LAND USE AND LAND COVER CHANGE DETECTION IN PAIKGACHA UPAZILA OF KHULNA DISTRICT IN BANGLADESH USING A MACHINE LEARNING AND REMOTE SENSING-BASED APPROACH

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ABSTRACT

Large-scale changes in land use and land cover (LULC) have been occurring throughout Bangladesh due to urbanization, agricultural growth, and industrialization. In particular, dynamics of LULC changes in the coastal floodplains of the country are very crucial, as these areas are highly susceptible to environmental changes caused by frequent occurrences of cyclones, storm surges, and sea level rise. The current study has explored the spatiotemporal dynamics of LULC in Paikgacha Upazila of Khulna, Bangladesh, over the past 30 years, from 1990 to 2020 using a machine learning and remote sensing-based approach. The objective is to assess the temporal shifts and spatial distribution of five key LULC categories, including river, built-up area, wetland, vegetation, and bare land at five-year intervals. These categories were selected based on their importance to the region's socio-economic activities and environmental sustainability. High-resolution satellite imagery and cloud-based remote sensing techniques were utilized through the Google Earth Engine (GEE), applying Random Forest for supervised classification. Model reliability was rigorously confirmed through an accuracy assessment, with the classification consistently achieving high performance across all seven time slices (1990–2020), with an overall accuracy generally exceeding 83% and the kappa coefficient (κ) consistently above 0.67. Quantitative assessments of land cover change were conducted to measure net area variations in each category over time. Results reveal significant transformations across the study area. The built-up area expanded steadily from 65.06 km² in 1990 to 99.55 km² in 2020, indicating significant land use changes caused by rapid urban growth. Wetland areas fluctuated but showed a remarkable 110.55% increase by 2020, reaching a peak of 107.53 km², likely driven by the rise of brackish water aquaculture in response to increased salinity and coastal pressures. Vegetation experienced an initial decline followed by a minor recovery in 2000 but declined again by 2020. Bare land decreased sharply by 65.16% over the study period, from 121.46 km² in 1990 to 42.32 km² in 2020, reflecting shifts in land utilization and possible urban encroachment. These changes were mapped and analyzed to identify critical hotspots of LULC transition. The current study highlights critical spatial zones with prominent transitions, providing insight into the pressures exerted on natural landscapes by human development. The results emphasize the urgent need for sustainable land management strategies that integrate green space conservation and wetland protection. The current study provides a scalable methodology for long-term environmental monitoring using freely available satellite data and cloud computing tools, supporting informed land-use planning and biodiversity conservation in similar geographic contexts. These strategies are particularly important for managing the dual pressures of climate change and rapid urbanization, ensuring the preservation of valuable ecosystems such as wetlands while facilitating responsible development in vulnerable coastal areas.

Keywords: *LULC, Remote Sensing, Urbanization, Machine Learning, Google Earth Engine.*

1. INTRODUCTION

Land use and land cover (LULC) changes are one of the significant indicators of environmental changes in a watershed, particularly in rapidly developing regions like Bangladesh. These changes are driven by urbanization, agricultural expansion, and industrialization, especially in coastal areas such as Paikgacha Upazila of Khulna District in Bangladesh (Rahman et al., 2019). The natural environment, local economies, and social structure of the region are all significantly impacted by these transformations (Rai et al., 2017). Coastal floodplains, which are vital for agriculture, shrimp farming, and fisheries, are particularly vulnerable to climate change, including rising sea levels, cyclones, and saline intrusion. The expansion of urban settlements and agricultural land further threatens critical ecosystems such as the Sundarbans mangrove forest, one of the largest and most ecologically significant forests in the world (Clapcott et al., 2012; Islam & Tabeta, 2019).

The degradation of these ecosystems increases the susceptibility of local populations to natural disasters, including floods, cyclones, saline intrusion, and seasonal droughts (Shameem et al., 2014). Environmental deterioration, such as reduced fish catches and lower labor demand, often drives rural-to-urban migration, placing additional strain on urban resources and affecting vulnerable communities the most (Lipton, 1980). These existing vulnerabilities are projected to intensify due to climate change, with more frequent cyclones, erratic rainfall, rising sea levels, and enhanced riverbank erosion (Rahman et al., 2019). Given these escalating risks, understanding the dynamics of LULC changes in Bangladesh's coastal areas is essential for effective governance, disaster risk reduction, and climate adaptation strategies (Sarwar & Islam, 2013).

