultural transformation is one of the important factors of rural planning and sustainable land management. There are natural and man-made reasons of this transformation, which brings both positive and negative impacts on the physical environment, food security, and human livelihoods. This study aims to explore a case of land use conversion from traditional agricultural land to the man-made wetland for fisheries in Rajshahi, Bangladesh. The conversion might be a result of purposeful land use and land cover changes to continue agricultural production for the market demands. A hybrid model of logistic regression and water index has been used to investigate the dynamics of LULC (Land Use Land Cover) changes. Moderate-resolution multi-temporal Landsat imageries of 2000, 2010, and 2020 have been used for visual interpretation and quantitative analysis. During the study period of 20 years, wetlands for entrepreneurial pond culture were remarkably increased, while agricultural land and vegetation experienced a decreasing trend. It is predicted that wetlands are going to be further increased by diminishing agricultural land and vegetation until 2030. Despite the fact of suitable data unavailability, this study also shows that the remote sensing approach provides a powerful tool for analysing and monitoring spatiotemporal agricultural transformation. Moreover, the empirical findings of land use modelling might be useful for agricultural planning and decision-making in rural Bangladesh.

1. Introduction

Bangladesh agriculture has witnessed a remarkable transformation in terms of crop diversification, utilization of modern inputs, and orientation of production. Evidence suggests that the agriculture sector (crop, livestock, fisheries, and forestry) in the country has performed very well over the years (Deb, 2016). Studies have also documented contributions of agriculture to the growth of Gross Domestic Product (GDP), food and nutrition security, and poverty reduction (Khan, 2017). Despite the share of agriculture to the GDP has been declined, the value of agricultural GDP has increased by 5.8 times between 1973/74 and 2014/15 (Deb, 2016). New farming systems have been introduced for adapting to climate change with the help of agricultural training and extension programmes and technical innovations. Noticeably, commercial poultry farming has expanded in the urban fringes (Deb, 2016). Moreover, agroforestation has been a new but welcome farming option for the farmers. Rana and Moniruzzaman (Rana and Moniruzzaman, 2021) investigated the causes and factors of practicing agroforestation instead of traditional rice farming in the Barind region of Bangladesh. As they reported, besides many socioeconomic reasons, the impact of climate change (unreliable rainfall and temperature variations) in the study area was an important factor of adopting agroforestation by the farmers. However, this indicates that Bangladesh agriculture has successfully been transformed from crop-orientated subsistence to non-crop-orientated, less climate-dependant, and demand-driven commercial production (Rana and Moniruzzaman, 2021), (Timmer, 1988). Various studies have also conceptualized this transformation as a strategy of climate adaptation to lessen the potential damages (Zamasiya et al., 2017) by introducing new production methods for agricultural sustainability (Carter et al., 2018).

Another important but little-known transformation in Bangladesh agriculture is fisheries based on an open aquatic system in the man-made wetlands (Fagun et al., 2020), (Akter et al., 2019), (Ali, 2010), (Munir, 2009). This practice has tremendously changed the agricultural production system and land use patterns in various parts of Bangladesh (Dhaka Tribune 2020). Farmers are changing their choices from rice production to fish farming (Farid Uz Zaman et al., 2017), (Ali and Haque, 2011). A considerable portion of the rice-growing field has already been converted to wetlands. For instance, as Ali and Haque (Ali and Haque, 2011) noted, around 10.1% area has been converted to pangasius farm, which was previously used for rice production. Despite the facts, little attention has been paid to the conversion of land for adopting new transformation, which is arguably a significant factor of sustainable land use management. Several pieces of research have

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emphasized only on the socioeconomic importance of pond aquaculture or fish farming. As it was reported, fish is the second most valuable agricultural crop which provides more than 60% of animal protein intake (DoF 2016), (Belton et al., 2011); and contributes to the livelihoods and employment of millions of Bangladeshis (Ghose, 2014), (Mohsin et al., 2013), (Ali, 2010), (Munir, 2009). Farid Uz Zaman et al. (Farid Uz Zaman et al., 2017) identify expectation of getting more profit as the main reason of conversion of agricultural land to ponds. Studies also try to identify the challenges of fish farming (Akter et al., 2019), (Ghose, 2014), (Munir, 2009). For example, in the context of pangasius (*pangasianodon hypophthalmus*), Monir et al. (Monir et al., 2011) have urged for the development of technical knowledge and up-gradation of the existing pangasius management practices through institutional initiatives. Similarly, Akter et al. (Akter et al., 2019) have also identified some complexities of open aquaculture which is helpful for wetland management in Bangladesh.

However, there are three types of fisheries in Bangladesh. These are: (i) inland capture fisheries, (ii) inland aquaculture, and (iii) marine fisheries (Shamsuzzaman et al., 2017). The country is also one of the leading freshwater inland fisheries producers in the world. According to the Department of Fisheries (2016), inland fisheries or aquaculture contributes more than 55% of the total production (DoF 2016). The sources of fresh water for fish farming include earthen ponds, ditches, lakes, canals, small and large rivers, and estuaries (Ghose, 2014). Fish farming in the ponds represents the mainstay of aquaculture accounting for 85.80% of total production and covering 57.70% of total areas (Belton et al., 2011), (DoF 2010). This is commonly practiced all over the country of Bangladesh. However, pond culture can also be categorized as homestead pond culture and entrepreneurial pond culture. As Belton et al. (Belton et al., 2011) define, homestead pond culture is a small component of the larger household farming system. Many rural households in rural Bangladesh have a small pond near their homestead (Huda et al., 2010), (Hambrey et al., 2008), (Barman, 2001). On the contrary, entrepreneurial pond culture is relatively recent in Bangladesh, though it has got tremendous importance and popularity for the last three decades (The Financial Express 2018). Entrepreneurial pond culture is usually purposefully originated as a stand-alone enterprise involving a significant amount of capital investment (Belton et al., 2011).

