



Geo-Spatial Assessment of the Transformation of Land Use Pattern in Coastal Deltaic Landscape: A Case Study of Sandeshkhali Blocks, Indian Sundarbans.

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Abstract: This study examines the spatiotemporal dynamics of Land Use and Land Cover (LULC) in the Sandeshkhali-I and Sandeshkhali-II blocks of the Indian Sundarban Delta over a 30-year period from 1991 to 2021. The analysis employs multi-temporal Landsat satellite imagery and a supervised machine learning approach using the Random Forest (RF) classifier within the Google Earth Engine (GEE) platform to generate decadal LULC maps for the years 1991, 2001, 2011, and 2021. Ancillary datasets, including ALOS Digital Elevation Model and administrative boundaries from the Survey of India, were integrated to enhance classification accuracy and spatial referencing. Accuracy assessments indicate high classification performance, with all time periods achieving overall accuracies above 85% and Kappa statistics exceeding 80%, ensuring the reliability of classification outputs. The results reveal significant land transformation driven by anthropogenic pressures, particularly a sharp decline in cropland (−30.2%) and mixed vegetation (−31.2%) due to the expansion of aquaculture and built-up land. Aquaculture increased markedly between 1991 and 2011, indicating a shift in livelihood practices and resource use. Built-up land nearly doubled from 2011 to 2021, reflecting rapid urbanization in response to population growth and infrastructure development. Panchayat-level analyses reveal spatial heterogeneity, with some areas such as Bayermari-II and Sehera Radhnagar undergoing dramatic land conversion, while others experienced more stable patterns. Notably, mangrove cover, after previous degradation, exhibited minor gains in recent years, suggesting the positive effects of conservation initiatives and ecological restoration efforts. Overall, the study highlights the complex interplay between environmental vulnerability, socio-economic transformation, and land use dynamics in a fragile deltaic ecosystem. The findings underscore the urgent need for integrated land-use planning, ecological conservation, and sustainable development strategies to mitigate further environmental degradation in the Sundarban region.

Keywords: LULC Change, Random Forest, GEE, Aquaculture expansion

1. Introduction:

Land Use and Land Cover (LULC) change serves as a critical indicator of environmental transformation, revealing the interplay between natural processes and anthropogenic activities. In recent decades, rapid LULC changes have occurred across coastal and deltaic regions globally, significantly affecting ecological balance, resource sustainability, and socio-economic development (Lambin et al., 2001; Foley et al., 2005). The Indian Sundarban Delta, located in eastern coastal India, represents one such ecologically sensitive region undergoing profound LULC transitions due to anthropogenic pressure, climatic variability, and developmental interventions (Ghosh et al., 2018).

The present study focuses on Sandeshkhali-I and Sandeshkhali-II blocks in the North 24 Parganas district of West Bengal, India. These blocks, situated between 22°15'N to 22°30'N latitude and 88°45'E to 88°55'E longitude, form a crucial part of the Sundarban deltaic ecosystem. The region comprises tidal rivers, creeks, estuarine wetlands, and mangrove forests, making it vulnerable to environmental degradation through coastal erosion, saline intrusion, cyclones, and land conversion (Hazra et al., 2002; Roy et al., 2013). Over the past three decades, the region has witnessed significant transformations, especially

due to aquaculture expansion, declining croplands, and increased urban footprint. These dynamics impact agricultural productivity and ecological stability, necessitating systematic and temporal analysis using advanced geospatial tools.

This study utilizes multi-temporal Landsat data (1991–2021) and a cloud-based platform, Google Earth Engine (GEE), employing the Random Forest (RF) classifier for robust classification. Accuracy assessments ensure reliable outputs, and transition matrix analysis reveals inter-class conversions over three decades. Ancillary data such as ALOS DEM and administrative boundaries enhance spatial accuracy, while panchayat-level analysis enables micro-scale policy interpretation. The research contributes to understanding LULC drivers, informing sustainable land-use planning and climate adaptation strategies in this vulnerable deltaic environment.

