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RESEARCH ARTICLE

Hotspots of Land Use Land Cover Change: World's Largest Riverine Island Scenario

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Abstract

Objectives: The study gives priority to the Land Use Land Cover (LULC) changes and changing hotspot locations of Majuli, which is the largest riverine island in Assam. **Methods:** Satellite imageries for the years 2002, 2011, and 2022 have been utilized to observe spatiotemporal dynamics using the iso cluster unsupervised classification technique. The Iso cluster unsupervised classification method can identify clusters of an image automatically and classify it based on its clusters. The analysis of change has been taken into account by assigning six land use classes, viz. cropland, forest, waterbody, built-up, grassland, and sandbar. Hotspot identification has been done using Getis-OrdGi* statistical methods. This statistical method can distinguish between areas with strong and low spatial associations and detect a tendency for favorable spatial clustering. **Findings:** The results showed that waterbody, forest, built-up, and grassland have significantly increased by 9.58%, 1.01%, 6.22%, and 9.88% respectively. In contrast, the cropland and sandbars decreased by 25.22% and 1.46% respectively. The kappa accuracy for 2002 is 90.85%, 87.88% for 2011 and 90.22% for 2022. In hotspot analysis, a total of 5 high-range hotspot patches and 11 moderate hotspot patches are identified for the district. The main factors responsible for changing LULC in the study area are the occurrence of floods every year, the combined effects of river erosion, and human interventions. **Novelty:** Novelty lies in the implications of geospatial techniques in changing LULC in a spatio-temporal context. Thus far, no previous research has been conducted on the identification of LULC hotspots within the study area. This study is significant for managing and conserving land resources and preventing recurring shifts in land cover. It will also offer a fresh perspective on extensively examining the underlying reasons for such frequent changes. Furthermore, identifying the hotspots of changes in the area over twenty years indicates that the district exhibits a volatile landscape. The results will certainly guide stakeholders in the region's sustainable resource management.

Keywords: Change detection; LULC; Hotspots; Isocluster; Majuli

1 Introduction

The Land use land cover (LULC) data have grown increasingly significant and challenging for land resource managers, and planners in the contemporary context [1]. Utilizing satellite data for change detection has become essential for the efficient management of natural resources. Hotspot analysis is another method to identify areas with a noteworthy accumulation or concentration of particular occurrences or phenomena. The study focused on discovering areas where specific events or characteristics significantly differ from their normal distribution. Numerous researchers have conducted studies in various fields utilizing hotspot analysis, including the mapping of crime rates [2], assessment of forest fire hotspots [3], and examination of land use and land cover change hotspots [4]. LULC change hotspots are areas that have seen profound shifts in land cover and use as consequences of human activities like development, agriculture, deforestation, etc. [4]. The current study focused on the Majuli district of Assam, a riverine Island on the Brahmaputra River. However, the river that gives life is frequently considered a sign of impending tragedy [5]. LULC changes affect the river basin, especially on its morphology [6]. Changes in LULC caused significant relocation for the people of Majuli island, and cropland was significantly reduced between 1991 and 2022 [7].The island's yearly flood levels as well as its growing population have caused dramatic LULC changes, which has made it more susceptible to bank erosion. The majority of the studies focused on the quantitative changes in LULC brought by changes in population [7], floods, and riverbank erosion [8]. However, it is important to determine the scale and rate at which built-up is expanding. This article evaluates the annual growth rate of built-up areas. An improved land use planning also depends on identifying the hotspots of the changes. This study aims to address this gap by identifying the areas where land use has most recently changed. The findings will certainly assist stakeholders in making appropriate decisions for long-term land use planning and management.

1.1 Objectives of the study

1. To evaluate the spatiotemporal variation of LULC from 2002 to 2022.
2. To identify the locations of hotspots of LULC alterations.

1.2 Study area

The largest and most populated riverine island in the world is called Majuli Island [7], situated in the state of Assam along the middle course of the River Brahmaputra (Figure 1). It is located between 93°39′ and 94°35′ E longitude and 26°45′ and 27°12′ N latitude. The boundaries of this region are formed by the Subansiri River in the north, the Brahmaputra River in the south, and the Kherkatia Xuti spill channel to the northeast. The area of the island is 631.63 km^2. As per the population census 2011, the total population of Majuli is about 1, 67,641 with a population density of 364 persons per km^2. Majuli was designated as Assam's 35th district in May 2017. This island is host to Assam's pure cultural history and Vaishnavite holy places, also known as Satras. For instance, over the past 400 years, the island served as a primary pilgrimage destination. Majuli previously had 40 Satras, but by 2005, the number had decreased to 22 [9].

