



The trajectory of mangrove dynamics within the deep project area of the Kyaukpyu Special Economic Zone

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ABSTRACT

Mangroves provide vital coastal ecosystem services, including shoreline protection, fisheries support, biodiversity conservation, and blue carbon sequestration. Using multi-temporal remote sensing and shoreline change analysis from 2015 to 2024, this study evaluates mangrove dynamics in the environmental influence zone of the Kyaukpyu Special Economic Zone and Deep-Sea Port, Myanmar. Mangrove area declined from 15,427.9 ha to 12,754.8 ha, representing a net loss of 17.3% and an average decrease of 253.3 ha/yr. Within the 3-km direct-impact Core Area (CA), mangrove cover contracted from 953.9 ha to 599.9 ha (37% loss; 39.1 ha/yr). Net change shifted from slight gain during 2015–2018 to loss-dominated dynamics during 2018–2021 and accelerated decline during 2021–2024. Shoreline analysis showed weak net erosion along both riverbanks, with erosion dominating the Yanbye Island margin and comparatively more coherent accretion along Made Island. Mangrove loss was concentrated within persistent and newly established embankment landscapes, consistent with land conversion and hydrological modification as important pathways of decline. Early gains included localized recolonization, some of which persisted into the following interval, but gains became progressively smaller and more fragmented. Hydrometeorological disturbances and governance constraints provided additional context but were not isolated as independent drivers. This study establishes a quantitative baseline for future monitoring and impact assessment under ongoing coastal development.

1. Introduction

Mangrove forests are increasingly recognized as multifunctional coastal ecosystems whose importance extends beyond shoreline protection and carbon storage to include biodiversity support, food-web connectivity, fisheries and climate adaptation (Barbier et al., 2011; Donato et al., 2011; Alongi, 2014; Carugati et al., 2018; IPCC, 2019; Temmink et al., 2022). Recent syntheses have broadened this perspective by showing that mangrove values depend not simply on forest area, but also on biodiversity, structural complexity, and coastal landscape connectivity (Lee et al., 2014; Lovelock et al., 2024, 2025). In parallel, global assessments and recent monitoring frameworks have strengthened the evidence base for both their ecological significance and their continued exposure to land conversion, hydrological alteration, and climate-related pressures (Friess et al., 2019; Goldberg et al., 2020; Bunting et al., 2022; Hagger et al., 2022). Accordingly, mangroves are

now framed less as static stands of threatened coastal vegetation than as dynamic social-ecological systems central to blue carbon, coastal resilience, and nature-based solutions (Hagger et al., 2022; Lovelock et al., 2025).

Recent studies increasingly show that mangrove dynamics are far more heterogeneous than a simple narrative of uniform decline suggests (Friess et al., 2019; Bunting et al., 2022; Hagger et al., 2022; Contessa et al., 2023). Contemporary research clearly distinguishes among multiple trajectories such as shoreline retreat, landward migration, persistence, natural recovery, and seaward progradation, linking these divergent responses to the interacting controls such as relative sea-level rise, sediment supply, hydrodynamic regime, geomorphological structure, forest condition, and human disturbance (Besset et al., 2019; Samanta et al., 2021; Long et al., 2021; Saintilan et al., 2023; Xiong et al., 2024; Thant et al., 2025; Echeverry Hernandez et al., 2025). This process-based perspective has been strengthened by advances in

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mangrove remote sensing, which has progressed from spectral-index and threshold-based mapping toward dense time-series remote sensing, automated machine learning classification, and eco-geomorphic analysis. Recent global and large-scale studies, including 10-m global mangrove mapping and automated large-scale mapping workflows, demonstrate the increasing capacity of satellite observations to monitor mangrove extent consistently across broad regions (Jia et al., 2023; Lu and Wang, 2021). Spectral-index and threshold-based approaches remain useful for enhancing vegetation, water, and wetland contrasts, but fixed-index or threshold rules may be less effective in heterogeneous coastal mosaics where mangroves, non-mangrove vegetation, tidal flats, wet soil, and cultivated land exhibit overlapping spectral responses (Kuenzer et al., 2011; Tran et al., 2022). Machine-learning approaches address this complexity by integrating multispectral bands, SAR observations, spectral indices, and other predictor variables, while dense time-series algorithms allow disturbance, persistence, recovery, and long-term decline to be identified from spectral trajectories rather than single-date comparisons (Kennedy et al., 2010; Zhu and Woodcock, 2014; Ghorbanian et al., 2021; Qian et al., 2025). These approaches also help relate mapped mangrove changes to ecological and geomorphological processes, including shoreline migration, sediment dynamics, hydrological stress, and hydro-meteorological variability (Yao et al., 2025). For example, recent delta-scale analysis suggests that sea-level rise impacts on mangroves may be overestimated in some tropical settings where seaward advance offsets part of landward loss (Dai et al., 2024), while other studies show that wave energy, sediment supply, and geomorphological structure strongly influence mangrove development and resilience (Zhou et al., 2022; Wang et al., 2023). In parallel, targeted restoration, replanting, and strengthened conservation policies have enabled mangrove recovery and expansion in some settings, demonstrating that management interventions can shift mangrove trajectories where direct pressures are reduced and hydrological connectivity is maintained or restored (Ellison et al., 2020; Gerona-Daga and Salmo III, 2022). Overall, these findings underscore that mangrove dynamics are complex and driven by multifaceted, interacting factors rather than a single dominant mechanism (Friess et al., 2019; Worthington et al., 2020; Hagger et al., 2022; Bhowmik et al., 2022).

Special economic zones (SEZs) and other coastal industrial developments have become prominent instruments for promoting economic growth and integrating global trade (UNIDO, 2015; United Nations Conference on Trade and Development, 2019; Aggarwal, 2022). These zones are often strategically situated in low-lying coastal and estuarine environments, where advantages such as deep-water ports and connectivity concentrate infrastructure and attract investment (UNIDO, 2015; United Nations Conference on Trade and Development, 2019). A consistent concern in the SEZ literature is that while SEZ performance is extensively evaluated in economic terms, environmental consequences are often less systematically assessed, particularly where regulatory exemptions, accelerated approvals and fragmented governance can weaken oversight and cumulative impact assessment (Richardson, 2004; World Bank, 2017; Aung et al., 2022). Studies from diverse settings demonstrate that large-scale coastal development can drive rapid transformation of nearshore ecosystems, including direct habitat removal and degradation, shoreline reconfiguration, and altered sediment pathways and hydrodynamics and the displacement of land uses into adjacent wetlands, often extending beyond formal project boundaries (He et al., 2014; Aung et al., 2022; Chen et al., 2023; Nabila and Tsuyuzaki, 2025). Recent SEZ-focused case studies show that coastal economic zone development can cause measurable environmental change beyond project footprints, including impacts reported in Bangladesh, Nigeria, and Indonesia such as mangrove degradation/clearance, biodiversity loss, and water contamination (Aung et al., 2022; Nabila and Tsuyuzaki, 2025; Adunbi, 2019; Sultana and Mahmud, 2025). Together, this body of work motivates rigorous baseline and time-series assessment in coastal SEZ settings, where environmental

consequences may emerge through both direct land conversion and broader geomorphic and hydrological disruption.

In many SEZ and coastal development contexts, independent environmental monitoring is constrained by rapid change, limited baseline data, and restricted field access, increasing reliance on remote sensing to quantify land-cover dynamics consistently across space and time (Bunting et al., 2018; Friess et al., 2019). Over the past decade, advances in sensors and analytics have substantially improved coastal and mangrove monitoring, including national-to-regional time-series mapping and change attribution (Giri et al., 2011; Hamilton and Casey, 2016; Veetil et al., 2019). Methods now extend well beyond single-date classifications: multi-sensor fusion using optical and SAR imagery helps overcome cloud and inundation constraints while time-series approaches increasingly address tidal variability explicitly; and object-based and deep-learning models improve delineation in fragmented and dynamic coastal mosaics (Wang et al., 2004; Ghorbanian et al., 2021; Ye and Weng, 2025; de Souza et al., 2024). The new generation of trajectory-based monitoring approaches, including temporal segmentation and continuous change detection, fit models to spectral trajectories through time, enabling consistent identification of disturbance events and subsequent recovery (Kennedy et al., 2010; Zhu and Woodcock, 2014). Advances in cloud-computing platforms such as Google Earth Engine, further provide analysis-ready archives and scalable processing that support reproducible monitoring in data-sparse or logistically restricted regions (Gorelick et al., 2017; Tamiminia et al., 2020).

Despite major advances in global monitoring, important geographic gaps remain in long-term, spatially explicit assessments, particularly in conflict-affected or data-scarce coastal settings where field access is limited and development decisions still proceed. Myanmar exemplifies this challenge. Myanmar is internationally recognized as both mangrove-rich and a hotspot of mangrove loss, with satellite-based assessments documenting major declines over the past two decades driven by land-use conversion and weak enforcement in the coastal zone (Estoque et al., 2018; Goldberg et al., 2020; De Alban et al., 2020). However, published evidence is uneven across Myanmar's mangrove regions. Compared with major deltaic systems such as the Ayeyarwady, Rakhine State has comparatively more limited published spatial assessments and in-situ evidence, due to long-standing access constraints (Lee et al., 2021). Yet the best-available synthesis assessments still indicate high vulnerability in Rakhine's coastal mangroves. Accordingly, the recent IUCN Red List of Ecosystems classified "Rakhine mangrove forest on mud", as Critically Endangered, reflecting substantial historical losses and ongoing pressures, while also highlighting the conservation significance.

Remote-sensing assessments consistently identify Rakhine State as Myanmar primary mangrove-loss hotspot in the early 21st century. Using multi-sensor change analysis (1996-2007-2016), De Alban et al. (2020) estimated that Rakhine's mangrove extent declined from 3443 km² (1996) to 1780 km² (2007) and 1309 km² (2016), and their transition analysis shows loss was systematically linked to conversion into rice paddies, while aquaculture became more systematic in 2007-2016. Complementarily, Estoque et al. (2018) reported that Rakhine's mangrove experienced a net loss of -75,494 ha from 2000 to 2014, making it the largest net loss among states/regions across the nation, and argued that mangrove-cover change could be associated with measurable environmental shifts in surface conditions and ecosystem functioning. Building on earlier work, Lee et al. (2024) further documented widespread degradation in the region and concluded that Rakhine's mangroves remain under high threat. While acknowledging methodological and temporal differences among previous estimates, including those of Weber et al. (2014) and Estoque et al. (2018), Lee et al. (2024) also noted an important nuance: recent rates of mangrove loss in Rakhine may be slowing, even though the state still shows substantial net loss overall.

Within Rakhine, Kyaukpyu is a strategically important coastal setting

where SEZ-related planning is advancing, yet sub-regional, SEZ-relevant environmental baselines remain limited. To address this gap, this study establishes an environmental baseline for mangrove dynamics in the proposed Kyaukpyu Special Economic Zone (KPSEZ) and Deep-Sea Port (DSP) influence zone over the period 2015–2024. Specifically, it (i) quantifies mangrove extent and change trajectories across the environmental influence scale, (ii) characterizes spatial transition pathways and hotspots in relation to dominant coastal land-use and hydrological modification processes, and (iii) interprets the timing and persistence of changes in the context of hazards and governance constraints that shape management effectiveness.