2. Study Area:

The present study was conducted in the Sandeshkhali-I and Sandeshkhali-II Blocks, located in the southern part of the North 24 Parganas district, West Bengal, India (Figure 1). Geographically, the region lies between 22°15'N to 22°30'N latitude and 88°45'E to 88°55'E

longitude. These blocks form a significant part of the Indian Sundarban Deltaic region, characterized by a complex network of tidal rivers, creeks, and estuarine wetlands (Ghosh et al., 2018; Hazra et al., 2002). The area is highly susceptible to both natural and anthropogenic changes, including coastal erosion, land subsidence, cyclonic activity, and rapid land use land cover (LULC) transformations due to aquaculture expansion and population pressures (Bhattacharya et al., 2021; Mondal & Tatem, 2012).

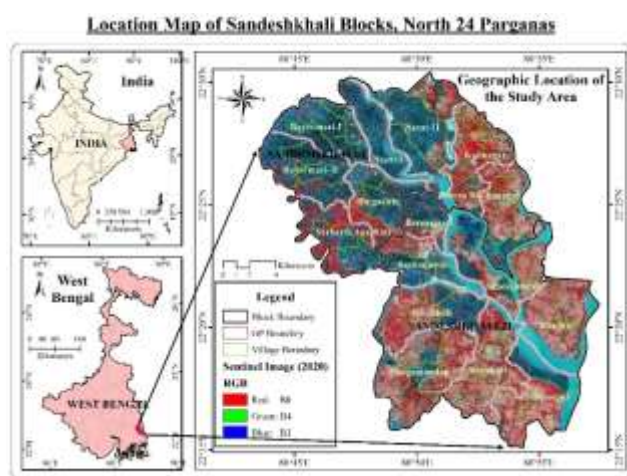


Figure 1: Location map of the study area

Administratively, Sandeshkhali I block comprises the Gram Panchayats (GPs) of Bayermari-I, Bayermari-II, Nazat-I, Nazat-II, and Hatgachhi. In contrast, Sandeshkhali II block includes GPs such as Bermajur-I, Bermajur-II, Jeliakhali, Durgamandap, Korakati, Khulna, and Manipur. Each of these Gram Panchayats contains multiple rural settlements and agricultural lands, interspersed with tidal creeks and mangrove

vegetation (Sarkar et al., 2019). The delineation of village and GP boundaries, as shown in the location map based on Sentinel-2 RGB composite imagery (2020), offers a detailed representation of land cover and administrative units. The selection of this region is significant due to its ecological sensitivity, socio-economic vulnerability, and dynamic land transformation patterns (Roy et al., 2013; Giri et al., 2008). The convergence of natural ecosystems and human activities in Sandeshkhali makes it a critical area for spatiotemporal LULC analysis, wetland monitoring, and sustainable land management research (Seto et al., 2012; Mitra et al., 2009).

3. Methodology:

The methodology adopted in this study follows a systematic and scientifically robust workflow encompassing several key stages: data acquisition, image pre-processing, image classification, spatial change detection, accuracy assessment, and interpretation and analysis (Figure 2). Each component is carefully designed to ensure the reliability and precision of land use/land cover (LULC) mapping and change detection (Lu & Weng, 2007; Jensen, 2015). The process begins with data acquisition, involving the collection of both satellite and ancillary datasets. Multi-temporal Landsat satellite imagery from 1991 to 2021 is used for temporal analysis. Ancillary data, including ALOS DEM, Survey of

India administrative boundaries, and LULC data from SISDP projects, are integrated to enhance spatial referencing and thematic validation (Roy et al., 2013). The image pre-processing includes the application of scaling factors, cloud masking to eliminate atmospheric interference, median compositing to reduce noise, and clipping to the study area to get maximum classification results (Huang et al., 2017). In the image processing phase, random sampling is employed to divide the dataset into training (80%) and testing (20%) subsets. Signature analysis is conducted on the training data to derive spectral characteristics for each land cover class. A supervised machine learning approach, specifically the Random Forest classifier, is applied due to its high classification accuracy and ability to handle high-dimensional data (Belgiu & Drăguț, 2016; Breiman, 2001). These yields classified maps representing different periods.

Accuracy assessment is subsequently performed using the independent testing dataset. Evaluation metrics such as Overall Accuracy, Kappa Statistics, Producer's Accuracy, and Consumer's Accuracy are computed to quantify the performance of the classification (Congalton, 1991). These measures provide a rigorous statistical basis for assessing the reliability of the LULC outputs. The classified outputs are subjected to post-processing to refine spatial boundaries and reduce classification noise. These

refined maps form the basis for spatial change analysis, enabling the detection and quantification of LULC transitions over time. The final stage involves interpretation and analysis, where the results are synthesized through map design, spatiotemporal change analysis, and the generation of transition matrices. These outputs facilitate a comprehensive understanding of landscape dynamics and provide critical insights for resource management and policy planning (Foley et al., 2005; Lambin et al., 2001).