Despite the critical need for research, long-term studies on LULC changes in the coastal floodplains are sparse and often limited in scope, focusing on regional data that overlook broader trends across the delta (Abdullah et al., 2019; Akber et al., 2018). To address this gap, remote sensing (RS) data combined with advanced analytical methods has become essential for monitoring LULC changes across large spatial and temporal scales (Griffiths et al., 2010). RS offers a cost-effective and efficient approach, while machine learning algorithms, particularly Random Forest, improve classification accuracy (Rodriguez-Galiano et al., 2012). This study integrates these techniques using Google Earth Engine (GEE) to enhance understanding of LULC dynamics, supporting sustainable development planning (Holloway & Mengersen, 2018).

The study focuses on Paikgacha Upazila in Khulna, a region affected by rising temperatures, saltwater intrusion, and irregular rainfall patterns (Sarwar & Islam, 2013). It aims to assess shifts in five key LULC categories: river, built-up area, wetland, vegetation, and bare land from 1990 to 2020. The study also detects and quantifies LULC changes at five-year intervals, considering both temporal and spatial patterns to provide a comprehensive understanding of the region's evolving landscape. The findings are expected to offer evidence-based information for stakeholders, policymakers, and resource managers guide land-use decisions and interventions (Riebsame et al., 1994). However, the inherent bias of the Random Forest classifier toward the majority class (Bader-El-Den et al., 2019) must be considered, as it may affect the classification of minority LULC features. Despite this limitation, the study reveals significant transformations, including the expansion of built-up areas and increases in wetland regions, highlighting the pressures from both human development and the need for adaptive strategies. Ultimately, it emphasizes the importance of sustainable land management practices, including green space conservation and wetland protection, to support resilient development and climate adaptation in coastal areas.

2. METHODOLOGY

The current study mainly focuses on the assessment of spatiotemporal changes of LULC in Paikgacha Upazila of Khulna district in Bangladesh during the 1990-2020 period. The complete methodological procedure, from study area selection to data acquisition and processing, from model development and evaluation to LULC change detection, is summarized through a flowchart, which is shown in Figure 1.

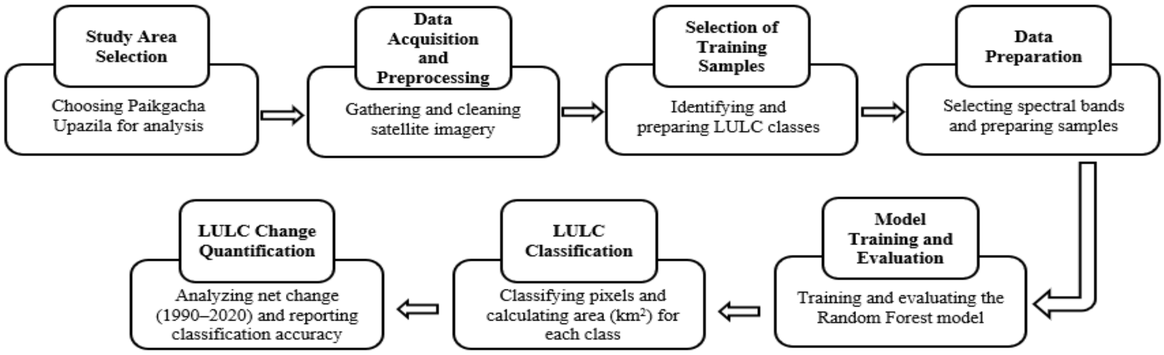

Figure 1: Methodological framework for LULC classification and change quantification steps

2.1 The Study Area

The study focuses on Paikgacha Upazila (Latitude 22.5889°N, Longitude 89.3361°E) in the Khulna District of southwestern Bangladesh. Spanning an area of 411.19 km², Paikgacha Upazila is representative of the region's diverse coastal environment and socio-economic characteristics. The administrative structure includes ten Union Parishads (Chandkhali, Deluti, Godaipur, Goroikhali, Horidhali, Kopilmuni, Loskor, Lota, Raruli, and Soladana) and Paikgacha Municipality. The geographical location of the study area is presented in Figure 2.