2. Materials and methods

2.1. Study area

The study area is located in Kyaukpyu Township, Rakhine State, western Myanmar, between approximately 19° N–19°45' N and 93°15' E–93°50' E, and includes Ramree (Yanbye) Island and Maday Island, the core site of the KPSEZ and DSP project. This extent was defined based on the ESIA scoping boundaries (10 km indirect and 3 km direct impact radii) and extends upstream along the Thanzit River for ~30 km toward the township boundary to capture broader off-site environmental influences (Consortium of MSR and International Consultants, 2023, Fig. 1). The 3 km direct-impact radius is hereafter referred to as the Core Area (CA), which is treated separately in subsequent analysis.

The regional climate is controlled by the southwest and northeast monsoon systems. Kyaukpyu is one of the wettest regions in Myanmar, with an average annual rainfall of approximately 4655 mm, and about 96% of total precipitation occurs during the wet season, especially from June to August when the southwest monsoon is strongest (Myanmar Environment Institute, 2017). Mean monthly wind speeds range from 3.2 to 7.1 m s⁻¹, with stronger winds more frequent during the monsoon season (Aung et al., 2017). Weather-related hazards include monsoon flooding, strong winds, coastal erosion, and tropical cyclones, all of which are recurrent in Rakhine State (Mishra et al., 2024).

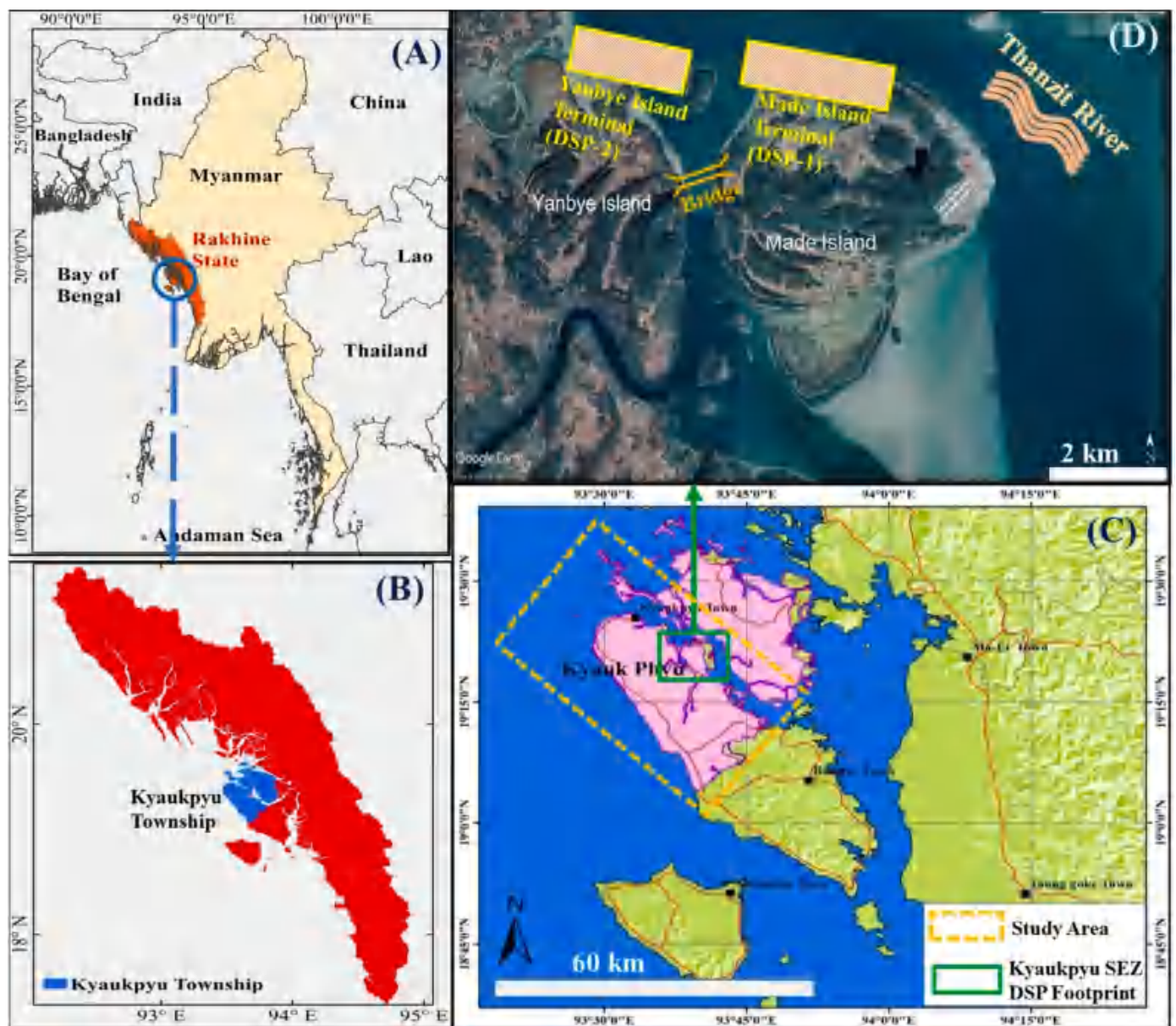


Fig. 1. (A) Location of Myanmar and Rakhine State, (B) Location of Kyaukpyu Township in Rakhine, (C) Extent of study area on the map, (D) Conceptual plan of KPSEZ DSP area.

Hydrologically, the area is characterized by a complex estuarine and tidal system. Rivers draining westward from the Arakan Mountains deliver freshwater and sediment into the coastal lowlands during the monsoon season, forming a network of estuaries, tidal channels, lagoons, and wetlands that remain partly saline throughout the year. Tides are semi-diurnal, and tidal levels typically range from 2.7 to 3.5 m during high tide and 0.6–1.4 m during low tide. Soils in the study area are predominantly sandy and alluvial in nature, with extensive deposits of silty alluvium across low-lying coastal plains (Myanmar Environmental Institute, 2017).

Ecologically, the study area supports extensive mangrove and riparian habitats along tidal channels and estuaries, and mangroves account for approximately 16% of total forest cover in Kyaukpyu District. Despite their ecological importance, there are currently no designated protected areas, Key Biodiversity Areas, or wildlife sanctuaries within the study area. At the same time, Kyaukpyu is increasingly treated as a strategically important coastal development node, and recent progress in formal ESIA scoping and consultation for the KPSEZ DSP has increased the need for robust baseline evidence to distinguish background coastal dynamics from future development-related change.

2.2. Materials

Open-access time-series Sentinel-2 images were acquired and processed within the Google Earth Engine (GEE) cloud computing platform to produce annual classified maps of mangrove distribution. Time-series imagery helps account for water-level and tidal variability in mangrove environments, improving classification reliability (Wang et al., 2019). The Sentinel-2 mission is equipped with the Multispectral Instrument (MSI), which records the Earth's surface in 13 spectral bands from visible through the shortwave infrared (SWIR), at 10–60 m resolution with an effective revisit time of 5 days. Because atmospherically corrected Sentinel-2 Level-2A surface reflectance is consistently available from late 2018 onward, Sentinel-2 Level 1C (Top of the Atmosphere) products were incorporated to extend annual mapping to 2015–2018. Both image collections were filtered by the study area, analysis period and scene-level cloudiness metadata (cloud cover < 20%). Clouds and cloud shadows were removed using standard quality layers available in each product (e.g., Scene Classification Layer (SCL) masking for Level-2A; QA60 for Level-1C) with refinement using the Sentinel-2 Cloud Probability product. Subsequently, annual composites were generated using a median reducer to minimize residual cloud contamination and radiometric outliers.

To support the machine-learning classification, reference information was obtained from the Global Mangrove Watch dataset, high-resolution historical imagery available in Google Earth, and annual Sentinel-2 composite images. The Global Mangrove Watch dataset was used as an auxiliary reference for mangrove identification, while Google Earth imagery and Sentinel-2 composites were used to visually verify mangrove and non-mangrove land-cover classes. Historical Google Earth imagery varied in acquisition date and spatial resolution across locations and years and was therefore used only as a qualitative reference. Wave direction and significant wave height (Hs) for 2024 were obtained from the ECMWF ERA5 hourly time-series dataset at the grid point nearest to the study area (19.5° N, 93.5° E; accessed 8 April 2025). Additionally, annual tide tables for Myanmar Coastal Ports (2015–2024) published by Myanmar Naval Hydrographic Centre (MNHC) were utilized to account for tidal variability during the image selection and shoreline-related analyses.

2.3. Methods

2.3.1. Mangrove area extraction

In this study, four bands of blue, green, red and near infrared (NIR) with 10 m spatial resolution and two bands of SWIR 1 and SWIR 2 with 20 m spatial resolution, were used as classification inputs. Spectral

indices are widely applied to enhance vegetation, water, soil, and wetland features and to improve class separability in remote-sensing classification (Rouse et al., 1974; Huete, 1988; Huete et al., 2002; McFeeters, 1996; Xu, 2006). Building on multispectral band combinations, several mangrove-specific indices have been developed to support more reliable mangrove detection and separation from non-mangrove vegetation and other coastal land-cover classes (Shi et al., 2016; Gupta et al., 2018; Baloloy et al., 2020).

Hence, eleven spectral indices were extracted for additional inputs for classification, including four vegetation indices- Normalized Difference Vegetation Index (Rouse et al., 1974; Tarpley et al., 1984), Enhanced Vegetation Index (Huete et al., 2002), Soil Adjusted Vegetation Index (Huete, 1988) and Transformed Difference Vegetation Index (Bannari et al., 2002), three mangrove vegetation indices- Mangrove Vegetation Index (Baloloy et al., 2020), Normalized Difference Mangrove Index (Shi et al., 2016) and Combined Mangrove Recognition Index (Gupta et al., 2018), other classes differentiation indices - Normalized Difference Water Index (McFeeters, 1996), modified Normalized Difference Water Index (Xu, 2006), Land Surface Water Index (Xiao et al., 2004; Chandrasekar et al., 2010) and Bare Soil Index (Rikimaru et al., 2002). The mathematical algorithms/formulae of all eleven spectral indices used as classification inputs are provided in Supplementary Table S1.

Mangrove mapping has increasingly relied on remote-sensing coupled with a range of machine-learning classification (Green et al., 1998; Ahmad and Quegan, 2013; Mondal et al., 2019; Manna and Raychaudhuri, 2020; Quang et al., 2020). With advances in computational capacity, increasingly, the adoption of machine and deep learning in improved environmental monitoring with remote sensing data have repeatedly been shown to outperform conventional methods (Campomanes et al., 2016; Reichstein et al., 2019; Ge et al., 2020; Yuan et al., 2020; Guo et al., 2021; Fan et al., 2022; Han et al., 2023).

Given this multi-dimensional predictor set and the heterogeneous coastal land-cover mosaic, this study used a Random Forest (RF) classification model, an ensemble machine-learning algorithm for remote-sensing land-cover classification owing to its robustness in handling high-dimensional predictor sets, nonlinear class boundaries, and complex interactions among input variables (Breiman, 2001; Rodriguez-Galiano et al., 2012). This capability is particularly relevant for mangrove mapping in Kyaukpyu, where Sentinel-2 spectral bands and vegetation, water, soil, and mangrove-specific indices must be integrated to separate mangroves from spectrally similar land-cover types. Compared with single-index or threshold-based approaches, RF provides a more flexible classification framework for heterogeneous coastal environments. Its compatibility with Google Earth Engine also supported efficient and reproducible annual mapping from multi-temporal satellite imagery (Tamiminia et al., 2020). RF-based approaches have been successfully applied in mangrove mapping and change-analysis studies at local, regional, and global scales, including the Global Mangrove Watch baseline, Sentinel-based mangrove ecosystem mapping, and global attribution of mangrove-loss drivers (Bunting et al., 2018; Toosi et al., 2019; Nababa et al., 2020; Zhao et al., 2020; Goldberg et al., 2020; Ghorbanian et al., 2021).