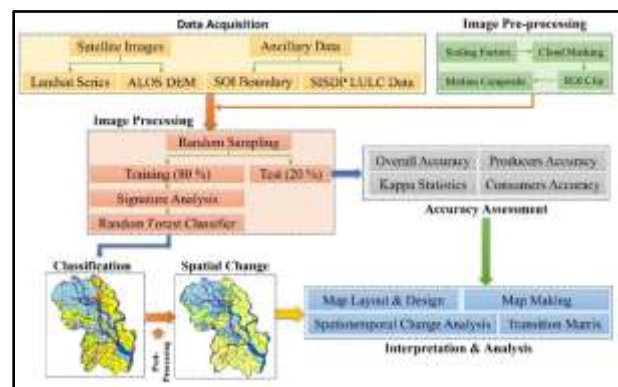


Figure 2: Methodological flow chart

4. Results and Discussion:

LULC classification facilitates the assessment of spatiotemporal changes across the Sandeshkhali blocks, providing critical insights for sustainable land management and environmental planning (Anderson et al., 1976; Lu et al., 2004). Image classification aims to automate the identification of features within the satellite imagery by using quantitative techniques (Lillesand et al., 2015). To estimate the changes in the study area, supervised classification is carried out in Google Earth

Engine (GEE) using the Random Forest (RF) classifier. Random training samples are collected for seven LULC classes (Figure 3), and the RF algorithm statistically analyzes the spectral signatures to accurately classify the image into the corresponding land cover categories (Lillesand et al., 2015).

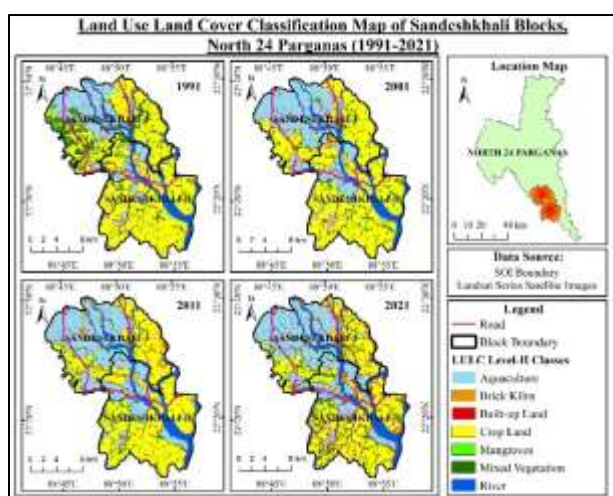


Figure 3: LULC classification of Sandeshkhali blocks from 1991 to 2021

Between 1991 and 2021, the land use and land cover (LULC) dynamics of the Sandeshkhali blocks exhibited significant transformations, primarily driven by anthropogenic pressures and economic transitions. Notably, aquaculture expanded markedly from 6,776 ha in 1991 to a peak of 11,943 ha in 2011, stabilizing slightly at 11,922 ha by 2021, reflecting a shift from traditional agriculture towards intensive fish farming practices (Mandal et al., 2020). Concurrently, cropland showed a continuous decline, shrinking from 19,312 ha in 1991 to 13,485 ha in 2021, indicating a loss of agricultural

land due to aquacultural encroachment and urban sprawl. Mixed vegetation cover fluctuated, initially declining but recovering to 3,783 ha by 2021, while mangrove areas, though initially degraded, showed signs of regrowth—rising from 292 ha in 2011 to 852 ha in 2021—possibly due to conservation interventions (Giri et al., 2011). Built-up areas and brick kilns demonstrated notable expansion and variability, particularly with built-up land nearly doubling from 1,979 ha to 3,878 ha by 2021, signifying increasing human settlement and infrastructure development. These trends underscore the intensifying pressure on natural ecosystems and highlight the need for sustainable land management strategies in fragile coastal zones (Seto et al., 2012).