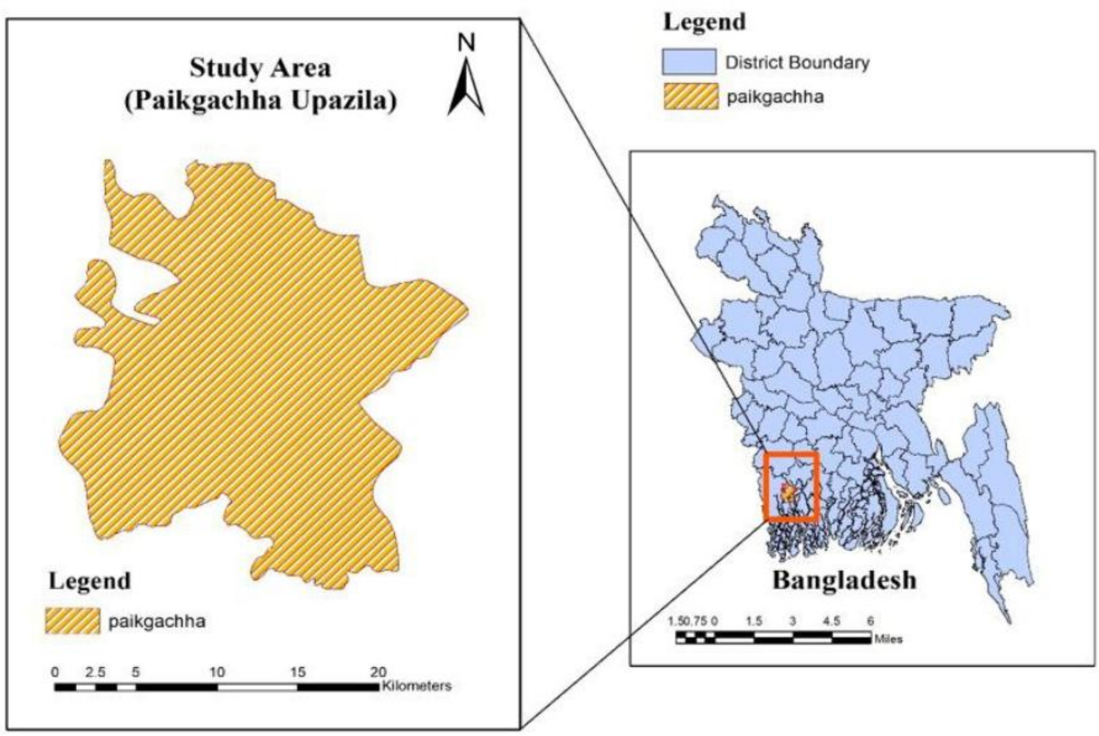

Figure 2: Location of Paikgacha Upazila (the study area) in Khulna district of Bangladesh

The Upazila is strategically located, bordered by the Mayur River to the west, which defines its geographical boundary and influences its hydrological dynamics. The region faces significant environmental risks, including salinity intrusion, rising sea levels, and land erosion, all exacerbated by human activities, such as shrimp farming. These factors have a direct impact on local livelihoods and land use patterns, making it an ideal area for LULC analysis.

2.2 Data Acquisition and Processing

For the assessment of LULC changes from 1990 to 2020, Landsat satellite imagery data were collected from the United States Geological Survey (USGS). The study utilized a series of seven time-series satellite images with less than 1% cloud cover to ensure data quality and minimize atmospheric interference. The imagery used includes Landsat-5 TM (1990, 1995), Landsat-7 ETM+ (2000, 2005, 2010), and Landsat-8 OLI-TIRS (2015, 2020). All images were resampled to a consistent 30m spatial resolution. Both Landsat 5 TM and Landsat 7 ETM+ have seven spectral bands and 8-bit radiometric resolution. The thermal bands for Landsat 5 TM (Band 6) and Landsat 7 ETM+ (Band 6) were resampled to 30m resolution. Landsat 8 OLI-TIRS offers eleven spectral bands with 16-bit radiometric resolution, with bands 10 and 11 resampled from 100m to 30m for consistency across the time series.