Training and validation samples were manually digitized in GEE, for seven land-cover classes: mangrove, other vegetation, cultivated land, surface water, built-up area, barren land and tidal flat. The 2024 sample dataset was first prepared as the baseline reference because the most recent high-resolution Google Earth imagery provided the clearest visual interpretation of current land-cover conditions. For earlier years, rather than a direct transfer, the baseline was checked and adjusted annually using historical Google Earth imagery, annual Sentinel-2 true/false-color composites and spectral-index layers. Samples affected by land-cover conversion, shoreline migration, embankment construction, or ambiguous spectral conditions were removed, revised, or newly added, ensuring year-specific representativeness.

For each year, the reference samples were randomly divided into two

independent subsets, with 80% used for RF model training and 20% reserved for accuracy testing (Refs). Because sample adjustment was conducted separately for each year, the total counts varied among years. The year-specific sample quantities are summarized in [Table S2](#). Classified outputs were exported for post-processing in ArcMap 10.8, where geospatial analyses were conducted to quantify mangrove area and change detection and to produce final cartographic outputs and supporting figures in combination with MATLAB.

2.3.2. Extraction of mangrove shoreline and footprint area

Due to persistently high cloudiness in the tropical Rakhine coastal zone, automated scene-level cloud and shadow masking did not consistently yield visually clear composites. Therefore, cloud-free Sentinel-2 scenes for 2015, 2018, 2021 and 2024 were manually screened and selected in GEE. For each selected acquisition, corresponding tidal stage was estimated from local tide tables ([Myanmar Naval Hydrographic Centre, 2015](#)) using the reported tidal offsets and constants. To minimize tidal bias in shoreline-related analyses, only images acquired under comparable water levels, targeting a tidal height of 0.7 ± 0.25 m, were retained and median composites for each target year were then generated and exported for subsequent analysis. Mangroves are widely recognized as valuable geomorphic indicators in shoreline-change studies ([Souza-Filho et al., 2006](#); [Long et al., 2022](#); [Xiong et al., 2024](#); [Zhou et al., 2024](#); [Thant et al., 2025](#)).

In this study, boundary pixels between mangrove, land and open water were used to define the mangrove shoreline, and the seaward edge for each target year was manually digitized from stacked true- and false-colour composites and reflectance bands. The Digital Shoreline System (DSAS) extension in ArcGIS was used to quantify shoreline change, including net shoreline movement (NSM), linear regression rate (LRR) ([Himmelstoss et al., 2018](#)). A shore-parallel DSAS baseline was delineated by smoothing and offsetting the 2024 shoreline to serve as the fixed reference from which all DSAS statistics were generated. Transects were spaced at 250 m intervals along the full riverbanks and at 100 m intervals within the Core Area to provide more detailed analysis near the proposed development footprint. In this study, negative shoreline-change rates are described as erosion and positive rates as accretion, referring specifically to landward retreat and seaward advance of the mapped mangrove front, respectively, rather than to direct measurements of sediment erosion or deposition.

Similarly, embankment (locally “Kari”) footprints were mapped for each target year using visually clear Sentinel scenes acquired within a consistent seasonal window (January–February; dry season) to reduce seasonal differences and improve comparability of surface patterns. Embankments that enclose low-lying intertidal lands for agriculture and aquaculture were delineated by manual interpretation of their distinctive linear dike morphology, which is discernible at Sentinel-2 spatial resolution, together with associated spectral and geomorphic contrasts; interpretations were cross-checked using historical high-resolution imagery in Google Earth. Delineations focused on embanked areas within tidal domain; some cultivated patches within tidal boundaries formed by blocked tidal creeks were included, while non-tidal inland cultivation was excluded. Abandoned embanked areas were also identified and digitized. Spatial overlay and geoprocessing tools (e.g., union, intersect, erase and area summarization) were then applied to quantify footprint areas and to assess mangrove extent and change in relation to these features over time.

2.4. Accuracy assessment

RF model classification accuracy was assessed in GEE using the built-in error matrix derived from an independent validation subset of the reference samples. For each mapping year, the validation samples were compared with the classified land-cover map to generate a confusion matrix. Overall accuracy (OA), Kappa coefficient, and class-specific producer's and user's accuracies (PA and UA) were calculated from the

resulting matrix. PA was used to evaluate omission error, indicating the proportion of reference samples of a given class that were correctly classified, whereas UA was used to evaluate commission error, indicating the reliability of pixels mapped as a given class. These metrics were used to summarize both overall classification performance and class-specific uncertainty, consistent with good-practice recommendations for thematic map accuracy assessment ([Stehman, 1997](#); [Olofsson et al., 2014](#)). The yearly class-specific PA and UA values are reported in [Supplementary Table S3](#).

Additionally, uncertainty in embankment footprint area mainly reflects boundary definition and detectability limits at Sentinel-2 scale, where narrow or partially obscured dikes and mixed pixels can introduce small edge offsets, and variable water/soil conditions can modify feature contrast. Additional uncertainty can arise from feature ambiguity in transitional zones and temporal mismatch between imagery and short-term management changes. However, these effects are expected to affect localized boundary segments rather than the overall footprint and change patterns.

3. Results

3.1. Classification accuracy

The RF classification results from 2015 to 2024 showed consistently high accuracy, with overall accuracy ranging from 0.91 to 0.94 and Kappa coefficients ranging from 0.90 to 0.92, indicating strong agreement between the classified maps and independent validation samples. For the final 2024 mangrove map, the overall accuracy and Kappa coefficient were 0.93 and 0.92, respectively ([Table S3](#)). The mangrove class was mapped reliably throughout the study period, with producer's accuracy ranging from 0.94 to 0.98 and user's accuracy ranging from 0.94 to 0.98; in 2024, these values were 0.95 and 0.96, respectively. Other vegetation and surface water also showed high producer's and user's accuracies, generally exceeding 0.94. In contrast, built-up/settlement areas had lower producer's accuracy (0.65–0.78), while barren land and non-mangrove tidal flats showed greater interannual variability. The detailed yearly accuracy results are provided in [Supplementary Table S3](#).

Classification uncertainty was mainly concentrated in the classes with lower or more variable accuracy rather than in the mangrove class itself (Refs). The lower accuracy of built-up/settlement areas and the variability in barren land and non-mangrove tidal flats were likely related to dry-season surface conditions in Rakhine State. Because all images were acquired during the winter dry season, fallow or harvested agricultural fields, exposed bare soil, settlement edges, and dry or partially wet tidal-flat surfaces could show similar reflectance characteristics, making cultivated land, barren land, built-up/settlement, and non-mangrove tidal flat more difficult to separate. Similar fallow and abandoned-field conditions have been reported in Rakhine agricultural landscapes ([Huang et al., 2019](#)).

Mangrove-related errors were more limited. Commission errors, where non-mangrove pixels were classified as mangroves, were mainly associated with dense non-mangrove vegetation, wet vegetated surfaces, and vegetation along tidal-channel margins, which can show vegetation-index and moisture signals similar to mangrove stands. Omission errors, where actual mangrove pixels were classified as other land-cover types, were more likely along fragmented mangrove edges, sparse or degraded patches, and tidally inundated margins, where mixed pixels may resemble other vegetation, wet soil, tidal flats, or surface water. Such spectral similarity, tidal effects, and mixed-pixel problems are common limitations in optical mangrove remote sensing and spectral-index-based classification ([Kuenzer et al., 2011](#); [Tran et al., 2022](#)). Overall, the high and stable mangrove producer's and user's accuracies indicate that these uncertainties were limited and did not substantially affect the detected decade-scale mangrove decline.

3.2. Variation in mangrove forest area

The mangrove area exhibited a consistent decreasing trend from 2015 to 2024 (Fig. 2A). The total area declined from 15,427.9 ha in 2015 to 12,754.8 ha in 2024, representing an overall decrease of approximately 17.3% across the ten-year period. Year-by-year patterns showed small fluctuations, including a modest increase in 2018. The values remained relatively steady until 2021, after which the steepest decline appeared from 2022 onward, accounting for roughly 77% of the total decrease observed. Linear regression analysis further showed a negative slope of 253.3 ha/yr, representing the average linear rate of decline over the study period. Additionally, the compound annual rate of decrease was calculated at 2.06%, consistent with the overall reduction in mangrove extent.

To further assess mangrove dynamics within the development footprint, the CA of the KPSEZ DSP was analyzed separately. The mangrove area showed a clear decreasing pattern from 953.9 ha in 2015 to 599.9 ha in 2024 (Fig. 2B). Although small fluctuations occurred in several intermediate years, the overall trend reflected a consistent reduction, with an average annual decrease of 39.1 ha, consistent with the broader decline shown in Fig. 2A. The CA also exhibited a substantially larger proportional reduction of about 37%, indicating a proportionally stronger contraction within the designated Core Area. Together, these results illustrated that both spatial scales experienced sustained decreases in mangrove extent over the study period.

3.3. Gain and loss in mangrove forest area

Across the three study intervals, the spatial distribution of mangrove change exhibited several consistent patterns (Figs. 3 and 4). Overall, mangrove loss occurred primarily as relatively large, localized patches concentrated along major tidal channels, creek networks, and fragmented interior zones, corresponding to small but discernible shifts at the mangrove–water interface (Fig. 3). In contrast, mangrove gains, while present in all periods, generally appeared as patchy expansions adjacent to existing stands. Such gains were often observed along channel banks, meandering creeks, headlands, or in formerly low-lying agricultural land. Remaining mangrove areas continued to dominate the broader landscape throughout the study decade (Fig. 3, Table 1), particularly in the more consolidated southern and southeastern upstream reaches of the river. Over time, however, the balance between loss and gain shifted markedly.

Despite these overarching similarities, each period showed distinct

differences in the intensity and distribution of change. During 2015–2018, a slightly positive net balance was observed, with mangrove gain of 2692.7 ha marginally exceeding loss of 2197.1 ha and producing a net gain of 495.7 ha (3.21%; Table 1). These gains were relatively widespread and scattered across the study area and included several spatially connected clusters, while losses remained localized and interspersed with extensive areas of remaining mangrove (Fig. 3A).

Between 2018 and 2021 (Fig. 3B), loss patches expanded and became more spatially cohesive, especially in central and southeastern sectors, leading to a negative net balance. This reversal was reflected in the increased loss area (2697.6 ha) and a net decline of 848.8 ha (5.33%). Compared with the preceding interval, gains were less spatially connected and occurred as more localized and discontinuous patches.

In the most recent period, 2021–2024 (Fig. 3C), mangrove loss reached its greatest spatial extent, widely dispersed along major tidal channels and interior fragmented zones. Concurrently, gains diminished further (967.6 ha; 6.4%), occurring only in small, isolated patches that were insufficient to counterbalance the large-scale loss, resulting in a pronounced net reduction of 2320.4 ha (15.39%). Overall, loss increased progressively across the three intervals, whereas gain declined in both area and spatial continuity, culminating in the strongest net mangrove decline during 2021–2024 (Table 1).

The enlarged views of the same southern sector revealed the sequential arrangement of gain, loss, and remaining mangrove within the embankment-modified landscape (Fig. 3D–F). During 2015–2018, gains formed several relatively coherent clusters, including prominent patches within footprints abandoned by the final year of the period, while remaining mangrove formed a comparatively connected matrix (Fig. 3D). In 2018–2021, some areas gained during the preceding interval persisted as remaining mangrove, and additional localized gains occurred along nearby margins, whereas loss also expanded within and around persistent and newly detected embankment footprints (Fig. 3E). During 2021–2024, gains became smaller and more fragmented, while loss was increasingly distributed across areas that had remained mangrove during the previous interval, reducing the continuity of the remaining cover (Fig. 3F). The sequence, therefore, showed partial persistence of early gains in some abandoned footprints, together with increasing loss and fragmentation in the latest period.