However, it is now nationally recognized for having experienced two disasters of nature: significant flooding and soil erosion [7]. The Brahmaputra is highly braided, and the silt and sand layers of the banks contribute most to erosion. The environmental and social impacts of the shifting riverbanks have placed Majuli in grave danger. The north-eastern part of India is an extremely seismically vulnerable region, belonging to tectonic Zone-V, and has witnessed the liquefaction event [10]. Majuli experienced significant socioeconomic and geographical changes due to substantial soil erosion caused by the huge earthquake in 1950 (8.7 Mw). From 1975 to 2008, the rate of erosion was 8.76 km2, and the river path has been continually moving [7]. The study area has 243 villages, 107 of which have been entirely or mostly submerged by the river [8].

2 Methodology

2.1 Material and Methods

In the present research, satellite imagery from three different years was used to fulfill the objectives of the study. Landsat- 5 for 2002 and 2011 and Landsat -9 for 2022 were used to assess the LULC. The Landsat series 9 was downloaded from the United States Geological Survey Website (https://earthexplorer.usgs.gov/) while the Landsat 5 series was downloaded from Google Earth Engine (Image courtesy: U.S. Geological Survey). The path and row of Landsat 9 is 135/41 and the date of acquisition is 09/01/2022. The resolution of all the images is 30 m. Landsat 5 TM Collection 2 Tier 1 (LANDSAT/LT05/C02/T1_TOA) is calibrated for top-of-atmosphere (TOA) reflectance. TOA-calibrated images offer the immediate benefit of eliminating complex atmospheric adjustment processing [11].

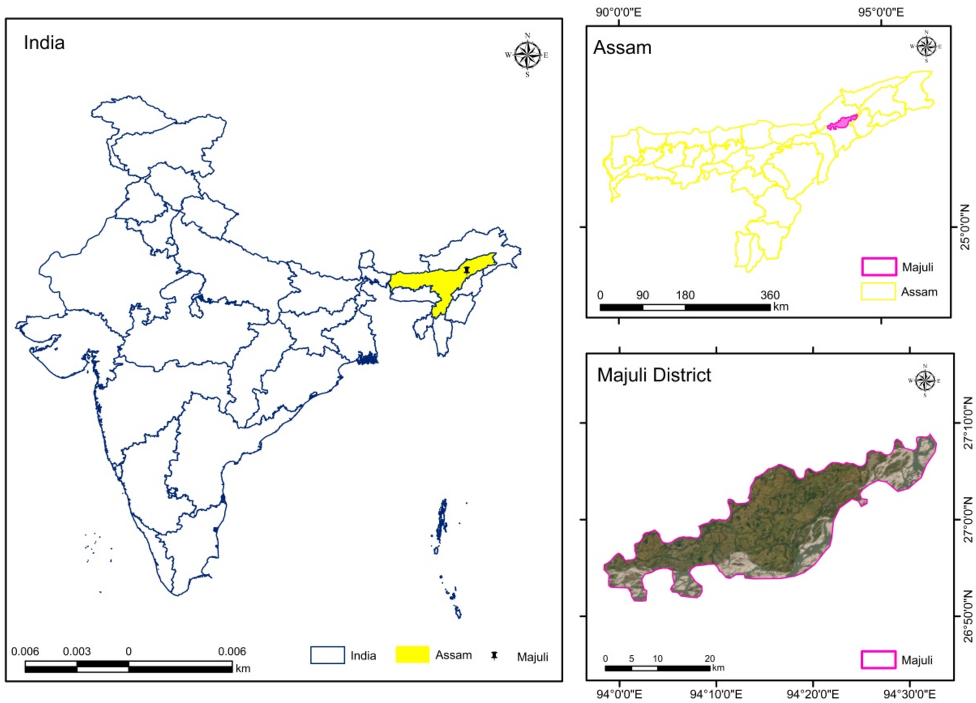

Fig 1. Location map of the study area

2.2 Image Classification

The study area is classified into five LULC classes namely, Cropland, Forest, Sandbar, Water Body, and Grassland based on NRSC LULC classification (https://bhuvan-app1.nrsc.gov.in/2dresources/thematic/2LULC/lulc1112.pdf). The description of different classes of LULC is shown in Table 1. The image classification process was carried out using the Isocluster Unsupervised Technique in ArcGIS.