The data pre-processing stage involved selecting appropriate spectral bands that offer vital information about the Earth's surface reflectance properties for different LULC classes. Pixel values corresponding to the training locations were extracted. For model validation, the extracted samples were partitioned using 80% training and 20% validation split to facilitate robust model training and unbiased accuracy assessment (Abdullah et al., 2019).

2.3 Selection of Training Samples

The classification scheme was defined by five key LULC categories relevant to the coastal environment, as detailed in Table 1. Training samples for these classes were manually collected using digitization (point/polygon features) based on expert interpretation and, where available, auxiliary data. These samples were integrated into a unified feature collection to serve as ground-truth data for the classifier.

Table 1: Details of different LULC classes

LULC Class	Description
River	River networks, canals, and active hydrological features
Built-up Area	Residential, commercial, industrial zones, and transportation infrastructure
Wetland	Inland water bodies, marshy ground, and seasonal wetlands
Vegetation	Mixed forests, scrublands, and agricultural fields
Bare Land	Exposed soils and construction sites

2.4 Model Training and Accuracy Assessment

The Random Forest classification algorithm was selected for its proven accuracy in complex LULC studies (Rodriguez-Galiano et al., 2012). The model was trained on the 80% training sample set using machine learning techniques. This allowed the classifier to identify spectral relationships necessary for building a robust predictive model.

The model's accuracy was evaluated using the 20% validation set. A confusion matrix was generated to analyze classification errors (true positives, false positives, etc.). The overall performance was quantified using overall accuracy and the kappa coefficient (κ) to assess the model's validity. The overall performance of the Random Forest classifier is assessed using two key metrics: overall accuracy and the kappa coefficient (κ). These metrics, derived from the confusion matrix assess how well the model classifies LULC features. The specific mathematical formulations used to determine these metrics are as follows:

2.4.1 Overall Accuracy

The overall accuracy is the ratio of correctly classified samples to the total number of validation samples, which can be expressed by Eq. (1).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where *TP* denotes true positives, *TN* signifies true negatives, *FP* represents false positives, and *FN* means false negatives.

2.4.2 Observed Agreement (P_o)

Observed agreement (Po) represents the proportion of samples that are correctly classified (i.e., the diagonal elements of the confusion matrix), which can be expressed by Eq. (2).

$$P_o = \frac{(TP + TN)}{\text{Total Samples}} \quad (2)$$

2.4.3 Expected Agreement (P_e)

Expected agreement (P_e) represents the agreement expected by chance, calculated from the products of the row and column sums of the confusion matrix, which is expressed by Eq. (3).

$$P_e = \frac{\sum_{i=1}^{N} (C_i C_i')}{(\text{Total Samples})^2} \quad (3)$$

Where N is the total number of classes; C_i is the sum of the actual class labels in i row (marginal row total), and C'_i is the sum of the predicted class labels in column i (marginal column total).

2.4.4 Kappa Coefficient (κ)

The kappa coefficient is calculated based on the aforementioned observed agreement (P_o) and the expected agreement (P_e), which can be expressed by Eq. (4).

$$\hat{\kappa} = \frac{(P_o - P_e)}{(1 - P_e)} \quad (4)$$

2.5 LULC Classification and Change Quantification

The trained Random Forest classifier was applied to the seven Landsat images to produce LULC maps. The classification results were visualized using a predefined color palette for each class. Area computation was carried out using pixel-based analysis, which quantified the extent (km²) and spatial distribution of each LULC class for each study year.

In order to quantify the long-term trends, a post-classification comparison was conducted to determine the net change in each LULC class. This analysis calculated the overall difference in each class between 1990 and 2020, providing a comprehensive measure of LULC conversion over the study period.

3. RESULTS AND DISCUSSION

3.1 Spatial and Temporal Changes of LULC

The spatio-temporal dynamics of LULC in Paikgacha Upazila, alongside the statistical validation of the Random Forest model, are presented visually through a series of figures in this section. The temporal evolution of LULC patterns over the three-decade study period is shown in Figure 3. This composite figure, as demonstated in Figure 3, features the classified maps for all seven years, highlighting significant land cover transformations. Most notably, the continuous spatial increase in Built-up Area and Wetland, while Vegetation and Bare Land cover reduce during the study period.