Table 1: Changes in Area of Different LULC Classes from 1991 to 2021

Sl. No	LULC Class	Area (Ha)			
		1991	2001	2011	2021
1	Mixed Vegetation	5498	2867	2985	3783
2	River	3688	3400	3579	3611
3	Aquaculture	6776	10695	11943	11922
4	Brick Kilns	81	201	978	311
5	Crop Land	19312	18303	16254	13485
6	Mangroves	509	322	292	852
7	Built-up Land	1979	2054	1811	3878
Total Area		37842	37842	37842	37842

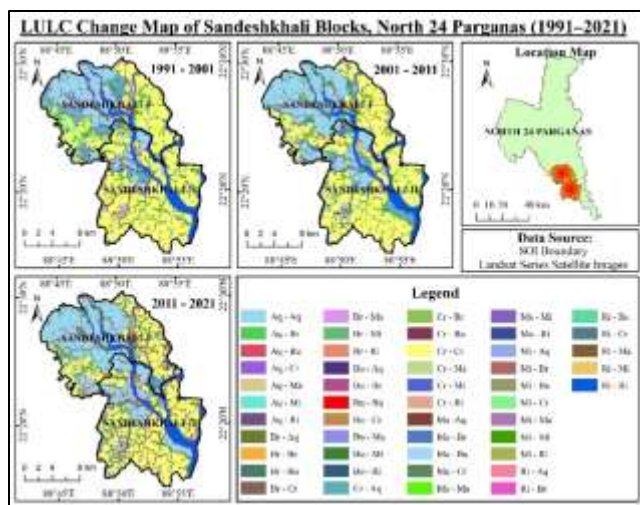


Figure 4: LULC change map of Sandeshkhali blocks (1991–2021)

The Land Use Land Cover (LULC) transition analysis of Sandeshkhali from 1991 to 2021 highlights dynamic shifts driven by agricultural expansion, aquaculture development, and urban growth. Between 1991 and 2001, significant conversions were observed from mixed vegetation and cropland to aquaculture and built-up areas, reflecting changing land-use practices. From 2001 to 2011, cropland and aquaculture emerged as dominant classes, expanding by converting mixed vegetation and other categories, while built-up land grew modestly. In the final decade (2011–2021), cropland remained the most extensive class, while built-up land saw rapid expansion, mainly at the cost of mixed vegetation and agricultural land. Meanwhile, rivers and mangroves remained relatively stable with minimal change. Overall, the landscape transformation over the three decades underscores a trend toward intensified agriculture, increased

aquaculture, and accelerating urbanization at the expense of natural vegetation and ecological land covers.

In Land Use Land Cover (LULC) classification, Overall Accuracy measures the proportion of correctly classified pixels, while the Kappa statistic accounts for chance agreement between the classified output and reference data (Congalton, 1991). Higher Kappa values and overall accuracy indicate stronger classification reliability. All classifications exhibit high reliability, with both overall accuracy and Kappa statistics exceeding 80%, indicating strong agreement between the classified results and reference data.

Table 2: Overall accuracy and kappa statistics of the following years

Sl. No.	Year	Overall Accuracy	Kappa statistic
1	1991	94.24	92.93
2	2001	88.30	85.64
3	2011	86.04	82.78
4	2021	85.99	83.38

The land use and land cover (LULC) dynamics in the Sandeshkhali blocks between 1991 and 2021 reveal distinct patterns of both gain and loss across different classes (Table 3). Cropland experienced a continuous and substantial decline over all three decades, with a cumulative loss of

15.4%, indicating a shift away from traditional agriculture, likely due to urban expansion and the rise of aquaculture. Aquaculture showed a significant increase between 1991–2001 (10.36%) and 2001–2011 (3.30%), reflecting its growing prominence as an economic activity; however, it slightly declined (–0.06%) in the last decade, possibly due to saturation or environmental constraints. Built-up land exhibited a notable surge of 5.46% from 2011 to 2021, highlighting rapid urbanization and infrastructure development in the region. Mixed vegetation, after an initial decline (–6.95%), gradually recovered with slight gains in the last two decades, while mangrove cover remained relatively stable with minor fluctuations, recording a modest increase (1.48%) from 2011 to 2021, suggesting some conservation or natural regeneration efforts. Brick kiln areas expanded notably between 2001 and 2011 (2.05%) but declined thereafter (–1.76%), possibly due to policy restrictions or land conversion. River areas remained largely unchanged, with negligible variations over the decades. Overall, the data indicate significant land transformation driven by anthropogenic pressures and changing land use priorities in the deltaic landscape of Sandeshkhali.