Drawing upon this agricultural transformation, the paper particularly focuses on how the land use and land cover have been changed through the conversion of previously rice-growing agricultural land to man-made wetlands for fisheries based on commercial or entrepreneurial pond culture in Rajshahi, Bangladesh. The specific objectives of this paper are: (i) to identify the land use changes during the periods of 2000–2010 and 2010–2020; (ii) to evaluate the conversion of agricultural land into wetlands (pond) for fisheries, and (iii) to discuss the impacts of agricultural land use changes and possible pathways of sustainable land use management.

2. Materials and methods

2.1. Study area

Paba and Durgapur Upazilas of Rajshahi District, Bangladesh, has been selected as the study area for this research (Fig. 1). Paba Upazila is located between 24°18′ and 24°31′ North Latitudes and in between of 88°28′ and 88°43′ East Longitudes. The Upazila is bounded by Mahanpur and Tanore Upazilas on the North, West Bengal, India and Charghat Upazila on the South, Puthia and Durgapur (Rajshahi) Upazilas on the East, and Godagari Upazila on the West (Banglapedia, 2015), (Sarker et al., 2021). The total area of this Upazila is 280.42 square kilometers. About 54.68% of this Upazila population is entirely dependant on agriculture (Sarker et al., 2021), which denotes that most of the area is covered by agricultural land. Similarly, Durgapur Upazila is located in between of 24°23′ and 24°32′ North Latitudes and in between of 88°40′ and 88°52′ East Longitudes. It is bounded by Baghmara and Mahanpur Upazilas on the North, Puthia Upazila on the South and East, and Paba Upazila on the West. It has a total area of 195.03 square kilometers, and most of the site is also covered by agricultural land (Banglapedia 2015).

2.2. Data collection

We have used both primary and secondary data for this study. Primary data was collected through short field observation and local people's perceptions. Along with various sources of governments and non-governmental organizations, spatio-temporal satellite images were also collected as secondary data. Landsat satellite images of 2000, 2010, and 2020 were downloaded from the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov). Landsat 5 (Thematic Mapper) and Landsat 8 OLI-TIRS (Operational Land Imager/Thermal Infrared Sensor) satellite imagery, multi-spectral data of 30 m resolution were used (Table 1). The multi-spectral satellite image of Landsat 5 TM carried seven spectral bands comprising a thermal band. In comparison, Landsat 8 OLI contained nine spectral bands, including a pan band, and TIRS brought only two spectral bands (USGS 2018). The Digital Elevation Model (DEM) of the study area was obtained from the Shuttle Radar Topography Mission (SRTM) of the USGS.

2.3. Data analysis and image pre-processing

After the acquisition of Landsat data, each raster image had to go through the pre-processing steps. All images were corrected regarding radiometric and atmospheric distortion. In the QGIS interface, using the SCP tool (semi-automatic classification), DOS1 atmospheric correction has been done for all images (Mukherjee et al., 2019) (USGS 2020). For sensor differences, radiometric calibration was applied by converting it into spectral radiance and TOA reflectance (Jabbar and Zhou, 2011). Since all downloaded raster images were already geometrically corrected as Universal Transverse Mercator (UTM) WGS84, Zone 45 North local projection, so it was unnecessary to rerun geometric correction. However, DEM data needed to be projected with WGS84, 45 North Zone, to prepare spatial variables such as slope, aspect, and hill shade. In addition, a few raster spatial variables (i.e., distance from road and distance from the river) was projected based on the same coordinate system. After completing all corrections, the multi-spectral raster imageries band layer (1–7 bands for both TM and OLI) was composited. Then, the study area was extracted from the composite layer. However, Fig. 2 shows the entire procedure of analysis. Notably, Quantum GIS (QGIS 3.16.2) and ArcGIS 10.3.1 software were used to conduct all the procedures discussed above.

2.4. Image classification and lulc change detection

Image classification indicates the task of finding out information classes from spatio-temporal raster data (Yedage et al., 2015). Landsat imageries carried several bands with wavelengths. For example, a total of seven bands contained Landsat 5 TM, and Landsat 8 OLI TIRS has eleven bands in total. The present study has used 1to7 bands combination of both satellite images to classify accurately based on supervised image classifications using Maximum Likelihood Classification (MLC) (Rawat and Kumar, 2015). For supervised classification, training samples were based on identifying and outlining the training sites using the ground observation points, Google Earth images and, by using false-colour tone map (Nugroho et al., 2018) (Shawul and Chakma, 2019). Firstly, a detailed land use and land cover (LULC) classification outline was established, as presented in Table 2. Since the study area is arguably going to be converted from agricultural land to human-made wetland, primarily three water indices viz. Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), and Normalized Difference Pond Index (NDPI) were performed to identify a suitable water index to detect water bodies in 2000, 2010, and 2020 (Solovey, 2020) (Brom et al., 2012). Noticeably, a little difference was