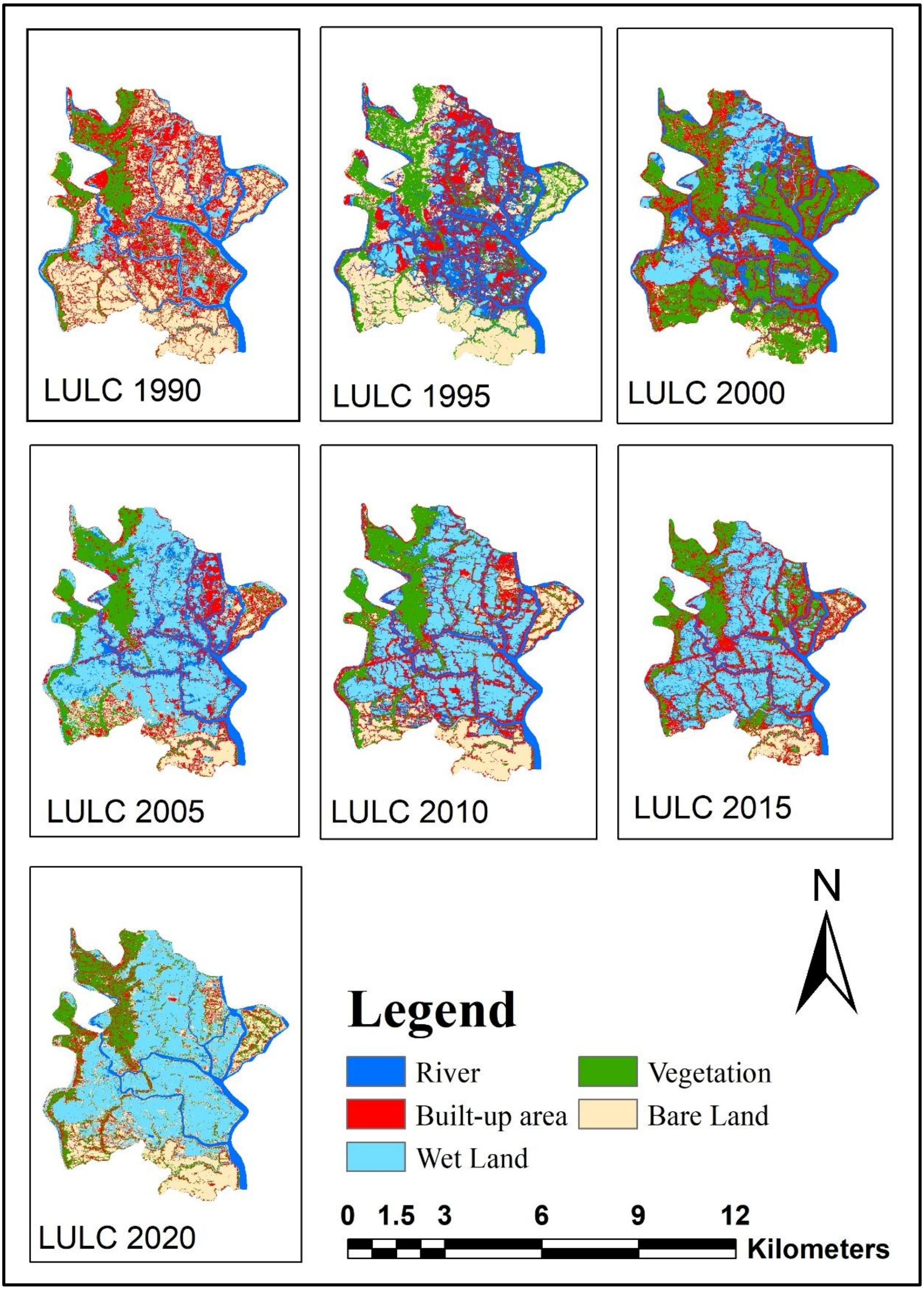

Figure 3: Temporal changes of LULC patterns in the study area during the 1990-2020 period

3.2 Assessment of Areal Changes

In order to quantify these observed spatial changes across the full time series, Figure 4 presents the temporal evolution of LULC patterns from 1990 to 2020, illustrating the major transformations in the study area.