Table 1. Description of different LULC classes

LULC class	Description
Cropland	It includes fallow land, plantations, and shifting cultivation areas.
Forest	This class includes evergreen/semi-evergreen, deciduous, scrub forest, littoral forest.
Waterbody	It includes wetlands, ponds, rivers, canals etc.
Builtup	This class consist of rural and urban builtup areas with settlements, transportation, industrial areas etc.
Sandbar	These covers accumulate in the flood plain in sheets as a result of river flooding.

2.3 LULC Change Detection

Change detection approaches that employ multi-temporal imagery provide a higher prospect of detecting the evolution of landscapes[12]. To distinguish between one another and identify changes, multi-temporal datasets can be employed from various dates. The post-classification comparison technique involves classifying images and comparing the pertinent classes to identify regions of change[13]. The post-classification comparison was carried out by transforming the categorized raster images into vector layers. For this inquiry, the LULC changes for each kind of land cover were calculated and depicted in distinct images. The following equation was used to calculate the degree of change (C) for each class:

$$Ci = Li - Bi \tag{1}$$

$$Pi = \frac{Li - Bi}{Bi} x100 \tag{2}$$

Where Ci denotes the magnitude of change in class "I", Li denotes the latest image, Bi denotes the basic image and Pi denotes the percentage of change in class "I".

2.4 An Annual land use change rate assessment

The annual growth rate of the built up, class has been calculated with the help of the Annual Land Use Change Rate (ALUCR), defined by Tian et al.[14] as follows:

$$ALUCRa,\, t = \frac{\frac{Lua,t - Lua,t-1}{Lua,\, t-1}}{Nt - Nt - 1} \tag{3}$$

Where ALUCRt (%) is the land use change rate; LUa,t and LUa,t-1 are areas of land use class in km at the time t (current year) and t - 1 (previous year); N is the total number of years from time 't' (current year) to time t -1 (previous year).

2.5 Hotspot analysis for LULC

This method is widely applied in disciplines like geography, urban planning, environmental science, criminology, and epidemiology. By examining spatial patterns, hotspot analysis provides insights into the concentration or aggregation of various phenomena. For conducting hotspot analyses, ArcGIS offers a variety of tools, including the Optimised Hot Spot Analysis and Hot Spot Analysis tools. These technologies automate the process of combining event data, choosing an appropriate analytical scale, and considering multiple testing and spatial dependence. The detection of hotspots using satellite data is a beneficial approach to studying LULC. Hotspot zones can be used to identify regions where recurrent and rapid shifts in land use may pose an imminent danger to the ecological diversity of the area. In the present study, hotspot identification is based on the frequency of land use/cover changes over 20 years, specifically from 2002-2011 and 2011-2022. In this research, after calculating the change detection over 20 years, a point layer was generated to focus on areas with high or frequent changes. The processed data were then integrated to prepare for hotspot identification using Getis-OrdGi*. Getis and Ord in 1992 introduced two local statistics known as Gi and Gi* that are utilized to identify hotspots or potential centers of statistically significant clustering[15]. The Gi* statistic generates a z-score for each position, indicating whether the attribute value is greater or less than the average value in the surrounding area. When the z-score is statistically significant and positive, a higher value suggests a more concentrated clustering of high attribute values, discovering hotspots. A smaller number, on the other hand, suggests a higher clustering of low attribute values, representing cold areas, for statistically significant negative z-scores.

The formula of Getis –OrdGi* is given below:

$$Gi^* = \frac{\sum_{j=1}^{n} w_{i,j}\, x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w^2{}_{i,j} - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}}$$

$$\overrightarrow{X} = \frac{\sum_{j=1^{x_j}}^{n}}{n}$$

$$S = \sqrt{\frac{\sum_{j=1^{x_j^2}}^{n}}{n} - (\overrightarrow{X})^2} \tag{4}$$

Where, Xj= The attribute value for feature j,

Wi, j=The spatial weight between features i and j, and n = the total number of features.

2.6 Accuracy assessment

The accuracy assessment for the LULC classification was computed using the kappa coefficient from 2002 to 2022. Satellite maps and Google Earth imagery were utilized to support the accuracy. The following formula is used to determine the accuracy of classified images:

$$Overall\ accuracy = \frac{\sum_{.} \overset{r}{i} = 1^{X} ii}{N} x100 \tag{5}$$

$$Kappa\ accuracy = \frac{N\Sigma_i^r = 1^{X} ii - \sum_{i=1}^{r}\left(x_{j_+ * x + i}\right)}{N^2 - \sum_{i\_=1}^{r}\left(x_i + *x + i\right)} \tag{6}$$