Beyond the broader extent, mangrove change within the CA was assessed to capture patterns occurring closer to the development zone. Spatial changes in the CA were concentrated within the coastal embankment, with substantial losses occurring in the first two periods and only modest, fragmented gains (Fig. 4A and B). The smaller

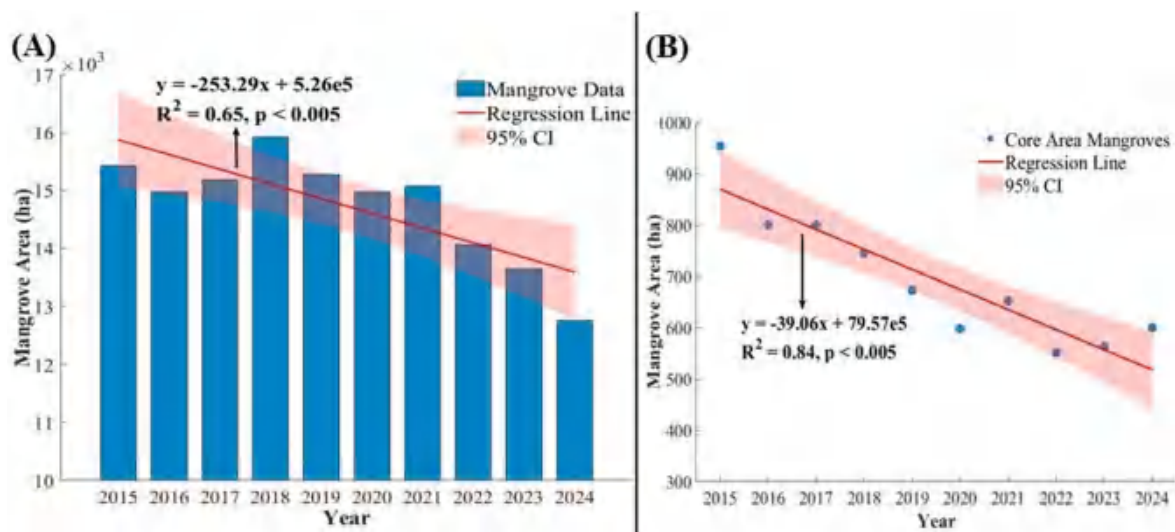


Fig. 2. Temporal variations in mangrove extent over the past decade for (A) the whole Area and (B) the Core Area of the KP SEZ DSP, representing 3-km radius.

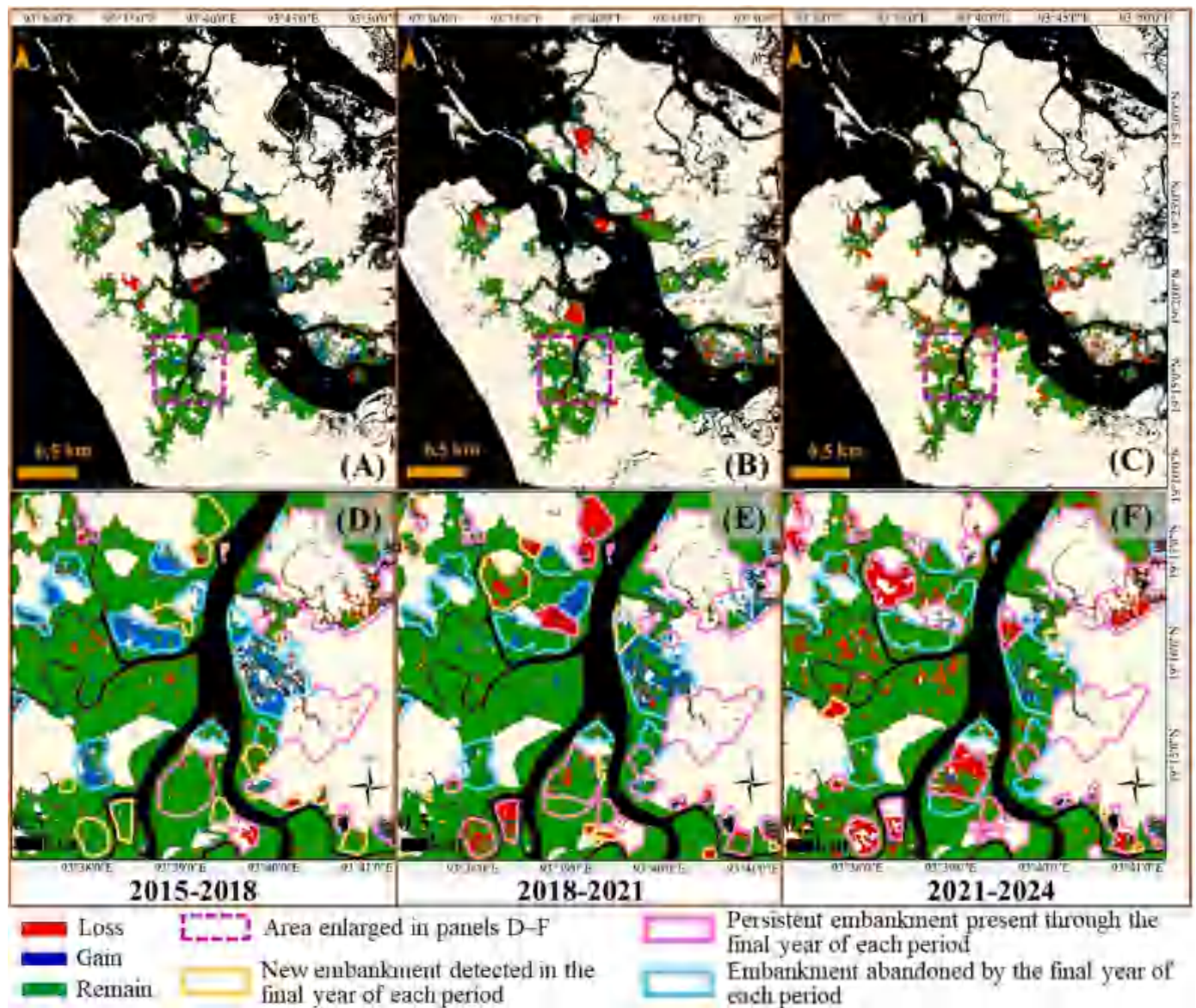


Fig. 3. Panels (A–C) show mangrove loss, gain, and remaining mangrove across three periods. Panels (D–F) are enlarged views of the areas indicated by the magenta dashed boxes in (A–C). In the enlarged panel for each respective period, orange outlines indicate new embankments detected in the final year, blue outlines indicate embankments abandoned by the final year, and magenta outlines indicate persistent embankments present through the final year.

magnitudes of both loss and gain in the final period occurred within the limited mangrove extent remaining (Fig. 4C). Sequential transitions were evident, with some gain patches persisting as remaining mangrove in later periods, while other areas that had previously remained mangrove experienced subsequent loss. Temporary gains associated with phases of embankment commissioning and decommissioning are followed by subsequent losses. Together, the two spatial scales provide a clearer understanding of how mangrove dynamics evolved across the study area, underscoring a persistent pattern of gradual spatial contraction.

3.4. Estuarine mangrove shoreline changes

The DSAS analysis revealed spatially heterogeneous mangrove-front movement along both riverbanks within the study area (Fig. 5). On the left bank (Fig. 5B), erosion occurred along 67.6% of the analyzed shoreline sections and averaged -0.7 m/yr, whereas accretion averaged 0.9 m/yr. The spatial pattern was relatively segmented, with discrete clusters of erosion and accretion separated by longer sections where

rates remained comparatively close to zero. A pronounced erosion-dominated section was evident within the central portion of the bank, while several shorter and discontinuous accretion-dominated sections occurred elsewhere along the shoreline. These localized accretion sections were insufficient to compensate for the more widespread erosion, resulting in a net mangrove-front change of -0.2 ± 0.2 m/yr.

The right bank exhibited a broader along-bank variation (Fig. 5C). Localized accretion occurred in the downstream reach, although the strongest and most spatially concentrated positive rates occurred within the middle reach, around transects 800–950. This middle portion also contained substantial negative rates farther upstream, producing a mixed pattern rather than a uniformly accretional frontage. Beyond approximately transect 1350, erosion became more spatially persistent, with only limited and discontinuous sections of accretion. Overall, erosion occurred along 56.7% of the right-bank transects and averaged -0.8 m/yr, whereas accretion averaged 0.7 m/yr. Despite locally pronounced positive rates, the bank-wide response remained a weak net erosion of -0.1 ± 0.2 m/yr.

Taken together, both banks showed localized accretion

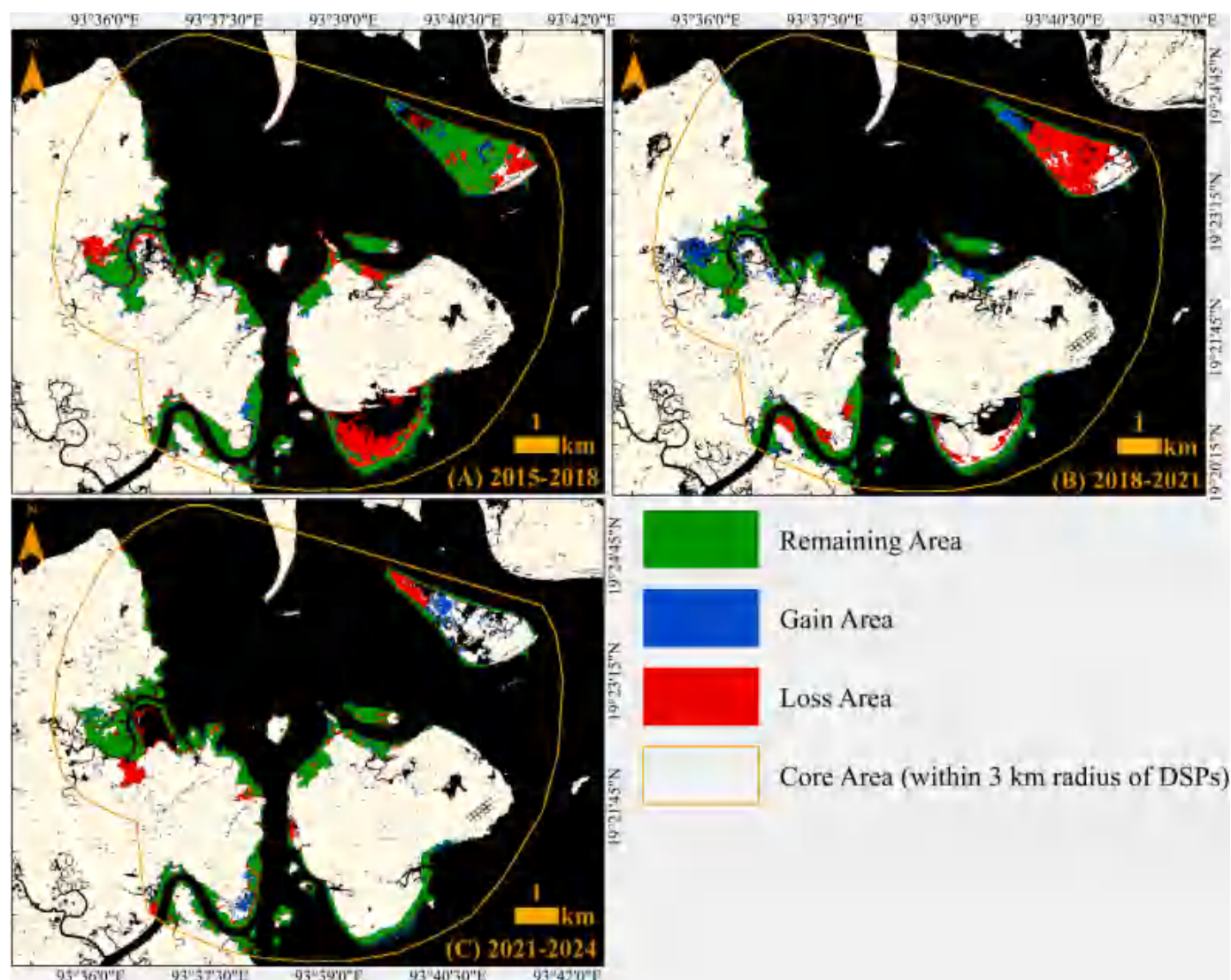


Fig. 4. Spatial distribution of mangrove changes within the CA across three periods. The orange boundary delineates the CA.