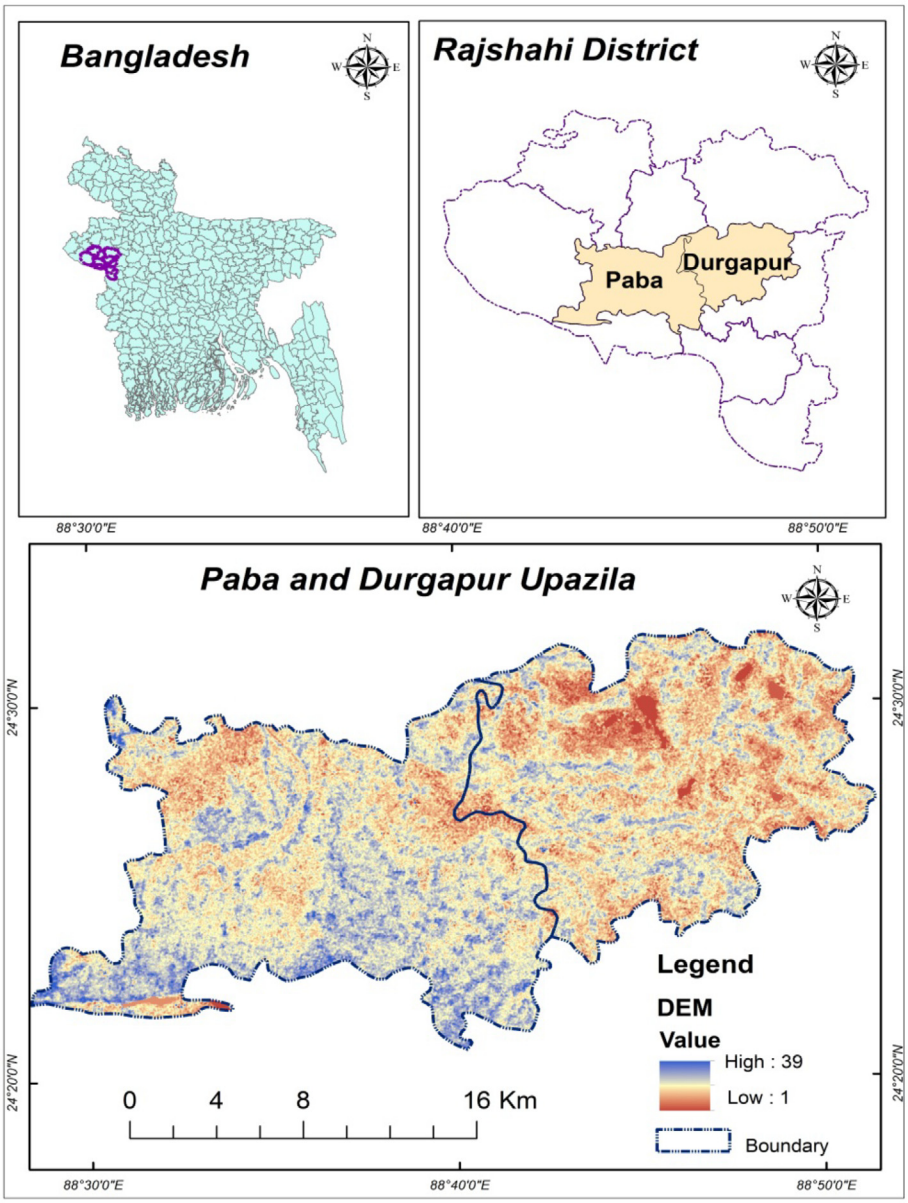

Fig. 1. Location maps of the study area.

Table 1
Acquired Landsat imageries information.

Year	Sensor	Path/Row	Acquisition Date	Cloud Cover	Resolution (m)
2000	Landsat 5 TM	138/043	26/01/2000	0.00%	30
2010	Landsat 5 TM	138/043	23/12/2010	0.00%	30
2020	Landsat 8 OLI TIRS	138/043	16/11/2020	1.61%	30

Table 2
LULC classification scheme.

Land cover outline	Description
Agricultural land	Cultivated land, crop fields, and fallow lands
Built-up land	Settlements, roads, villages, and other infrastructure
Wetlands	Fish farm, ponds, open water, inland water, and reservoirs
Vegetation	Homestead forest, mixed forest lands, trees, shrubland, and others

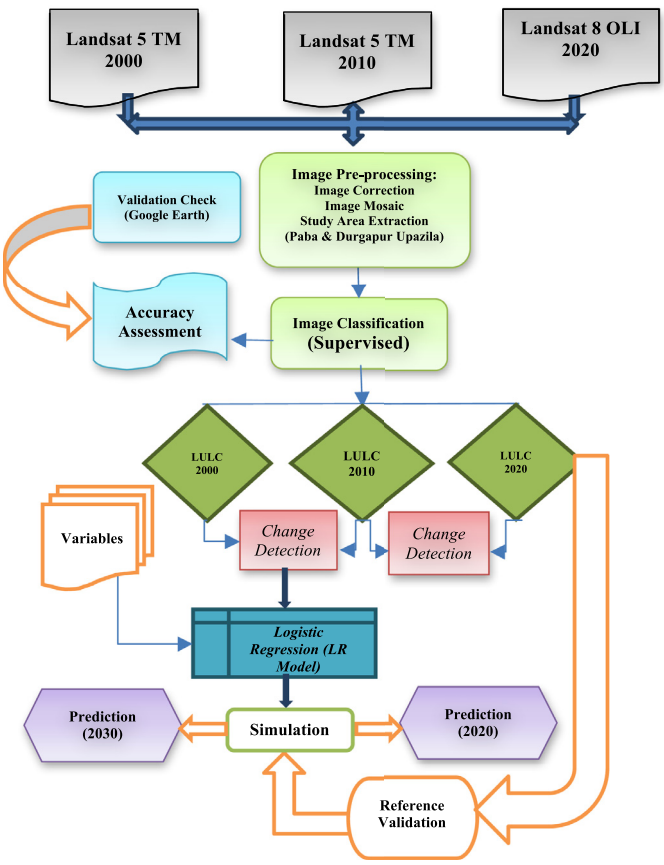

Fig. 2. Flowchart of data processing.

found between the indices. That is why NDWI was only used to visualize the wetlands of the study area. However, LULC change detection was performed by considering the aerial change of different periods, and the percentage of change was calculated based on the time frame. Change detection for the time frame of 2000 to 2010, 2010 to 2020, and 2000 to 2020 were conducted by the QGIS using the MOLUSCE (Module for Land Use Change Evaluation) plugin.