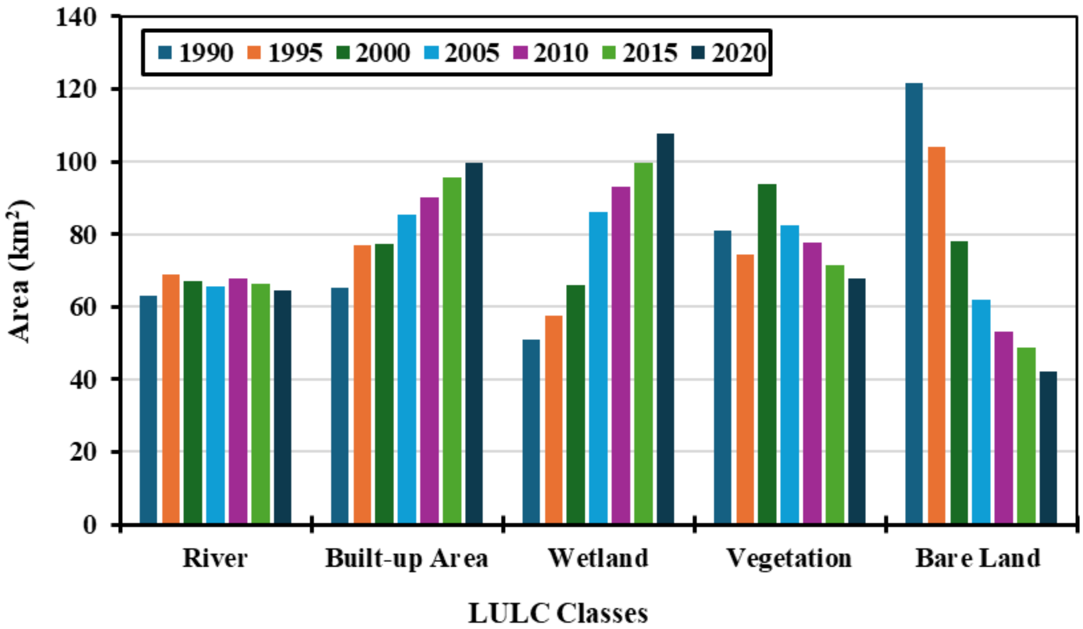

Figure 4: Area covered by the LULC classes in the study area during the 1990-2020 period

This chart is crucial for understanding both inter-annual and decadal trends in land cover distribution. Furthermore, Figure 5 visualizes the overall transformation by showing the net change in area (km²) for each LULC class between 1990 and 2020, quantifying the total gain or loss for each class over the three-decade period.