Table 3: Gains and Losses (G&L) of each category (in Percentage).

Sl. No	LULC Class	Percentage Change		
		1991-01	2001-11	2011-21
1	Mixed Vegetation	-6.95	0.31	2.11
2	River	-0.76	0.47	0.08
3	Aquaculture	10.36	3.30	-0.06
4	Brick Kilns	0.32	2.05	-1.76
5	Crop Land	-2.66	-5.42	-7.32
6	Mangroves	-0.49	-0.08	1.48
7	Built-up Land	0.20	-0.64	5.46
Total Area		0	0	0

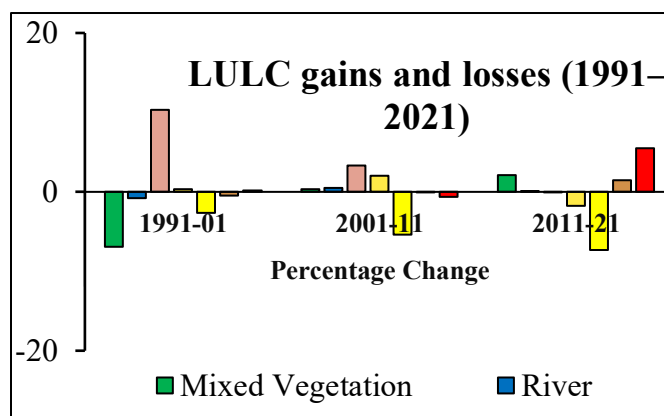


Figure 5: LULC gains and losses (1991–2021).

The temporal analysis of Land Use Land Cover (LULC) changes across the Sandeshkhali-I and Sandeshkhali-II blocks from 1991 to 2021 reveals significant spatial dynamics at the panchayat level. In Sandeshkhali-I, major increases are observed in Bayermari-II, which expanded from 514.80 ha in 1991 to 1768.36 ha in 2021, and in Sehera Radhnagar, which grew from 59.72 ha to 361.77 ha over the same period. Similarly, Nazat-II exhibited a steady increase from 1009.09 ha in 1991 to 1778.93 ha in 2021, indicating substantial

land use transformation likely driven by population pressure and developmental activities. In contrast, some areas like Nazat-I and Hatgachhi showed fluctuating trends, reflecting either land reclamation or seasonal variability in land use. In Sandeshkhali-II, Bermajur-I and Manipur demonstrated sharp increases, particularly Manipur, which rose from 42.68 ha in 1991 to 491.13 ha in 2011 before slightly declining to 443.43 ha in 2021. This pattern indicates a dynamic shift in land utilization, possibly linked to agricultural expansion, settlement growth, or changes in wetland boundaries. Such temporal and spatial variations are consistent with earlier studies that highlight the impact of socio-economic factors and human interventions on deltaic landscapes (Roy et al., 2013; Ghosh et al., 2018).

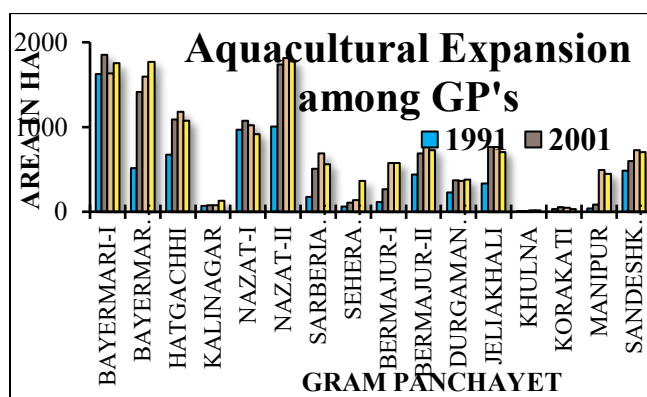


Figure 6: Aquacultural changes among the gram panchayats of Sandeshkhali blocks from 1991 to 2021