Table 1

Overall mangrove change metrics per period.

Time period	Remain (ha)	Gain (ha)	Gross Gain %	Loss (ha)	Gross Loss %	Net Change (ha)	Net change %
2015–2018	13231.2	2692.7	17.45	2197.1	14.24	495.7	3.21
2018–2021	13226.4	1848.8	11.61	2697.6	16.94	−848.8	−5.33
2021–2024	11787.3	967.6	6.42	3287.9	21.81	−2320.4	−15.39

superimposed on a weak net-erosion tendency, but their spatial configurations differed. The left bank was characterized by relatively discrete and spatially separated clusters of accretion and erosion. In contrast, the right bank showed a broader along-bank transition from localized downstream accretion, through a strongly mixed middle reach, to more persistent erosion upstream. These differences demonstrated that mangrove-front movement varied between banks and among shoreline subsections rather than following a uniform estuary-wide trajectory.

Shoreline change within the DSP area, was then assessed to evaluate coastal responses near the development footprint. The results revealed contrasting patterns between the Yanbye Island and Made Island coastlines (Fig. 6). Along the Yanbye Island side (Fig. 6A), erosion was the dominant process, with mean erosion rates of approximately -0.6 m/yr and only limited, scattered accretion, leading to an overall

net change of -0.3 ± 0.5 m/yr. By contrast, the Made Island shoreline (Fig. 6B) displayed a more mixed pattern characterized by comparatively stronger and more spatially coherent accretion signals. Accretion was the prevailing process along much of this downstream margin of Made Island, with several transects recording relatively high positive regression rates. Mean accretion reached 0.6 m/yr, while erosion, though present, was less dominant and averages -0.4 m/yr, producing a slight net accretion of 0.2 ± 0.6 m/yr. Together, the two sections illustrated a spatial asymmetry in shoreline response around the proposed DSP area, with erosion pressure along the Yanbye margin and modest but more spatially consistent accretion along the downstream Made Island shoreline.

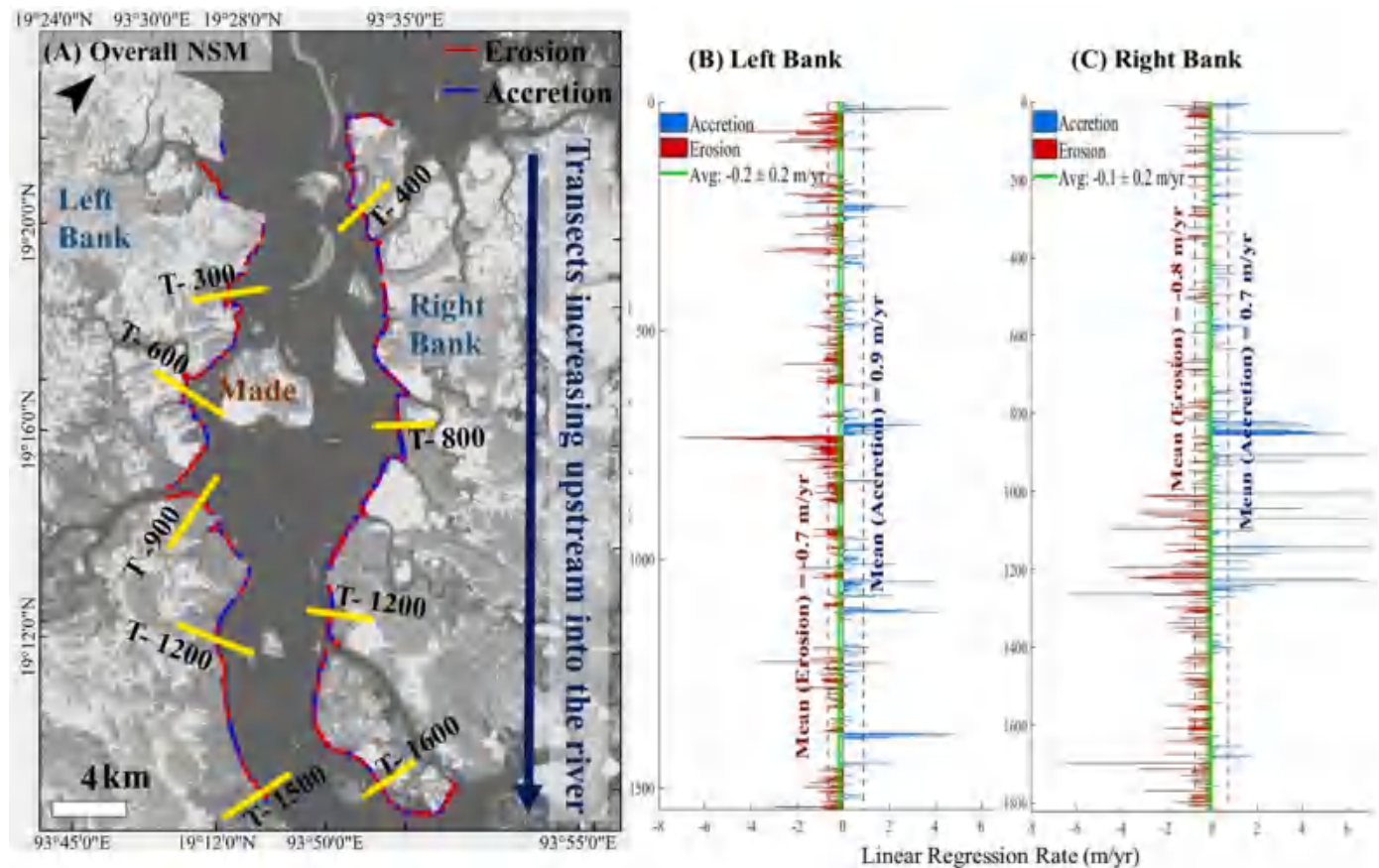


Fig. 5. Mangrove-front change along the estuarine riverbanks from 2015 to 2024. (A) Spatial distribution of erosion and accretion; yellow lines indicate selected reference transects, with transect numbers increasing upstream. (B–C) Linear regression rates along the left and right banks, respectively. Negative and positive values represent mangrove-front retreat and advance.

3.5. Mangrove dynamics across landscape footprints

Mangrove loss and gain exhibited contrasting distributional patterns across the three study periods within footprint-specific zones (Table 2). Losses associated with the any-time embankment footprint remained substantial throughout the decade, with the middle interval showing the highest concentration, when nearly four-fifths of all losses fell within this zone. Conversely, gains originating within any-time abandoned areas declined steadily, both in absolute area and contribution.

Losses were dominated by conversion to tidal flats and bare land, which consistently accounted for most degradation, while other categories contributed relatively minor fractions (Fig. 7). A considerable share of these losses occurs within the any-time embankment footprint, as indicated by the dark portions of the stacked bars (Fig. 7). The contribution of embankment-associated losses increased from the first to the second period and remained high in the third. The distribution of losses across categories within the footprint closely mirrored the overall loss composition across periods.

Mangrove gains showed a parallel temporal pattern, with transitions from tidal flats and bare land constituting the dominant gain-source transitions (Fig. 8). These pathways contributed 75.6%, 91.9%, and 68.7% of total gains in the three intervals. The gain-distribution plot of the three key categories (Fig. 8) showed that gains within the abandonment footprint form a progressively decreasing share of total gains across periods, with an increasing proportion arising outside this zone in later years. Together, these results demonstrated that mangrove variations are shaped by both dominant conversion pathways and the varying proportions of change occurring inside the landscape footprints.

4. Discussion

4.1. Land-use conversion and hydrological modification

The combined spatial and footprint analyses show that mangrove change in Kyaukpyu differed among persistent, newly established, and abandoned embankment landscapes. Across all three intervals, a substantial proportion of gross mangrove loss occurred within the any-time embankment footprint, while loss transitions were dominated by conversion to tidal flats and bare land (Table 2; Fig. 7). In contrast, abandoned footprints contributed to localized mangrove gains, particularly during the earlier interval, although their contribution to total gain declined through time (Table 2; Fig. 8). The footprint-based synthesis further reinforces this contrast by showing that persistent and newly established embankment areas account for the greatest cumulative depletion, whereas abandoned footprints retain relatively higher within-patch persistence but occupy a progressively smaller area over time (Table 3). The enlarged spatial sequence similarly shows localized early gains and subsequent persistence within some abandoned footprints, followed by greater fragmentation and loss in the later intervals (Fig. 3D–F). Together, these results indicate that mangrove decline in Kyaukpyu is not randomly distributed across the landscape but varies with the persistence, expansion, and abandonment of embankment modification.

This spatial pattern aligns with the structure of local Kari-based farming systems in Rakhine State. Paddy Kari generally require near-complete tidal exclusion through earthen bunds, which can drive rapid and direct mangrove clearance at the time of enclosure, whereas shrimp Kari may initially retain some mangrove cover but often undergo

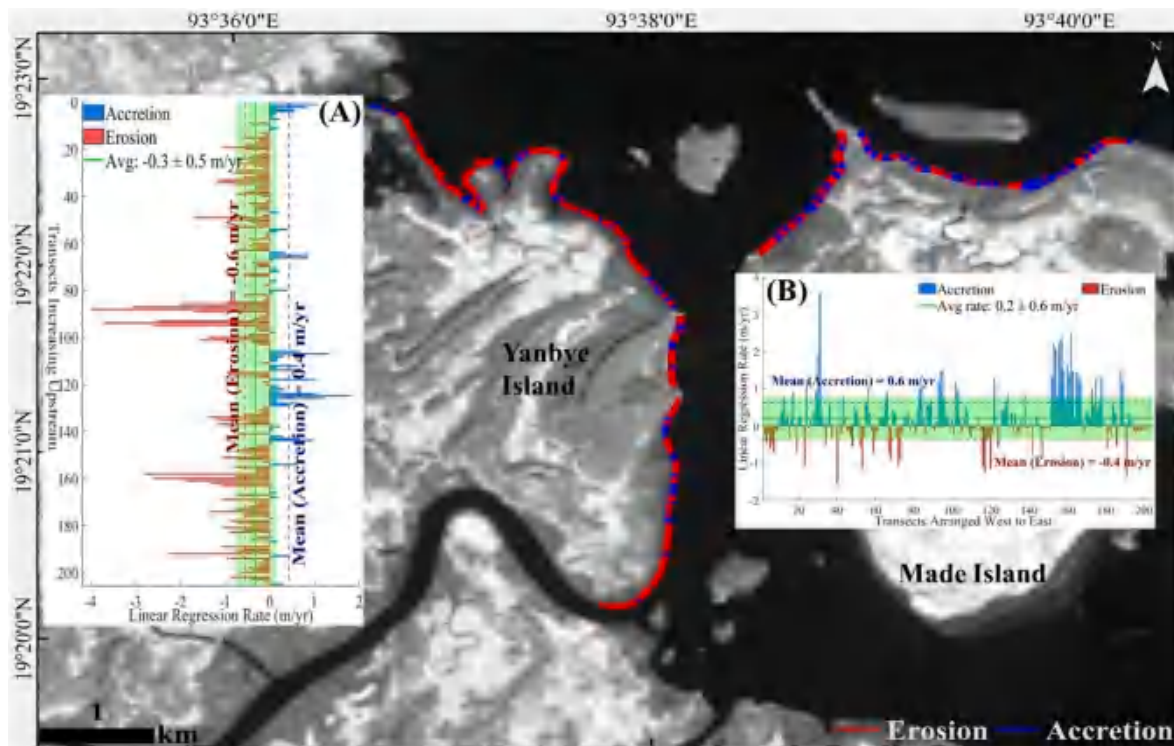


Fig. 6. Shoreline change analysis within the DSP area from 2015 to 2024. (A) Erosion and accretion rates along the Yanbye Island shoreline. (B) Shoreline change along the Made Island side.