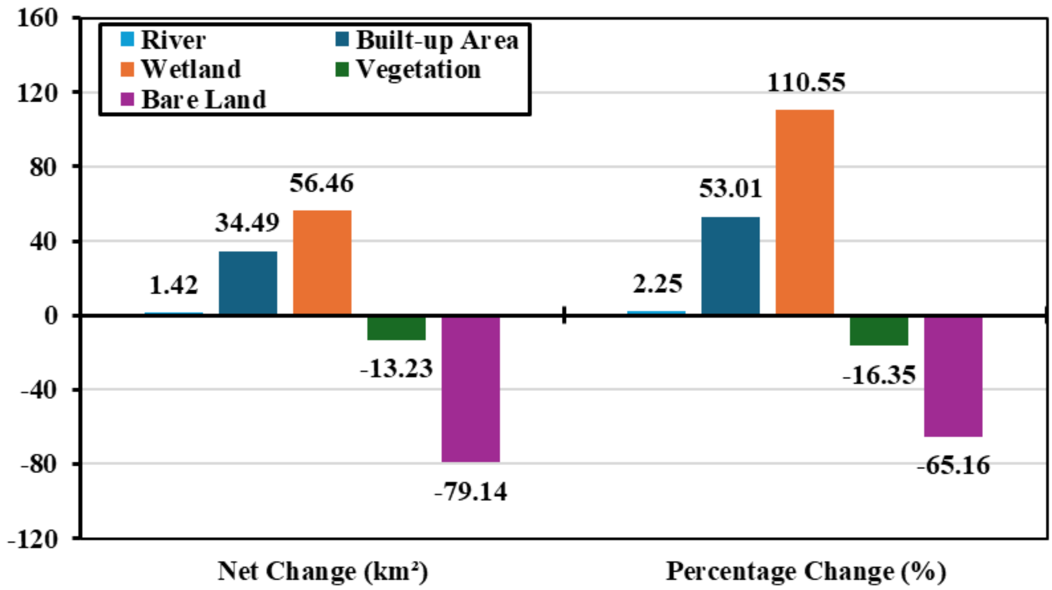

Figure 5: Net changes in areas of LULC classes in the study area during the 1990-2020 period

3.3 Validation of Model Performance

Figure 6 demonstrates the statistical quality and reliability of the classification process. This graph displays the overall accuracy and kappa coefficient (κ) for each of the seven classified LULC maps. The consistently high accuracy metrics confirm the robustness and reliability of the Random Forest classification model across the entire 1990-2020 time series.

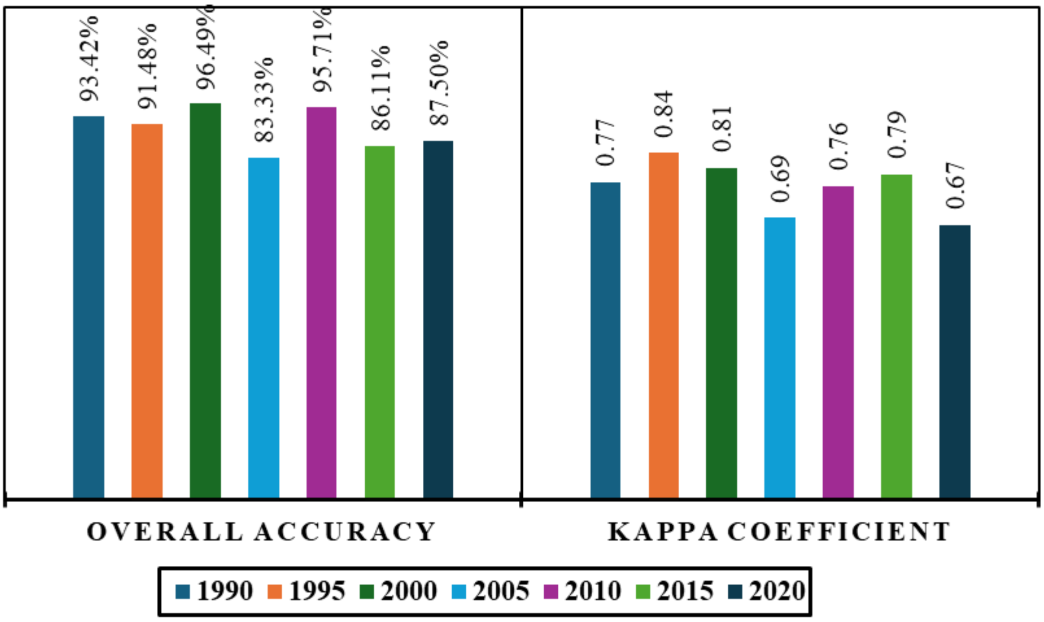

Figure 6: Annual classification performance of the random forest model based on the overall accuracy and kappa coefficient

3.4 Accuracy Assessment of LULC Classification

The classification accuracy of the Random Forest model was evaluated using two primary metrics derived from the validation confusion matrix, the overall accuracy and the kappa coefficient (κ) as calculated by the Eqs. (1)-(4). Table 2 presents the overall accuracy and kappa coefficients obtained for LULC classes in different years during the study period. As can be seen from Table 2, the consistently high values across the entire time series (1990-2020) indicate the model's exceptional robustness and statistical reliability. The accuracy metrics confirm the high level of agreement between the classified LULC maps and the ground truth data used for validation.