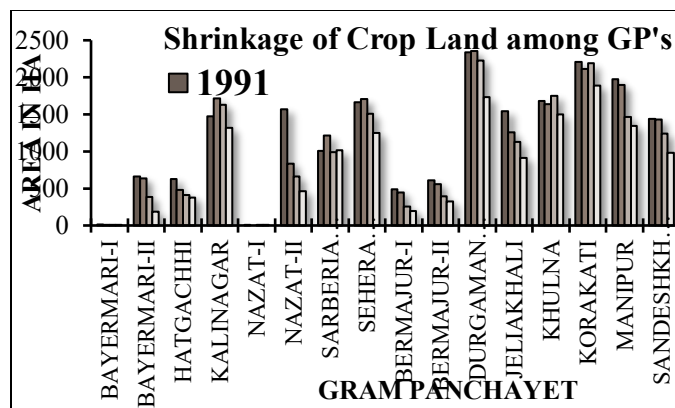


Figure 7: Agricultural area changes among the gram panchayats of Sandeshkhali blocks from 1991 to 2021

The analysis of cropland area across the Sandeshkhali-I and Sandeshkhali-II blocks from 1991 to 2021 reveals a noticeable declining trend, indicating progressive land use transformation and possible intensification of non-agricultural activities. In Sandeshkhali-I, major reductions are evident in Bayermari-II, where cropland decreased dramatically from 662.89 ha in 1991 to just 188.55 ha in 2021, and in Nazat-II, which declined from 1568.88 ha to 461.10 ha over the same period. Similar decreases are seen in Sehera Radhnagar and Hatgachhi, suggesting a shift away from traditional agricultural practices, possibly due to urbanization, aquaculture expansion, or changing livelihood patterns. Kalinagar, although showing fluctuations, also declined from a peak of 1715.42 ha in 2001 to 1315.53 ha in 2021. In Sandeshkhali-II, a significant drop is noted in cropland for Korakati and Manipur, with Korakati falling from 2206.29 ha in 1991 to 1886.31 ha in 2021, and Manipur from 1973.17 ha to 1346.04 ha. The most substantial decline is observed in

Durgamandop, reducing from 2336.65 ha in 1991 to 1730.18 ha in 2021. These patterns suggest increasing land pressure and conversion of croplands to settlements or other uses, aligning with regional studies that have highlighted agricultural land loss in coastal and deltaic regions due to socio-economic transitions and environmental stressors (Mondal & Tatem, 2012; Ghosh et al., 2018).

5. Conclusion:

This study presents a detailed spatiotemporal analysis of Land Use Land Cover (LULC) changes in the Sandeshkhali-I and Sandeshkhali-II blocks of the North 24 Parganas district, West Bengal, over the period from 1991 to 2021. By integrating multi-temporal Landsat imagery and applying the Random Forest classifier within the Google Earth Engine (GEE) platform, the research demonstrates a robust, scalable methodology for high-accuracy land cover classification (Belgiu & Drăguț, 2016). The classification achieved overall accuracies above 85% across all periods, with Kappa coefficients indicating strong agreement between classified and reference data (Congalton, 1991). The results reveal a pronounced transformation in the landscape, marked by the steady decline of cropland and mixed vegetation, and a concurrent increase in aquaculture and built-up land. Aquaculture expanded significantly between 1991

and 2011, driven by livelihood shifts and economic incentives, consistent with regional trends observed in the Indian Sundarban delta (Mandal et al., 2020; Ghosh et al., 2018). Built-up areas also showed substantial growth, particularly in the last decade, reflecting increased urbanization and population pressure (Seto et al., 2012). Although mangrove areas initially declined, a modest increase in recent years suggests some success of conservation efforts, aligning with findings by Giri et al. (2011) on mangrove regrowth in the Sundarbans.

Transition matrix analysis confirmed major inter-class conversions, especially from cropland and mixed vegetation to aquaculture and urban areas. These changes are indicative of shifting land use priorities influenced by both socio-economic drivers and environmental stressors, including salinization, flooding, and resource constraints (Hazra et al., 2002; Roy et al., 2013). Panchayat-level data further reveal spatial heterogeneity in land transformation, underscoring the importance of localized planning strategies. Overall, the findings point to an urgent need for integrated and sustainable land management policies that balance development with ecological conservation. The use of cloud-based remote sensing platforms like GEE combined with machine learning algorithms offers powerful tools for real-time LULC monitoring and policy formulation, particularly in vulnerable coastal regions like the Indian

Sundarbans (Lambin et al., 2001; Foley et al., 2005).

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