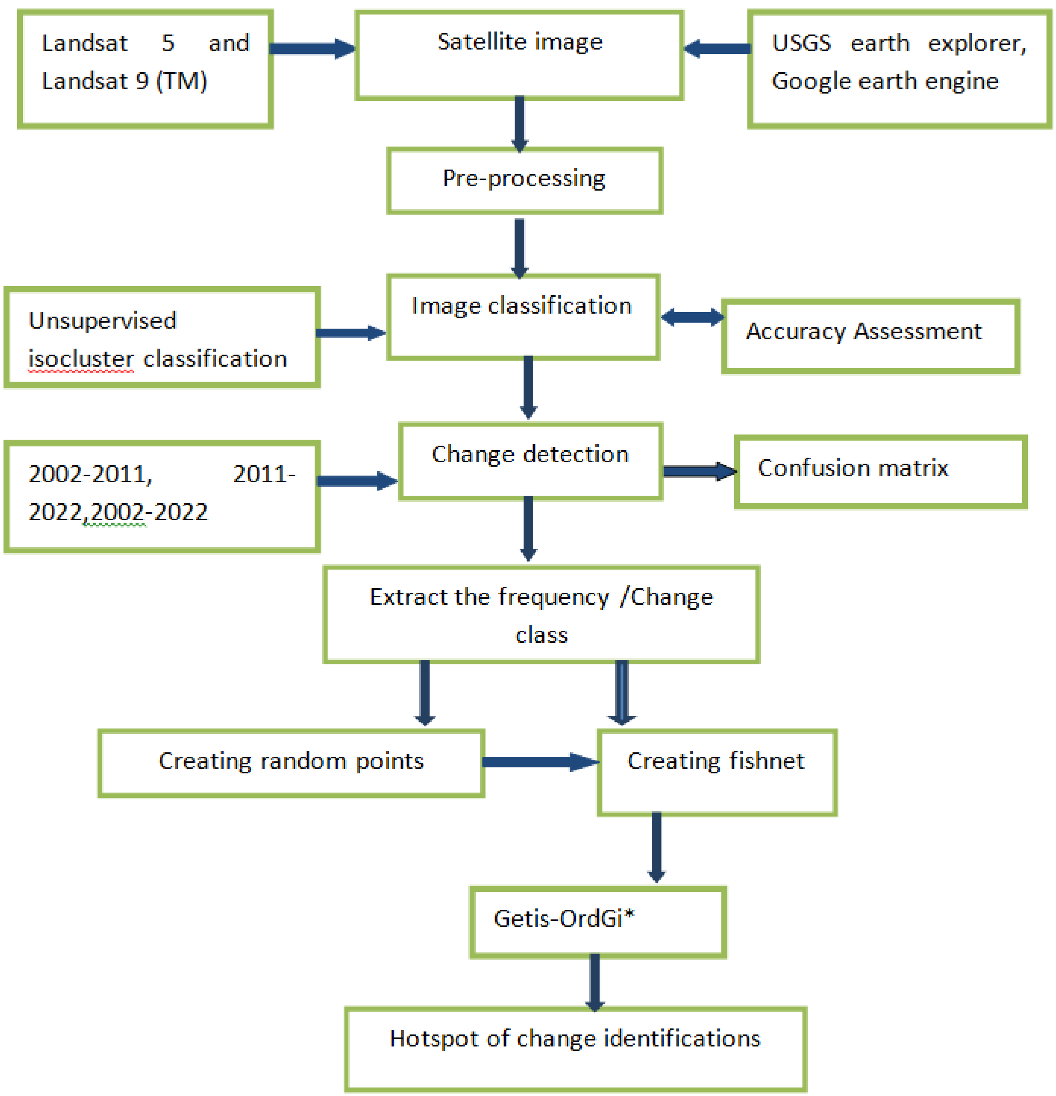

Fig 2. Framework of the study

2.7 Accuracy Assessment

Overall accuracy (OA) for all three years is more than 90%. For 2002 OA is 92.7%, for 2011 and 2022 90.2% and 93% respectively. The Kappa coefficient is 90.85% for 2002, 87.88 for 2011, and 90.22% for 2022.