Table 2: Summary of the accuracy metrics in LULC classification

Year	Overall Accuracy (%)	Kappa Coefficient (κ)
1990	93.42	0.77
1995	91.48	0.84
2000	96.49	0.81
2005	83.33	0.69
2010	95.71	0.76
2015	86.11	0.79
2020	87.50	0.67

3.5 Quantification of LULC Area and Its Changes over Time

The quantitative results of the LULC classification are presented in Table 3, which details the areal extent (in km^2) occupied by each of the five LULC classes for every study year from 1990 to 2020. This comprehensive table is the foundation of the change analysis, highlighting significant transformations in land cover over the three decades.

Table 3: Changes of LULC areas during the 1990-2020 period

Year	River	Built-up area	Wet land	Vegetation	Bare land
1990	63.12	65.06	51.07	80.89	121.46
1995	68.86	76.84	57.41	74.27	104.22
2000	66.98	77.15	65.82	93.69	77.96
2005	65.74	85.46	86.02	82.35	62.03
2010	67.69	90.16	93.02	77.51	53.22
2015	66.35	95.72	99.57	71.39	48.57
2020	64.54	99.55	107.53	67.66	42.32

In order to quantify the overall transformation of LULC characteristics, the net change in area (km^2) for each class from the initial year (1990) to the final year (2020) has been calculated, which is presented in Table 4. As can be seen from the table, the LULC changes clearly indicates major changing trends, with the built-up area and wetland demonstrating substantial gains, while bare land and vegetation cover are exhibited by considerable losses.

The 53% expansion of built-up areas indicates ongoing urbanization in the coastal region, particularly influenced by the rapid spatial expansion of Khulna City and rural-to-urban migration intensified by climate change effects such as flood and rising soil salinity (Alam et al., 2023; Bernzen et al., 2019). The remarkable 110% increase in wetland areas is because of the expansion of shrimp aquaculture, driven by increasing soil salinity and higher economic returns compared to conventional crop production (Ahmed & Ambinakudige, 2024; Dasgupta et al., 2015). Due to both urban expansion and shrimp aquaculture expansion there is a decrease in vegetation and bare land. Such changes of LULC will have severe implications on the runoff generation and thereby the overall water resources management in the study area.

Table 4: Net change of LULC quantification during the 1990-2020 period

LULC Class	1990 (km²)	2020 (km²)	Net Change (km²)	Percentage Change (%)
River	63.12	64.54	+1.42	+2.25
Built-up Area	65.06	99.55	+34.49	+53.01
Wetland	51.07	107.53	+56.46	+110.55
Vegetation	80.89	67.66	-13.23	-16.35
Bare Land	121.46	42.32	-79.14	-65.16

4. CONCLUSIONS

The current study focuses on the assessment of spatiotemporal changes of LULC within Paikgacha Upazila of Khulna district in Bangladesh between 1990 and 2020. It is found that significant LULC is occured in the study area during the aforementioned study period based on classification results validated by consistently high accuracy metrics (overall accuracy > 83% and kappa coefficient κ > 0.67). The most notable LULC changes are identified in the built-up area and wetland classes, which exhibit a substantial increase. In particular, the built-up area increased by 34.49 km^2 (a 53.01% rise), reflecting rapid urbanization and infrastructure expansion. Furthermore, the wetland category experiences a remarkable 110.55% increase, expanding by 56.46 km^2, which is primarily attributed to the expansion of brackish water aquaculture in the coastal zone. On the other hand, the bare land category is decresed intensely by 79.14 km^2 (or 65.16%), underscoring the severe competition for land as both urban and aquaculture areas expanded. Furthermore, Vegetation decreased by 13.23 km^2 (16.35%), suggesting a considerable loss of natural ecosystems due to escalating land-use demands.

The findings of the current study thus provide a crucial insight into the rapid land-use dynamics of Paikgacha Upazila of Khulna district in Bangladesh, emphasizing the critical shifts towards urbanization and aquaculture. Understanding such quantified trends in LULC is essential for the effective land management and the formulation of climate adaptive policies in the vulnerable coastal areas of Bangladesh.

DECLARATION OF USE OF AI

We declare that AI tools were used for grammar correction, language polishing, and improving clarity in the paper where necessary. However, no AI tools were used for developing the research methodology, LULC analysis, generaton and interpretation of results, and/or writing of discussion in this paper. We also declare that all research ideas, problem formulations, table and figure preparations, interpretation of results, and writing different secctions of the paper are solely the authors' own work.

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