Table 2
Mangrove gross loss and gain in embankment and abandoned footprints.

Time period	Loss in Embankment Footprint		Gain in Any-time Abandonment	
	Area (ha)	% Loss	Area (ha)	% Gain
2015–2018	970.6	44.18	1016.8	37.76
2018–2021	2117.7	78.50	595.2	32.19
2021–2024	2049.6	62.34	212.3	21.94

indirect and progressive degradation as blocked or restricted water exchange, prolonged bunding, and continued maintenance alter hydrological conditions (FAO, 2003; Saw and Kanzaki, 2015; San, 2020). In this context, the strong depletion associated with persistent and newly-established footprints suggests that actively managed or expanding embankment areas function as recurrent disturbance zones, where both direct clearing and delayed hydrological stress reduce the likelihood of sustained mangrove persistence. The mapped transition pathways are consistent with this interpretation, especially where enclosed coastal-production landscapes show repeated loss and limited evidence of durable recovery (Fig. 7; Table 3). This interpretation is visually supported by Fig. 9, which shows mangrove clearance and Kari establishment following tidal-creek blockage and the persistence of cleared conditions in subsequent years. Similarly, Figs. 10 and 11 further illustrate that Kari embankment systems not only expanded through time but also remained under active maintenance, reinforcing the interpretation of persistent management pressure within these landscapes.

By contrast, abandoned embankment footprints show relatively limited additional loss and higher within-patch mangrove persistence than do persistent or newly established footprints. The localized gains and subsequent persistence visible within some abandoned footprints in Fig. 3D and E are consistent with this broader footprint pattern. Fig. 8 further shows that abandoned footprints contributed to mangrove gain, particularly during the first interval, although their absolute and

proportional contributions declined thereafter. These findings suggest that reduced management pressure following abandonment may locally support mangrove persistence or recolonization. However, the smaller and more fragmented gains and the increasing loss of previously remaining mangrove during 2021–2024 indicate that such recovery was not uniformly durable (Fig. 3F). Thus, abandonment may moderate depletion locally but does not necessarily ensure sustained recovery. However, this pattern does not offset the broader landscape trend, in which active and expanding embankment systems account for most cumulative mangrove loss (Tables 2 and 3).

Taken together, the spatial patterns, footprint contrasts, transition pathways, and Kari examples indicate that embankment-associated mangrove decline involves both immediate vegetation conversion and longer-term modification of tidal habitat. Direct loss results from vegetation clearance during Kari construction, land enclosure, pond establishment, and conversion to agricultural or aquaculture uses (Goldberg et al., 2020; Bhowmik et al., 2022). Indirect degradation may occur where embankments and tidal blockages restrict tidal exchange and alter inundation regimes, sediment and propagule transport, and salinity or waterlogging conditions, thereby limiting mangrove resilience and natural recovery (Lewis, 2005; Ellison et al., 2020). Although these hydrological processes were not measured directly, they provide a plausible explanation for the continued depletion of persistent and newly established footprints and the partial but fragile recovery observed after abandonment. The observed decline should therefore be viewed not simply as direct deforestation, but as the cumulative outcome of vegetation conversion, hydrological alteration, and habitat degradation. These findings highlight the importance of controlling new enclosure and restoring tidal connectivity in degraded or abandoned embankment areas.

4.2. Localized recovery, hydrometeorological disturbance

The temporal trajectory indicates that mangrove recovery remained possible in Kyaukpyu but was spatially uneven and only partly

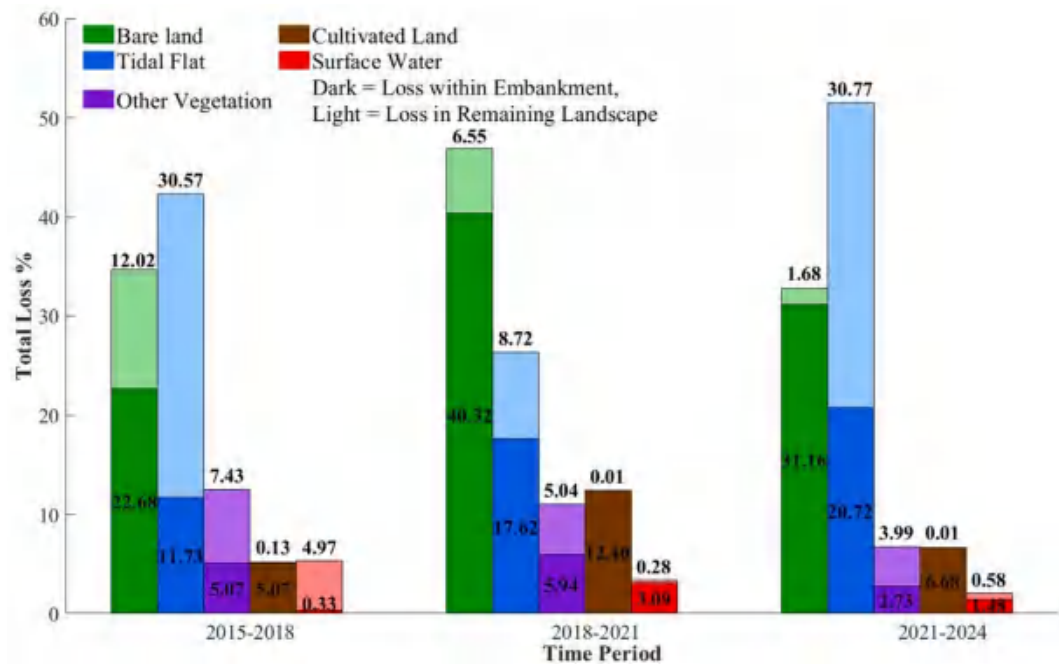


Fig. 7. Summary of land-cover loss patterns across the study area. (Dark bars represent loss within the embankment footprint, while light bars indicate loss across the remaining landscape. Numerical labels above the bars denote total loss percentages for each category).

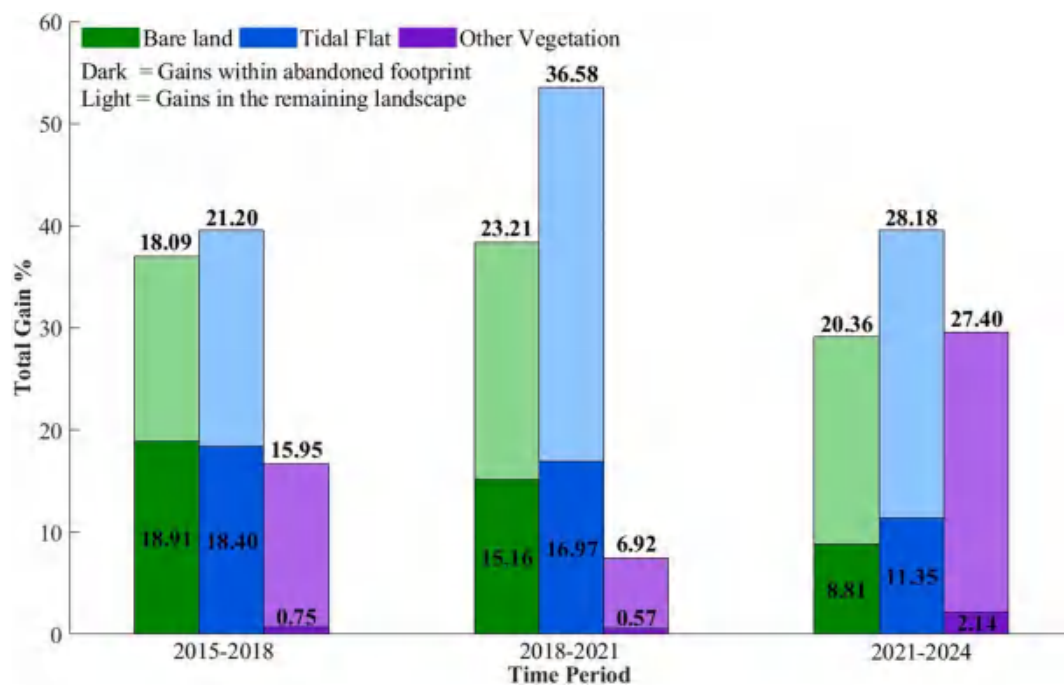


Fig. 8. Summary of gain patterns by land-cover category across three periods. (Dark bars represent gain within the abandonment footprint, while light bars indicate gains across the remaining landscape. Numerical labels above the bars denote total gain percentages for each category).

sustained. The slight net gain during 2015–2018 shifted to net loss during 2018–2021 and stronger decline during 2021–2024 (Table 1). Early gains included relatively coherent local clusters and smaller scattered additions, and some persisted as remaining mangrove during the following interval before gains became smaller and more fragmented in 2021–2024 (Fig. 3D–F). This sequence is more consistent with localized recolonization than with a sustained reversal of the broader declining trajectory.

Hydrometeorological disturbance provides important context for the

temporal variability in mangrove change observed in this study, although the interval-scale trajectories do not support a simple one-to-one relationship between individual events and landscape-scale forest loss. Rakhine State is highly exposed to cyclones, storm surges and flooding (Rakhine State natural disaster risk management plan, 2019; Soe et al., 2021), with the study period encompassing major disturbance years such as Cyclone Komen in 2015, high-tide flooding and embankment failures during 2017–2018, and Cyclone Mocha in 2023 (FAO-WFP, 2016; OCHA, 2023; Mishra et al., 2024). Despite these

Table 3
Summary of mangrove dynamics and embankment footprint shifts across the study area, organized by spatial footprint types and time periods. (A) Mangrove change metrics by embankment changes across time periods (in ha).