2.5. Accuracy assessment

Accuracy assessment of image classification to check data validity was carried out through the assistance of Google Earth and the participatory field verification method. Multiple random sampling was followed to this validation process. Based on the error matrix, the overall accuracy and Kappa statistic were calculated. First, the Kappa coefficient was calculated from a confusion matrix that suggested the most efficient and accurate remote sensing image classification method for effective land use mapping (Gomez and Montero, 2011). Kappa represents the proportion of agreement obtained after removing the proportion of agreement (Foody, 1992). Recently, Kappa is also considered a required component of most image analysis software packages (Bharatkar and Patel, 2013). The following equation (*eq.1*) was used to quantify the Kappa agreement (Hossain and Moniruzzaman, 2021) (Shawul and Chakma, 2019).

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+1} \times x_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{i+1} \times x_{+i}\right)} \tag{1}$$

Here, r = number of rows in the matrix,

x_{ii} = number of observations in row i and column i,

x_{+i} and x_{i+1} are the marginal totals of row i and column i, respectively; and

N = total number of observations.

2.6. Spectral index

The Normalized Difference Water Index (NDWI) is one of the most suitable water indexes to detect water bodies of land surface area. The NDWI counted open water surfaces by using Near IR and Visible Green-light to enhance water and to disregard the presence of soil and terrestrial vegetation covers (Jiang et al., 2015). The equation for water index is shown below (Eq. (2)).

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \tag{2}$$

Here, NIR = Near-Infrared; and GREEN = Visible green spectral bands of the image. The value of NDWI ranges between −1 and +1. The index defines the content of water within the vegetation-water state of vegetation and the positive range of this index is signified by water (Rahman and Esha, 2020).

2.7. Simulation model of land use and land cover (LULC) change

Several hybrid models have widely been developed for modelling LULC changes over the last two decades (Han et al., 2015). Markov Chain Model, Logistic Regression (LR), Cellular Automata–Markov Model (CA–Markov), Weights of Evidence, Artificial Neural Network (ANN), Multi-criteria Evaluation, SLEUTH Model are some of the most frequently used for land use prediction and simulation (Rahman et al., 2017), (Yatoo et al., 2020). In the present study, Logistic Regression (LR) Model has been executed for the best outcome of future prediction, while it does not weigh the influence of the neighbouring pixel into the conversion of probability statistics (Tine et al., 2019). Since the study area continues to transform into man-made wetlands, the model needs to be fitted to describe the probability of changes between various LULC for each pixel of the study area. The logistic regression model does function within predefined time intervals with the probability of change from one single class to another. Binary logistic equation (eq. (5)) represents the relationship of LULC change factors.

$$log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_n X_{n,i} \tag{5}$$

Here, *pi* is the probability that the land-use of grid i will change, *Xn* is the land-use change factor, and *βn* is the regression coefficient for each land-use change factor (Lee and Jeon, 2020). The simulation model LR was performed in MOLUSCE (Module for Land Use Change Evaluation) tool provided in QGIS (Quantum GIS) software. In the MOLUSCE plugin, a few spatial variables were used (i.e. slope, aspect, hill shade, distance from the road, distance from the river, etc.) to evaluate the correlation between variables (Rahman et al., 2017), (Ullah et al., 2019). However, the simulation model was run through several steps. Firstly, initial (2000) and final (2010) layers were selected to produce the simulated land use of 2020. Then, the simulated and original classified image of 2020 was compared by checking the accuracy of two rasters. Finally, the predicted land use map of 2030 was generated by using the classified images of 2010 and 2020. The LR model was executed considering physical and spatial (independent) variables such as slope, aspect, hill shade, distance from the road, and distance from the river (Hossain and Moniruzzaman, 2021).

2.8. Validation of simulated model

The validation process considered Kappa statistic, which was based on four constraints (Kappa histogram, Kappa location, Kappa overall, and percentage of correctness. The equations for the validation parameters are shown below (Satya et al., 2020).

$$K = \frac{P(A) - P(E)}{1 - P(E)} \tag{6}$$

$$K_{loc} = \frac{P(A) - P(E)}{P_{max} - P(E)} \tag{7}$$

Table 3
Accuracy assessment of classified images.

Year	Overall Accuracy (OA)	Kappa Statistic (K)
2000	89.36%	0.8577
2010	88.68%	0.8472
2020	92.06%	0.8937

$$K_h = \frac{P_{max} - P(E)}{1 - P(E)} \tag{8}$$

Where $P(A) = \sum_{i=1}^{c} P_{ii}, = \sum_{i=1}^{c} p_{iT} p_{Ti}, P_{max} = \sum_{1=i}^{c} min(p_{iT} p_{Ti})$

Here, Pij is the i, j^{th} cell of a contingency table, Pi_T is the sum of all cells in the ith row, P_{Tj} is the sum of all cells in the jth column, and c is the count of raster categories.

3. Results

3.1. Accuracy assessment of image classification

Land use and land cover image classification were validated by the accuracy assessment based on the overall accuracy (OA) and the Kappa statistic for the years 2000, 2010, and 2020 (Table 3). As can be seen from Table 3, the overall accuracy indicates a level of strong acceptance for all classified images. Kappa statistic follows the measure of agreement between 0 to +1. According to Bharatkar and Patel (Foody, 1992), if the value of Kappa (K) is less than 0.4, it denotes a poor agreement; while the range from 0.4 to 0.75 and more than 0.75 indicates good and excellent agreements respectively. Accordingly, the accuracy measure of the Kappa statistic for this study certifies as an excellent agreement (Table 3).

3.2. NDWI water index

The NDWI map in Fig. 3 shows the location of wetlands in different years of the study areas. The blue colour denotes water bodies (ponds/wetlands), which shows the difference between natural wetlands and man-made wetlands of the images of (a) 2000, (b) 2010, and (c) 2020 respectively. The natural wetlands cover of 2000 and 2010 were limited within a small area; but in 2020, the made-made wetlands for fisheries have encroached almost four times of the wetlands in comparison to 2010 (Table 2). The water index also reveals that the wetlands coverages of 2000 and 2010 were the natural part (*beel* and *haor*[1]) of the water bodies. However, likewise, these natural water bodies and the adjacent agricultural lands have also been transformed into wetlands for fisheries based on entrepreneurial pond culture. Undoubtedly, this conversion of land use and land cover has seriously affected the agricultural system and natural environment.