3 Results and Discussion

3.1 Spatio-temporal variation of LULC

Cropland was the most dominant land use pattern in Majuli Island during the reference period (2002-2022) (Figure 3). The cropland in 2002 was 378.03 km^2 but it decreased to 340.16 km^2 in 2002 and covered 218.75 km^2 in 2022. Sandbars occupied 122.56 km^2 in 2002 and it followed a decreasing trend of changing area 106.22 km^2 in 2011 and 113.31 km^2 in 2022. The area under forest decreased from 53.61 km^2 (2002) to 49.29 km^2 (2011). But in 2022 it was 59.98 km2. The waterbody was 49.98 km^2 in 2002 and it has tremendously increased to 57.08 km^2 in 2011 and 110.48 km^2 in 2022. Moreover, the impact of anthropogenic activities is evident from the increasing pattern of built-up areas from 1991 to 2022 in Majuli[7]. The results show built-up was 16.44 km^2 in 2002, 17.55 km^2 in 2011, and 59.98 km^2 in 2022. Grassland also accounts for a small fraction of land usage, increasing from 11 km^2 in 2002, to 61.35 km^2 in 2011, and 73.37 km^2 by 2022. The annual land use change rate for built-up areas was 0.75% per year from the year 2002 to 2011, from 2011 to 2022 19.77%, and within 20 years (2002-2022) the growth was 11.94%. The LULC outcome shows that the built-up over the previous 11 years was more apparent. Conversely, the vicinity's frequent shifts in land use also have an impact on the decreasing quantity of cropland.

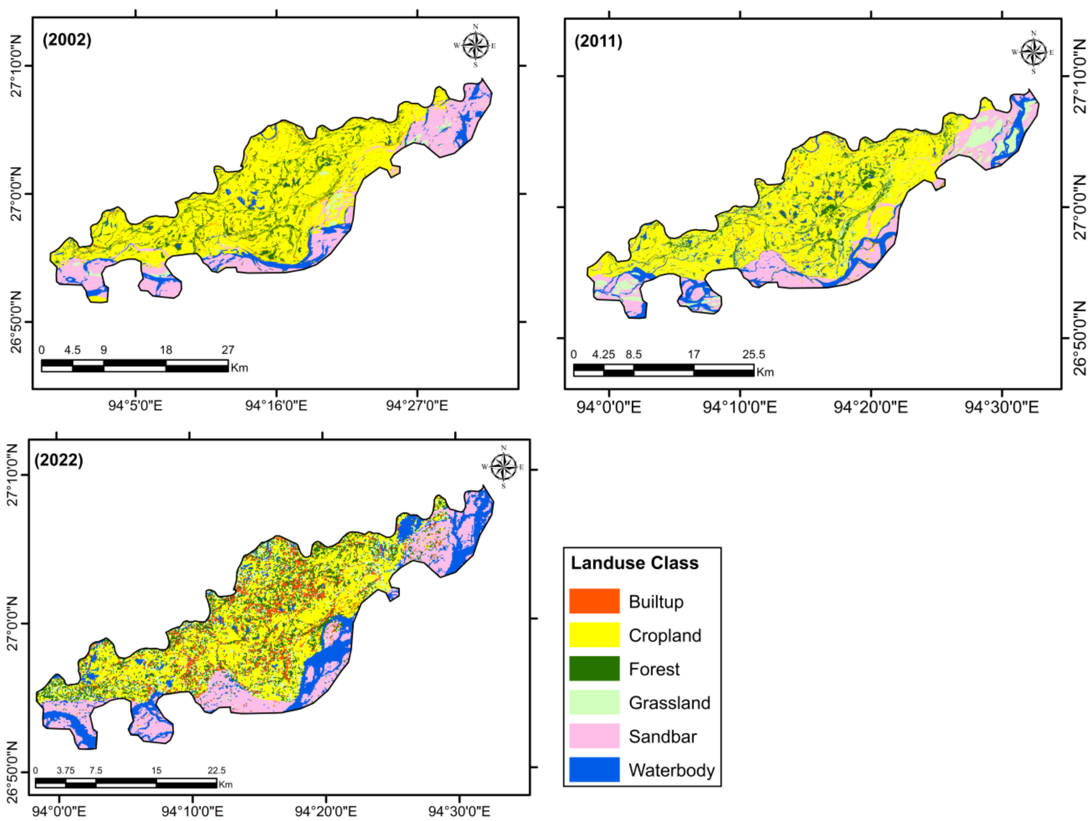

Fig 3. Classified LULC map for 2002, 2011, and 2022

3.2 Change detection analysis

During the period 2002-2011, Majuli experienced an increase in waterbody extent by 1.12%, built-up by 0.18%, and grassland by 7.97%. On the contrary, the forest, cropland, and sandbar experienced a decrease of 0.69%, 6%, and 2.59% respectively.