Period	In Persistent Area (ha)			In New Established Area (ha)			In Abandoned Area (ha)		
	Gain	Loss	Remain	Gain	Loss	Remain	Gain	Loss	Remain
2015–2018	226.4	396.3	408.0	58.6	457.4	898.8	1014.8	117.6	759.5
2018–2021	247.4	1035.4	488.7	81.9	1077.4	727.5	94.0	5.0	62.7
2021–2024	282.0	1003.7	520.5	15.0	1043.0	302.3	21.5	2.9	18.4

(B) Proportional loss and remain by embankment changes across time periods

Period	In Persistent Area (%)		In New Established Area (%)		In Abandoned Area (%)	
	Loss	Remain	Loss	Remain	Loss	Remain
2015–2018	49.3	50.7	33.7	66.3	13.4	86.6
2018–2021	67.9	32.1	59.7	40.3	7.4	92.6
2021–2024	65.9	34.1	77.5	22.5	13.6	86.4

(C) Cumulative depletion and long-term remaining proportion from 2015 to 2024

Embankment Types	Depletion %	Remain %
Persistent	302.8	64.7
New	190.1	22.3
Abandoned	14.3	2.1

(D) Percentage changes in absolute footprint area across periods

Period	Persistent Area Change (%)	New Area Change (%)	Abandoned Area Change (%)	Footprint Change (%)
2015–2018	0.0	0.0	0.0	0.0
2018–2021	26.9	61.4	−90.9	−7.0
2021–2024	78.9	8.1	−98.0	7.8

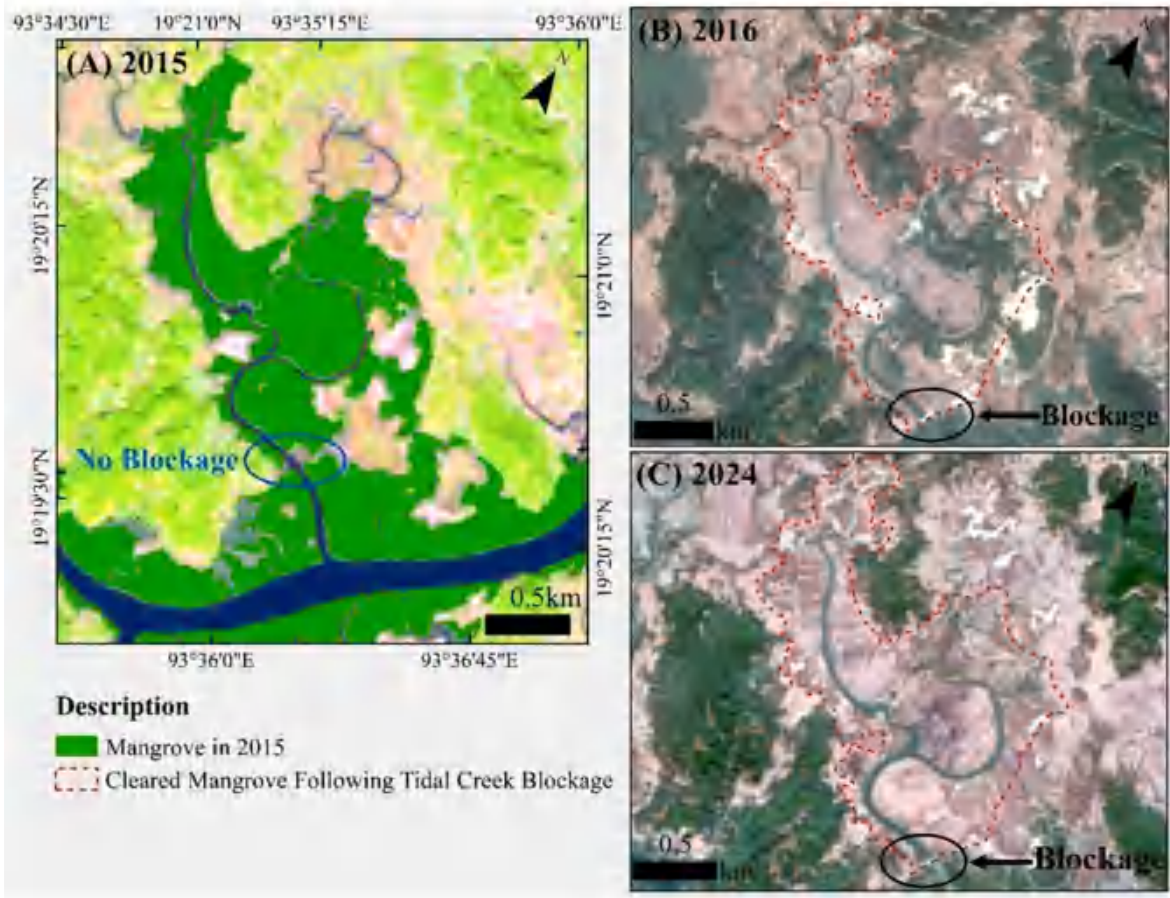


Fig. 9. Example of mangrove clearance following tidal channel blockage for agricultural development. (A) 2015: mangroves intact, with no blockage observed. (B) 2016: mangrove clearance following creek blockage. (C) 2024: cleared area remained unvegetated, showing no evident mangrove recovery.

disturbances, the 2015–2018 interval recorded a slight net gain, whereas net loss became dominant in 2018–2021 and intensified in 2021–2024.

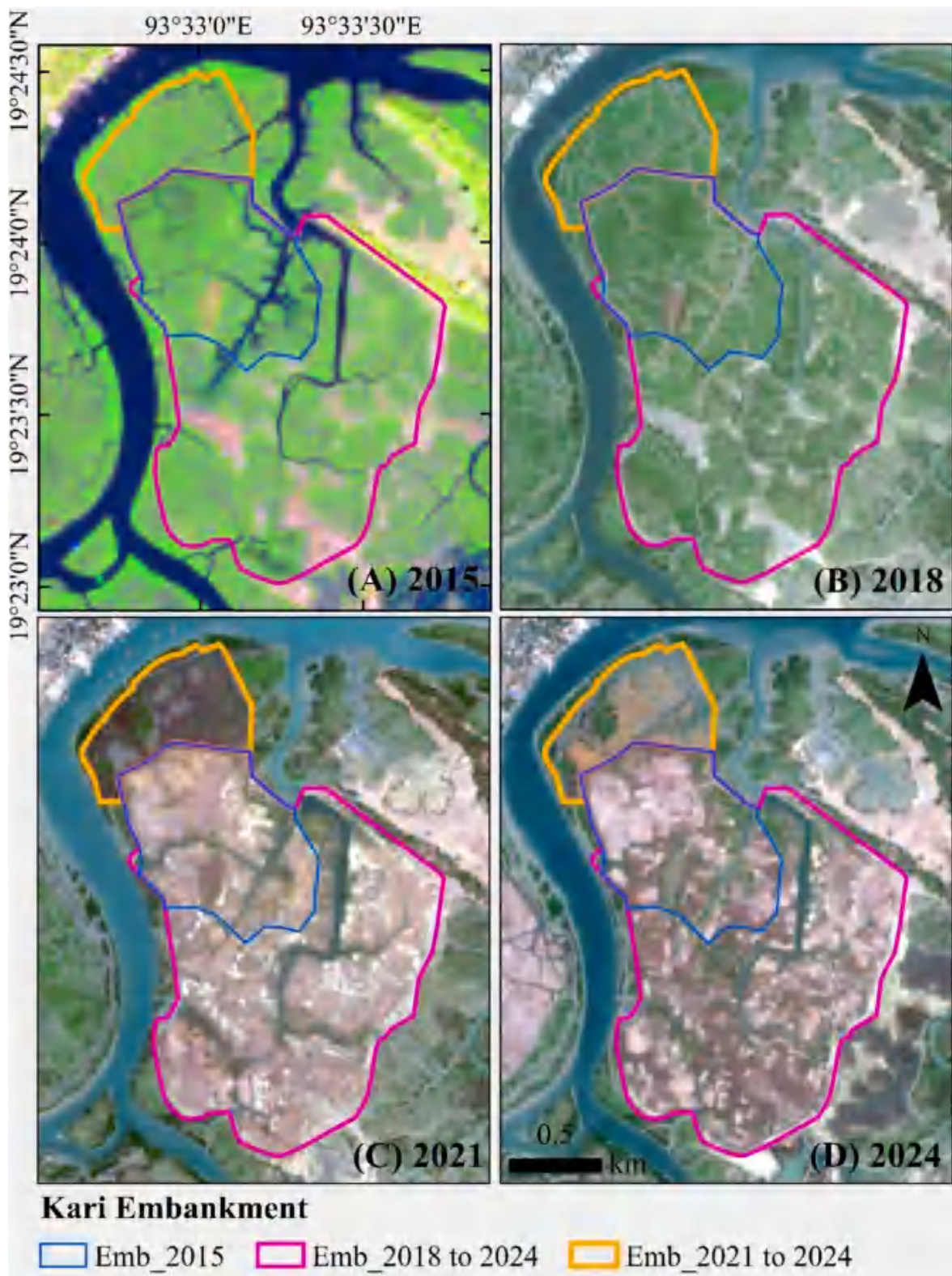


Fig. 10. Progressive expansion of Kari embankments and associated mangrove loss from 2015 to 2024. Blue, magenta, and orange outlines indicate embankment boundaries mapped in 2015, 2018–2024, and 2021–2024, respectively. Purple segments result from overlap boundaries and do not represent a separate embankment category.

This absence of a consistent correspondence between these events and the interval-scale balance of gain and loss indicates that hydrometeorological hazards alone cannot explain the observed trajectory. At the same time, the contribution of individual cyclones or flooding events to

the mapped changes cannot be isolated from the present analysis.

The mapped gains represented two spatially distinct forms: recolonization within or adjacent to the established mangrove landscape and localized advance of the seaward mangrove front. The first included



Fig. 11. Maintenance of a ~400-acre shrimp pond near the Kyaukpyu–Yangon Road (2017): (A) condition prior to rehabilitation; (B) rehabilitation/maintenance underway using heavy machinery.

clustered or scattered gains within previously disturbed surfaces, whereas only the second represented seaward expansion (Fig. 3). Because the riverine front retained weak net erosion interrupted by localized accretion (Fig. 5), the gains did not form a continuous landscape-wide expansion gradient. Instead, Kyaukpyu showed localized recolonization and limited frontline advance occurring within an overall loss-dominated landscape. This differs from the more spatially ordered seaward colonization of accreting tidal flats and hierarchical land-to-sea change reported in some prograding mangrove systems, although expansion trajectories also vary among deltaic settings (Long et al., 2022; Fu et al., 2023; Dai et al., 2024).

Storm effects in embayed estuarine and embankment-modified

mangrove settings may be mediated not only by wind but also by storm surge, prolonged inundation, ponding, sediment redistribution, and disruption of hydrological connectivity (Alongi, 2008; Krauss and Osland, 2020; Bhargava and Friess, 2022). Within Kari landscapes, flooding, overtopping, or breaching of embankments may temporarily alter water exchange and reduce management intensity, potentially creating short-lived opportunities for mangrove establishment in abandoned ponds, blocked creeks, and other disturbed low-lying surfaces. Fig. 12 illustrates the relevant disturbance context through examples of flooded fields, breached embankments, and subsequent local repair activities in Rakhine and Kyaukpyu. Independent assessments of Cyclones Komen and Mocha, likewise document severe flooding, agricultural



Fig. 12. Examples of coastal flooding and embankment (“Kari”) damage in Rakhine State and Kyaukpyu: (A) flooded fields in Rakhine following Tropical Cyclone Komen (July 2015; photo by FAO-Bu Thi Lan); (B) seawater entering through a breached embankment during an unusually high tide in Kyaukpyu (2017) (BBC, 2018); (C) breached Kari embankment in Kyaukpyu during high tide (Myanmar Now, 2018); and (D) local residents repairing storm-damaged Kari embankments after a tropical storm (Eleven, 2021).

disruption, and major livelihood impacts in Rakhine State (FAO-WFP, 2016; Rakhine State natural disaster risk management plan, 2019; FAO, 2023; OCHA, 2023; Mishra et al., 2024). Together, these observations make episodic changes in hydrological connectivity and management pressure plausible, although they do not establish that particular flooding or breaching events caused the mapped mangrove gains.