3.3. Major lulc classification and change analysis

The study has identified four major land cover categories, which are: built-up land, vegetation, agricultural land, and wetlands (Fig. 4). As the aim of the study was to visualize wetlands utilization by commercial fish farming, only major land cover categories were selected after considering all empirical and technical difficulties to compare between land use categories. Table 2 depicts specific land uses under different land covers.

The primary results of field survey and land use and land cover (LULC) changes show that the dominant LULC was agricultural land, whereas wetlands cover was a small portion of the study area at the beginning (Fig. 4). Table 4 shows that agricultural land was covered by around 27,882.45 hectares (ha) (63.66%), built-up 2858.85 ha (6.53%), vegetation 12,295.17 ha (28.07%), and wetlands 765.09 ha (1.75%) in 2000. In the year 2010, agricultural land remained almost steady, but other categories experienced remarkable changes. For instance, agricultural land, built-up land, and wetlands reached up to 28,568.25 ha (65.22%), built-up area 4162.77 ha (9.50%), and 2500.65 ha (5.71%) respectively; while vegetation cover declined to 8569.89 ha (19.57%). This indicates a significant increase in built-up areas and wetlands. In 2020, the land use changing scenario in terms of man-made wetlands became clearer (Fig. 3), although agriculture remains the largest land use category with a noticeable decline. As it stands in 2020, the agricultural land was 21,659.49 ha (49.45%), built-up land was 5981.22 ha (13.65%), vegetation was 7743.24 ha (17.67%), and wetlands were 8417.61 ha (19.21%).

As can be seen in Fig. 4, agriculture remains the largest land use category in the study area during the period of 2010–2020, though experienced a decreasing trend. In the whole study period (2000–2020), 6222.96 hectares (ha) of agricultural land was converted to wetlands or built-up areas (see Tables 5 and 6). Similarly, a decreasing trend was also observed for vegetation. During the study period, 4551.91 ha area of vegetation was converted to wetlands or built-up areas. In 2000, almost 28% of the study area was covered by vegetation. Unfortunately, this amount was decreased to less than 18% in 2020. Obviously, built-up areas and wetlands are increasing in the study area. In comparison to the period of 2010–2020, this increasing trend was not that apparent between 2000 and 2010. In 2000, only 765.09 hectares (1.75%) of land was under the category of wetlands. But, in 2020, wetlands covered almost one-fifth (8417.61 hectares) of the total area, which was mostly used for fish farming based on entrepreneurial pond culture (Fig. 4). In addition, the built-up land was only 6.53% in 2000, which increases up to 9.50% in 2010 and 13.65% in 2020. This indicates the built-up land has almost been doubled in twenty years. As it was found, the construction of new settlements is the major reason of the increasing trend of built-up land. However, the area of agricultural land and vegetation has decreased, and the area of wetlands and settlements has increased in comparison with the earlier periods (2000 and 2010) (Table 4 and 5).

3.4. Transition matrix of lulc

The transition probability matrix of LULC is calculated based on the probability of transformation of the land use pattern to another class. This matrix is attributed to the logic of the Markovian Model, and the measurement of conversion was calculated from two classified raster data in the logistic regression module. The probability matrices were generated from the raster for 2000–2010, 2010–2020, and 2000–2020 by the interface of the MOLUSCE plugin in QGIS. However, during 200–2020, it was found that the most dynamic land use categories are vegetation and agricultural land with the transition probabilities of 0.29 and 0.48 respectively. Between 2000–2010, the vegetation cover was more dynamics to be converted into agricultural land (Table 6). But, for the change period of 2010–2020, the most dynamic land use transformation probability was agricultural land to wetlands. The overall probability matrix for the period of 2000–2020 demonstrates that vegetation and agricultural land are converting to built-up land and wetlands. Fig. 4 also confirms that most of the conversions have occurred in natural water bodies, which were previously used as agricultural land for rice farming.

3.5. LULC simulation and validation

When compared with the actual classified raster of 2020 with the predicted raster of LULC, the Kappa statistic suggests the nature of the agreement between the rasters and their probabilities. $K_{overall}$ was used to evaluate the overall success of simulation and $K_{location}$ was used to evaluate the ability of the simulation to identify a location. Kappa

[1] *Beel* and *Hair* is locally known as large wetland comprise of series of depressions interconnected by various channels.