Moreover, from 2011-2022 the waterbody, forest, built-up, grassland, and sandbar increased by 8.45%, 1.69%, 6.04%, 1.90%, and 1.12% respectively and cropland decreased by 19.22%. In the period 2002-2022, the waterbody, forest, built-up, and grassland have increased by 9.58%, 1.01%, 6.22%, and 9.88% respectively. The results show a significant decline in cropland and sandbars by 25.22% and 1.46% respectively.

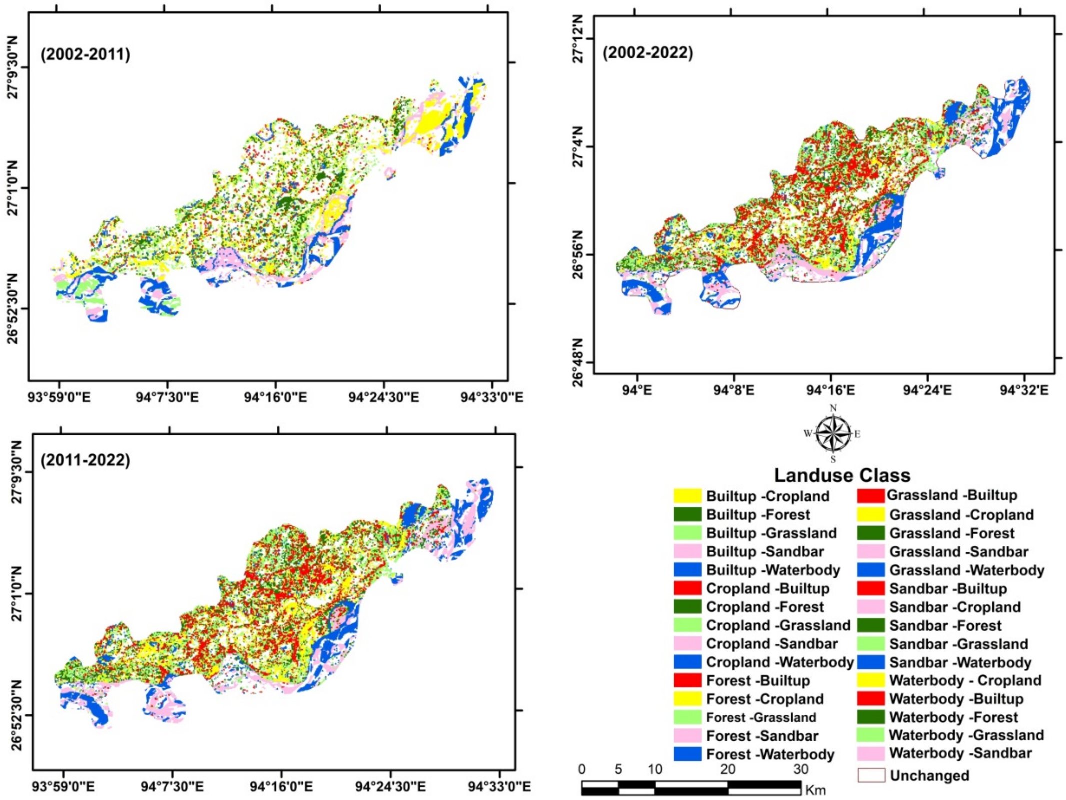

Fig 4. LULC conversions for 2002-2011, 2011-2022, and 2002-2022

3.3 Conversion of LULC analysis

It was observed that from 2002-2011, the highest LULC class transformation occurred from cropland to grassland, while the lowest LULC class conversion was observed from sandbar to forest (Figure 4). From 2011 to 2022, the cropland-to-forest transformation was among the highest, and forest to sandbar transformation was among the lowest. The conversion of cropland to forest was highest within 2002-2022 while the lowest transformation was observed in forest to sandbar (Table 2).

Table 2. Area of changed class

Changed LULC Class	2002-2011	2011-2022	2002-2022
	Area(km^2)	Area(km^2)	Area(km^2)
Builtup-Cropland	7.08	4.52	3.41
Builtup-Forest	1.86	2.40	2.04
Builtup-Grassland	1.77	2.16	2.67
Builtup-Sandbar	1.54	1.24	1.41
Builtup-Waterbody	1.14	1.97	1.59
Cropland-Builtup	9.57	29.04	34.42
Cropland-Forest	27.66	59.31	68.91
Cropland-Grassland	33.81	51.52	59.76
Cropland-Sandbar	17.17	19.06	14.00

Continued on next page

Table 2 continued

Cropland-Waterbody	9.97	27.60	28.20
Forest-Builtup	2.20	14.13	16.78
Forest-Cropland	17.46	12.86	9.38
Forest-Grassland	7.86	5.82	5.38
Forest-Sandbar	0.26	0.05	0.17
Forest-Waterbody	2.03	2.45	2.96
Grassland-Builtup	0.08	8.95	0.85
Grassland-Cropland	4.75	15.83	0.32
Grassland-Forest	0.44	9.14	0.58
Grassland-Sandbar	2.91	7.21	5.59
Grassland-Waterbody	1.28	4.77	2.12
Sandbar-Builtup	1.16	1.43	1.44
Sandbar-Cropland	22.66	1.69	2.52
Sandbar-Forest	0.03	3.47	3.39
Sandbar-Grassland	8.68	3.88	3.97
Sandbar-Waterbody	25.89	30.68	41.29
Waterbody-Builtup	1.21	1.87	1.55
Waterbody-Cropland	8.12	1.93	1.64
Waterbody-Forest	1.18	2.36	2.50
Waterbody-Grassland	1.80	2.10	1.76
Waterbody-Sandbar	19.88	22.50	23.62

The above observations prove that there has been a substantial LULC shift in the research area over the 20 years of the study period. A substantial portion of coveted agricultural land is lost owing to channel migration in Majuli Island's downstream part[16]. The island's LULC undergoes considerable changes as a result of both natural and manmade activity, particularly frequent floods and bank erosion[16]. Flooding and a changing Subansiri river bank line on the Majuli Islands' northwestern bank pose an imminent threat to residents living in the floodplain[17]. Moreover, cropland is being transformed into built-up modifying the land use in the region.

3.4 Hotspot map of LULC change

Hotspots between 90% to 99% confidence level have been identified in the area (Figure 5), indicating the level of statistical certainty in the identification of those hotspots. A hotspot identified with 90% confidence suggests that there is a 90% probability that the observed pattern of activity or intensity in that particular area is not due to random chance. It indicates a relatively high level of certainty that the area is indeed a hotspot, meaning it has a significantly higher level of activity or intensity compared to the surrounding areas. A hotspot identified with 95% confidence implies that there is a 95% probability that the observed pattern of activity or intensity is not due to random chance. 99% level of confidence suggests a very high degree of certainty that the identified area is a genuine hotspot[15], with a significantly higher level of activity or intensity compared to the surrounding areas. Two cold spots with 90% confidence spotted in the western part and north-eastern part (Figure 5) of the district indicate that there is a 90% probability that the observed pattern of activity or intensity in a particular area is not due to random chance. A 1 km x 1km fishnet grid has been created for a better visual understanding of the hotspot (Figure 6). The total grids are under 90% confidence level =11 grid, 95%=31and 99 %=57. Three intensities of hotspots of change have been identified such as low, moderate, and high. The higher intensity hotspots of change are observed in the middle and southwestern part of the district. The light green color indicates the area with no change. The northeastern part of the district exhibits a low to moderate frequency of changes in the LULC of the area. A total of 5 high-intensity hotspot patches covering 12.76 km^2 and 11 moderate-intensity hotspot patches covering 33.59 km^2 are identified for the district. By conducting LULC and hotspot analysis, researchers can pinpoint specific locations within a geographical area where a particular phenomenon is highly concentrated. Similarly, in the Upper Meghna River watershed, Bora et al. 2023 identified 20 hotspot regions exhibiting significant LULC transformations[4].

The transformation of LULC is accelerated by population pressure, which shapes the surface of the planet in response to human demands and desires. As the need for residential, commercial, and industrial areas grows, natural landscapes are being transformed into developed environments. The population of the riverine island Majuli has a major impact on how the LULC changes. A significant issue facing Majuli is the population growth and subsequent land loss, which has resulted in the intrusion of several wetlands, including beels, swamps, and marshes. According to the 2011 Census, Majuli is home to 1,67,304 people or 346 people per km^2. In 2001, 1,53,362 people were living in Majuli. This remarkable rise in population has occurred despite the serious threat to the unique river island's survival. The population growth may be a consequence of the island's gradual shrinkage, which reflects the island's growing man-to-land ratio. However, the Brahmaputra River is primarily responsible for the uneven population distribution and intra-island population mobility. Flooding and bank erosion are significant factors that also influence shifting LULC, causing the district to exhibit a volatile landscape.