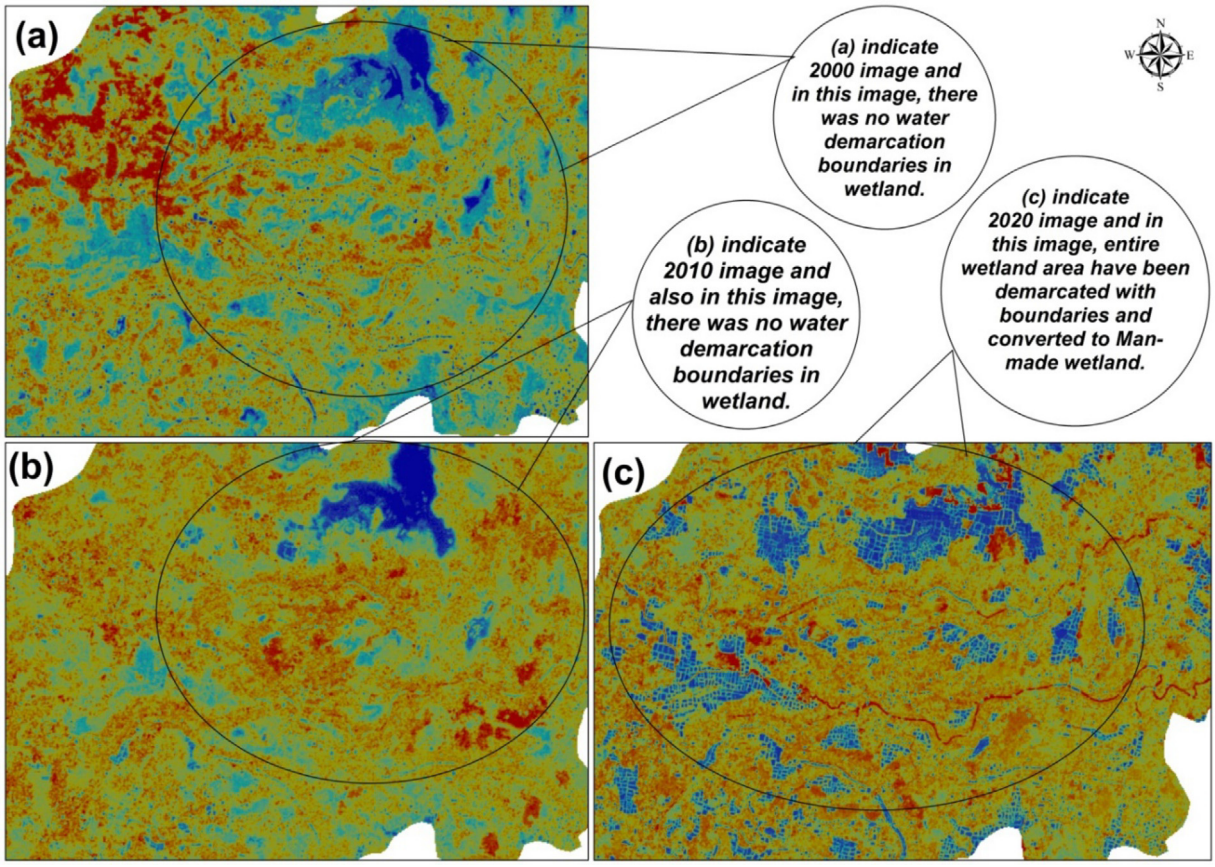

Fig. 3. NDWI indicates wetland cover comparing three different images (2000, 2010, and 2020). [Note: Blue colour denotes wetland cover].

Table 4
Area per LULC class in hectares (ha) and percentages (%) (2000–2020).

Land use categories	Aerial coverage in hectares			Aerial coverage in percentage		
	2000 (ha)	2010 (ha)	2020 (ha)	2000 (%)	2010 (%)	2020 (%)
Built-up land	2858.85	4162.77	5981.22	6.53	9.50	13.65
Vegetation	12,295.17	8569.89	7743.24	28.07	19.57	17.67
Agricultural land	27,882.45	28,568.25	21,659.49	63.66	65.22	49.45
Wetlands	765.09	2500.65	8417.61	1.75	5.71	19.21

Table 5
LULC change detection in hectare (ha) and percentage.

LULC Categories	Area Change in hectares (ha)			Area Change in percentage (%)		
	2000–2010	2010–2020	2000–2020	2000–2010	2010–2020	2000–2020
Built-up land	+1303.92	+1818.45	+3122.37	+2.98	+4.15	+7.13
Vegetation	−3725.28	−826.65	−4551.91	−8.50	−1.89	−10.39
Agricultural Land	+685.80	−6908.76	−6222.96	+1.57	−15.77	−14.21
Wetland	+1735.56	+5916.96	+7652.52	+3.96	+13.50	+17.47

[N.B: (+) sign specifies increase and (–) sign a decrease].

statistic with 0% indicates that there is no agreement while 100% indicates perfect agreement (Aneesha Satya et al., 2020). Table 7 shows the results to check the agreement between simulated 2020 and the actual classified raster of 2020. The estimation of Kappa (histogram) is 0.86187, Kappa (location) is 0.93236, and Kappa (overall) is 0.80357, while the percentage of correctness is 87.42182. This shows the consistency between the predicted 2020 LULC and the real 2020 LULC situation, which is good and the model is reliable for further prediction. However, the validation statistic of the predicted 2030 raster is given in Table 8. The prediction for 2030 shows a further increase of built-up land (6.41%) and wetlands (3.62%) from the year 2020. On the contrary, during the same period, vegetation and agricultural land might be decreased by 3.53% and 6.50% respectively. Table 8 also depicts that agricultural land would remain as a single dominating category of land use, but with a decreasing trend. As it was found, the agricultural land was 63.63% of the total area in 2000. But this amount might be decreased to 42.95% in 2030. On the contrary, the percentage share of wetlands in 2000 was only 1.75%, which might be increased to 22.83% in 2030. In addition, a large area under vegetation and agricultural land might be converted to built-up land (Fig. 5).