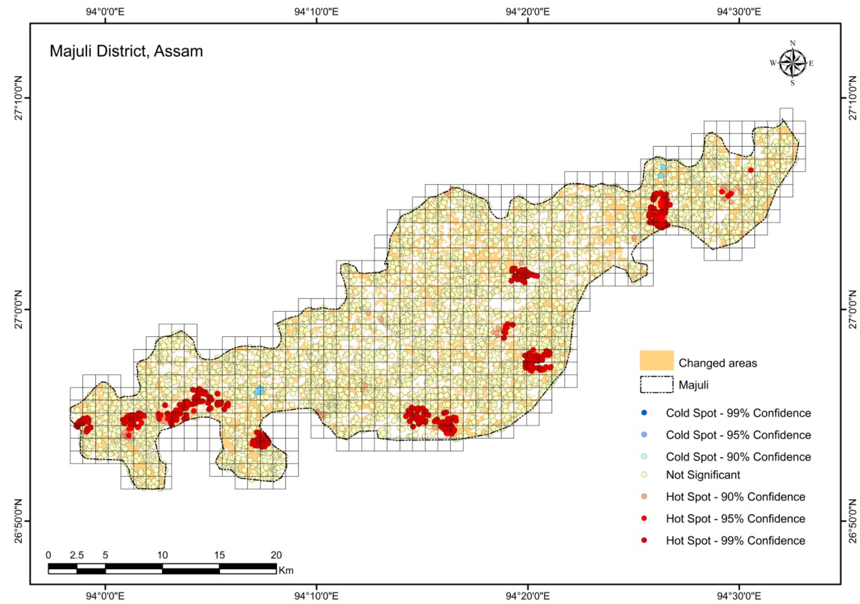

Fig 5. Hotspots and cold spots distribution within Majuli

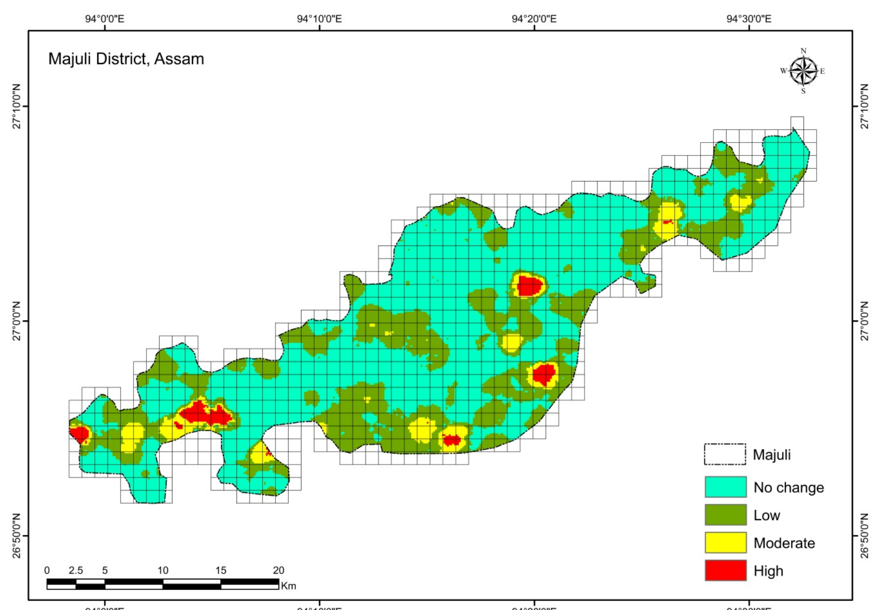

Fig 6. Hotspot map of the area

4 Conclusion

The analysis places more emphasis on the study area's recurrent LULC variations driven by the continuous shifting of riverbanks due to the migration of surrounding rivers. A detailed understanding of historical LULC is also crucial to understanding the ecological structures, processes, and functions that depend on it, as well as for explaining the current LULC patterns. Noticeable LULC changes have been observed between 2002 and 2022 in Majuli with a decrease in croplands and sandbars, and an increase in waterbody, forest, built-up, and grassland. LULC findings are typical for the region, and uncovering the hotspots of the changes provided novel data to the research. The investigation revealed that the entire 57-grid area (1 km by 1 km) is highly likely, with 99% confidence, to have hotspots of LULC changes because the frequency of these changes is certain. It will provide a new perspective on how to sustainably preserve natural resources while thoroughly investigating the hub of frequent land-use changes and its underlying causes. However local stakeholders, communities, and indigenous people need to be involved in the decision-making process to achieve better outcomes for the sustainable use and management of land resources. Introducing sustainable agricultural practices among the local people of Majuli will protect the soil, water, and other natural resources. Raising community awareness of flood risks and afforestation will undoubtedly contribute to mitigating the challenges in the region.

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