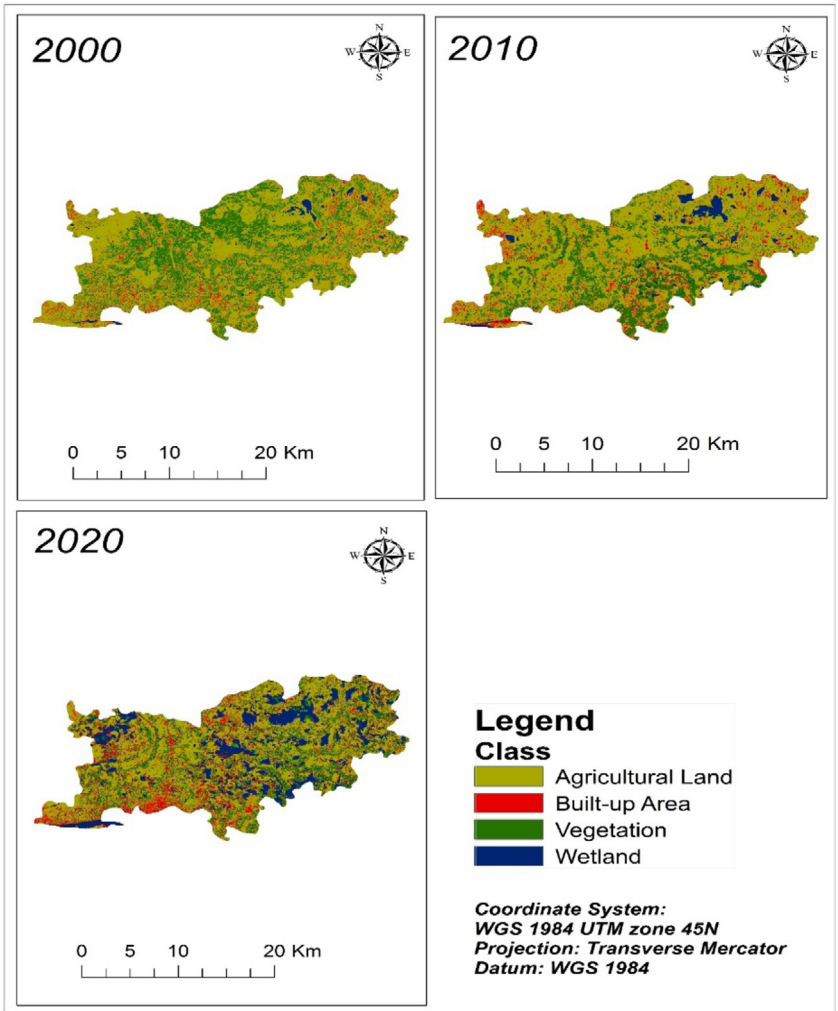

Fig. 4. LULC classification of Paba and Durgapur Upazilas.

Table 6
Land Use Transition Probability Matrix (2000–2010, 2010–2020, and 2000–2020).

Transition periods	LULC Class	Built-up land	Vegetation	Agricultural Land	Wetlands
2000–2010	Built-up land	**0.738076**	0.083960	0.170093	0.007870
	Vegetation	0.044988	**0.374847**	0.566117	0.014047
	Agricultural Land	0.109734	0.133271	**0.696532**	0.060464
	Wetlands	0.083284	0.006705	0.100224	**0.809787**
2010–2020	Built-up land	**0.525263**	0.051694	0.171492	0.251551
	Vegetation	0.128627	**0.454238**	0.365245	0.051890
	Agricultural Land	0.143962	0.118047	**0.568421**	0.169571
	Wetlands	0.020911	0.105129	0.041605	**0.832356**
2000–2020	Built-up land	**0.562789**	0.101968	0.205415	0.129828
	Vegetation	0.125376	**0.292388**	0.539385	0.042851
	Agricultural Land	0.137929	0.135821	**0.480163**	0.246087
	Wetlands	0.008705	0.091166	0.039995	**0.860134**

Table 7
LR Model validation for simulated 2020 raster.

Kappa Indices	Value (%)
Kappa (histogram) (K_h)	0.86187
Kappa (location) (K_{loc})	0.93236
Kappa ($K_{overall}$)	0.80357
(%) of correctness	87.42182

4. Discussion

The findings of LULC analysis for the period of 2000–2020 have revealed a continuous increase in built-up areas and wetlands, while the vegetation and agricultural land continue to decrease. For example, during the 20-year, wetlands had increased by 13.50%, while the main source was agricultural land with a decreasing rate of 15.77%. It was also noticeable that the extensive growth of man-made wetlands (ponds) took place after 2010. As it appears, the farmers purposefully accepted this transformation to continue agricultural production for their survival and growing demands of the fish market in the cities (Dhaka Tribune 2020). This growth of wetlands can also be associated with the recent climate change impacts (irregular rainfall and temperature fluctuations) on traditional rice farming (Rana and Moniruzzaman, 2021), (Sarker, 2012). Arguably, this transformation has given a massive boost and self-sufficiency in fish production based on commercial or entrepreneur pond culture in the region (The Financial Express 2018), (Ali and Haque, 2011). As a result, previously known agricultural

Table 8
Predicted land use and land cover change, 2020–2030.

LULC Categories	LULC Distribution				2020–2030	
	Hectares (ha)		Percentage			
	2020	2030	2020%	2030%	Change (ha)	Change (%)
Built up land	5981.22	8789.94	13.66	20.07	+2808.72	+6.41
Vegetation	7743.24	6196.59	17.67	14.17	−1546.65	−3.53
Agricultural Land	21,659.49	18,813.60	49.45	42.95	−2845.89	−6.50
Wetlands	8417.61	10,001.43	19.21	22.83	+8834.40	+3.62

[N.B: (+) sign point out as increase and (–) sign as decrease].

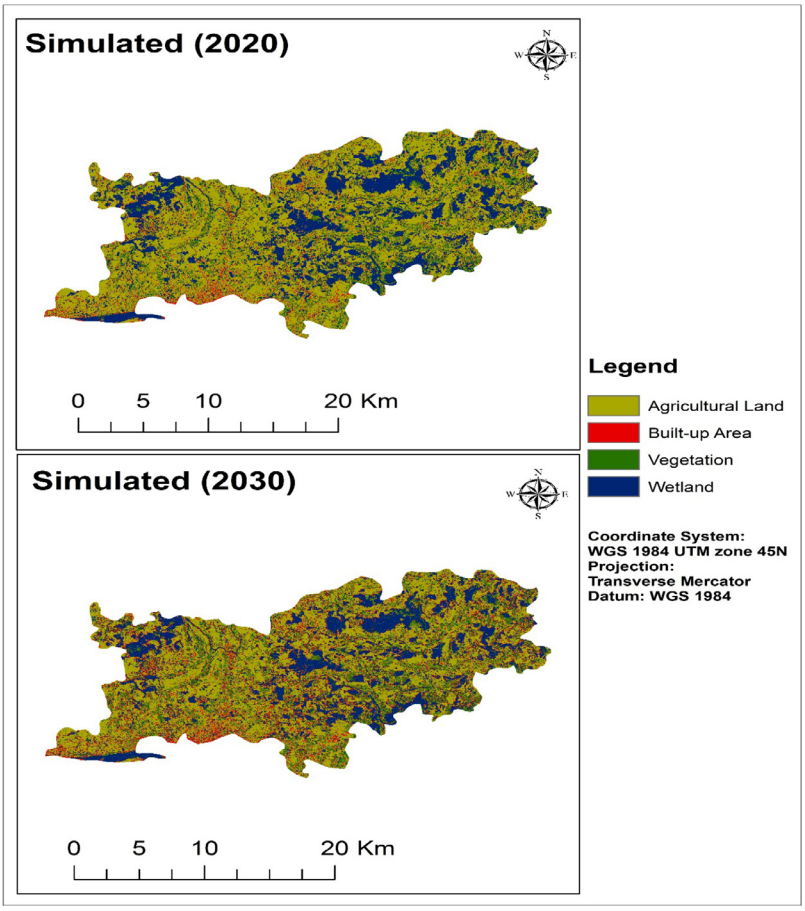

Fig. 5. Prediction LULC map of Paba and Durgapur Upazila (2020 and 2030).

land for rice farming has been converted to the big pond for fisheries after receiving huge investments in recent years. Particularly, the wealthy entrepreneur farmers in the study area have invested in fisheries. Many smallholder farmers have leased their lands to the entrepreneur fish farmers for certain periods in the region (Mohsin et al., 2013).

However, the transformation of agriculture in the region has been occurred only by the choices of farmers for getting alternative income-earning opportunities for survival without based on any prior agricultural policy formulated by the Government of Bangladesh. This uncontrolled land conversion for fisheries has thus raised an immense concern for the loss of vegetation and biodiversity, food security, and rural land use management. The spatial analysis in this study has depicted that a remarkable area of vegetation has been converted to wetlands and agricultural land. Most importantly, extensive patches of vegetation in 2000 first came under agricultural land and built-up land, and then recently (2010–2020) many agricultural patches had been converted to wetlands. This has definitely led to a change in the agricultural system, rural biodiversity, and food security. For example, the traditional rice-based monoculture has now going to be changed to entrepreneurial fisheries or aquaculture-based monoculture. There is no question that the new wetlands in the rural areas have offered a different type of aquatic ecosystem and employment opportunity, but unfortunately, it has brought changes to rural ecosystems and livelihoods. In addition, the present agricultural system has experienced different patterns of crop diversities and rotations, which is new to the farmers.

The predicted results of LULC also indicate that the growth of wetlands is likely to continue in the coming years. Particularly, the low-lying natural water bodies (*beel* or *haor*) might be converted to man-made wetlands after diminishing agricultural land in both of the Upazilas in Rajshahi. If this is the reality, watershed or aquatic environment management would be a big task, while there are multifaceted impacts of fish farming on the environment (Jia et al., 2015). For instance, the use of chemicals during fish farming would be harmful to the aquatic and land ecosystems (Hassan et al., 2005). In addition, the ponds would need an underground water supply during the dry seasons (December to May/June). This will certainly impact the fluctuation of ground water-table in the regions (Aziz et al., 2015), (Jahan et al., 2010).

This study, therefore, provides empirical evidence of agricultural transformation and helps to understand how rural Bangladesh is going to be changed in the future. The findings would be conducive for a better understanding of entrepreneurial fisheries in particular and the agricultural transformation in the age of climate change in general. Based on the predicted results, the rural and agricultural development planners and policymakers would be able to make decisions .regarding the priority areas for long-term and short-term planning as well as to conserve rural biodiversity and ensure sustainable livelihoods. More attention is to be paid to wetlands or watershed development and management in the rural areas and potential impacts on food security. Additionally, the vegetation cover is expected to decrease as they are gradually converting into wetlands and built-up areas including settlements, roads, and other infrastructures. Thus, the overwhelming excavation of ponds for fisheries would increase the potential of flooding and waterlogging in the region during heavy rainfall. It is therefore inevitable to regulate the process of land use changes, such as agricultural transformation for ensuring socio-economic and environmental sustainability.

The method of land use modelling and simulation might be useful in rural development planning and policy formulation. An integrated model consisting of land use change, population, and economic data might be an effective decision-making framework to predict the future demands of lands of different categories and to monitor their changes. However, the limitation of this modelling was the unavailability of spatial and socioeconomic data of different categories. Methodologically, another limitation was to classify data according to our needs. For example, it was not possible to differentiate the entrepreneurial ponds from others. In addition, it was hard to fix the amount of built-up land while many of them are hidden by the homestead vegetation. Regardless of the limitations, the outcomes of the study might play a pivotal role in better land-use planning and decision-making.

5. Conclusion

The study aimed to explore the land use and land cover (LULC) change, particularly the growth of wetlands (for fisheries) converted from agricultural land and vegetation in Rajshahi, Bangladesh. During the study period of 20 years (2000–2020), wetlands were remarkably increased while agricultural land and vegetation areas experienced a decreasing trend. The main reason was to continue agricultural production according to the marker demands and profitability. Based on the findings, it is expected that more ponds for fisheries are going to be excavated through diminishing agricultural land and vegetation. Despite the fact of suitable data unavailability, this study also shows that the remote sensing approach provides a powerful tool for analysing and monitoring spatial and temporal land use and land cover changes. Moreover, the empirical findings of land use modelling might be helpful for land use planning and decision-making in rural Bangladesh. Further studies should consider regional land use changes on a broader scale to investigate the connectedness or independence of individual land use change happening in the rural and urban fringe areas. Most importantly, how adjacent urban markets may influence a particular rural land use such as wetlands might be a good research question.

Declaration of Competing Interest

There is no competing interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envc.2021.100400.

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