The later intervals nevertheless show that recovery was only partly sustained. Although some early gain areas persisted as mangrove during 2018–2021, the declining extent and continuity of gain and the increasing loss of previously remaining mangrove during 2021–2024 show that this recovery was insufficient to reverse the broader decline. Mangrove loss became dominant in 2018–2021 and reached its maximum in 2021–2024, the latter interval including Cyclone Mocha. Even so, the present analysis does not isolate event-specific mangrove mortality or reconstruct specific storm-surge, wave and inundation conditions associated with individual cyclones. Hydrometeorological disturbances are therefore best interpreted as potential amplifiers of vulnerability in an already modified landscape, where embankment expansion, restricted tidal exchange, and fragmented mangrove edges had reduced ecological resilience (Krauss and Osland, 2020; Bhargava and Friess, 2022). They may have influenced the timing and persistence of localized recovery, but they do not independently explain the longer-term landscape trajectory. The central pattern is therefore one of localized recolonization and limited frontline advance that remained insufficient to offset continuing landscape-scale mangrove loss.

4.3. Spatially asymmetric mangrove-front change

The shoreline results show bank-specific patterns of mangrove-front adjustment rather than a uniform estuary-wide response. Although both riverbanks exhibited weak net erosion, their spatial patterns differed. The left bank contained relatively discrete clusters of erosion and accretion, whereas the right bank showed localized downstream accretion, a mixed middle reach, and more persistent erosion farther upstream (Fig. 5). Within the CA, the erosion-dominated Yanbye Island margin contrasted with the comparatively coherent accretion along Made Island (Fig. 6). These patterns indicate that shoreline response varies with local geomorphic position rather than following a uniform estuary-wide trajectory.

Viewed together, the land-cover and DSAS results describe complementary but non-equivalent components of mangrove change. The land-cover analysis captures interval-based gains and losses across the mangrove landscape, including early recolonization and subsequent persistence within some interior or abandoned areas (Figs. 3 and 4). In contrast, net shoreline movement and linear regression rate summarize the overall 2015–2024 displacement and annual trend of the riverine mangrove front (Figs. 5 and 6). Mangrove gain should therefore not be treated automatically as shoreline accretion: only gains occurring along the seaward margin can contribute to frontline advance, whereas interior recolonization may increase mangrove area without shifting that boundary. Because the land-cover transitions were not spatially matched with individual DSAS transects, their relationship is interpreted at the broader landscape scale.

Kyaukpyu's channelized estuarine geometry, semidiurnal tidal regime, and partial enclosure by islands and headlands provide a plausible physical setting for this shoreline variability. The predominantly low-to-moderate significant wave heights and mainly southwesterly wave approach observed in 2024 are consistent with limited direct exposure to ocean-wave forcing (Fig. 13). Shoreline variability may therefore be influenced more strongly by tidal-channel hydraulics, bank orientation, sediment availability and redistribution, and adjacent mangrove condition than by continuous high-energy wave attack (Zhou et al., 2022; Wang et al., 2023). However, because the wave record represents only 2024, it provides environmental context rather than a direct explanation for shoreline changes measured over 2015–2024.

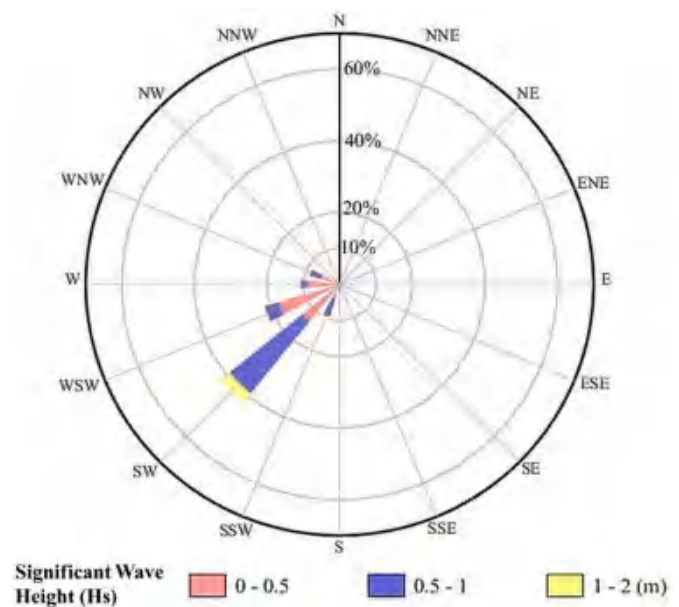


Fig. 13. Wave rose showing the frequency distribution of hourly significant wave height and wave direction during 2024 at the ECMWF ERA5 grid point nearest to the study area (19.5° N, 93.5° E; accessed 8 April 2025).

Relative sea-level rise may further increase mangrove-edge vulnerability by raising baseline water levels and restricting hydrological adjustment or landward migration, particularly where embankments limit accommodation space (Alongi, 2015; Ward et al., 2016). Although this process was not directly measured here, low vulnerability shouldn't be interpreted from limited wave exposure mentioned above because severe mangrove disturbance can also occur in geomorphically sheltered settings under extreme inundation (Lagomasino et al., 2021; Zhang et al., 2025). Overall, mangrove vulnerability in Kyaukpyu reflects both interior land-use conversion and spatially uneven edge instability shaped by estuarine configuration, hydrodynamic-sedimentary conditions, relative sea-level rise, and anthropogenic modification.

4.4. Governance constraints and socio-political instability

Mangrove trajectories in Kyaukpyu may also be conditioned by the continuity and effectiveness of governance. Despite Myanmar's long-standing recognition of mangroves' protective and livelihood value, policy intent and on-the-ground implementation have often diverged. Agricultural expansion, fisheries-related land conversion, ambiguous land tenure, and weak enforcement continue to shape coastal decision-making (Oo, 2002; Storey, 2015; San, 2020). The coexistence of embankment expansion, localized but only partly sustained recovery, and continuing net loss is consistent with uneven implementation and limited landscape-scale protection, although governance effectiveness was not measured directly in this study.

These constraints are especially important in Rakhine State, where environmental governance has been repeatedly affected by social unrest, armed conflict, restricted mobility, and wider political disruption. Armed conflict is widely recognized as an indirect but powerful driver of environmental change, acting primarily through weakened governance, reduced institutional capacity, disrupted livelihoods, and declining continuity of monitoring and restoration rather than through direct ecological destruction alone (IUCN, 2021; Ware, 2015). In Rakhine, these pressures accumulated from the ethnic and communal violence of 2012, through the rise of the Arakan Army insurgency in the mid-2010s and its intensification in 2018–2020, to the post-coup upheaval from 2021 and renewed clashes from late 2022 onward (OCHA, 2012; Seekins, 2020; Bashar, 2019; Kyi Sin, 2021). Although Kyaukpyu has not

consistently been a frontline conflict zone, regional instability may nevertheless have constrained mobility, administrative reach, routine monitoring, enforcement and restoration across coastal and estuarine systems. However, the transition from localized gains in 2015–2018 to increasingly loss-dominated conditions in later intervals cannot be attributed directly to conflict or governance using the present data.

Weakened management continuity is evident in broader regional examples. Escalating conflict has reportedly disrupted conservation by curtailing international funding and technical support, forcing some officials and environmental practitioners to suspend activities or relocate for safety. Under such conditions, formal field assessment becomes more limited and information increasingly depends on local reporting and interviews. Reports of unregulated exploitation in Wunbaik Mangrove Forest, pressures within the nominally designated Ramsar sites in northern Rakhine, and degradation of unprotected mangroves in Mon and Tanintharyi illustrate the potential consequences when routine enforcement and management presence contract (Development Media Group, 2022; Mekong, 2024; Mekong, 2025). For Kyaukpyu, this risk environment may be intensified by fighting in townships around the port area. Thus, socio-political instability is best understood not as a direct cause of mapped mangrove loss, but as a contextual constraint that may reduce the durability of protection, restoration, and recovery.

4.5. Restoration limits and implications for future monitoring in Kyaukpyu

Within this constrained governance setting, the localized gains observed in 2015–2018 are still meaningful. They indicate that mangrove recovery remained possible in parts of the landscape, although this recovery was only partly sustained. The Kyaukpyu Township Environmental Assessment provides relevant supporting context, reporting that mangrove degradation had declined during this period and linked that improvement to better control of agricultural, shrimp-farm, and salt-pan expansion, reductions in unauthorized farms, and increased community awareness supporting regeneration of previously damaged forests (Myanmar Environment Institute, 2017). The pattern seen in this study is therefore consistent with a short period in which improved management conditions and reduced local pressures may have supported localized recovery, without fundamentally changing the broader landscape trajectory. However, the present analysis cannot separate the relative contributions of management improvement, embankment abandonment, temporary hydrological change, and natural recolonization.

This interpretation also fits the wider restoration and conservation context in Rakhine State. Government policy statements and departmental reporting indicate that forest restoration and conservation programmes and activities have been formally established, including annual seedling distribution and planting, establishment of additional mangrove plantation areas under a ten-year programme from 2017 to 2018 to 2026–2027, expansion of designated mangrove forest areas, and promotion of community forestry and agroforestry approaches in degraded forest and mangrove zones. In line with the Myanmar Forest Policy 1995, future arrangements have also been proposed for community-owned forest plantations along the Rakhine coastline. At the same time, local civil-society reporting suggests that, while conservation and replanting activities exist, large-scale effective restoration has not yet been achieved. The Rakhine Coastal Environmental Conservation Association expressed this view in reporting by the Democratic Voice of Burma (DVB, 2021). This contrast is important: it suggests that the issue is not the total absence of restoration effort, but the difficulty of translating formal programmes and targets into durable landscape-scale outcomes.

The same pattern is visible at the programme scale in Kyaukpyu itself. NGO-supported work has reportedly combined replanting with assisted natural regeneration, and the Mangrove Service Network reported that about 1460 ha of mangroves were protected and restored in

Kyaukpyu between 2008 and 2018 through planting and natural regeneration, including more than 18 million planted seedlings, together with a small area of community-based ecological mangrove recovery without planting (~3.7 ha). These figures indicate local engagement and technical capacity, but the results of the present study suggest that such efforts remained spatially bounded relative to the broader footprint of embankment-driven conversion and hydrological disruption indicated by the embankment and land-cover analyses. In other words, restoration and stewardship were present, but they were not yet sufficiently continuous or extensive to offset the wider landscape pressures operating across the study area.

In the context of the KPSEZ and DSP, the implications of this study extend beyond documenting recent mangrove decline. Future development will occur within a mangrove landscape already undergoing land conversion, hydrological modification, localized recovery, and spatially uneven shoreline adjustment. Project-related impacts may therefore extend beyond direct clearance through further alteration of tidal connectivity, fragmentation of remaining stands, and pressure on adjacent mangrove margins. These effects may also be difficult to distinguish from the active background changes documented during 2015–2024. For this reason, environmental management in the KPSEZ should not focus only on site-specific clearance control, but must adopt avoidance-planning, strict control of hydrological alteration, retention of intact mangrove stands, and sustained long-term monitoring of geomorphic and ecological change. Monitoring should also include tidal connectivity so that interior habitat degradation can be distinguished from direct vegetation removal and movement of the seaward front. Restoration should prioritize the maintenance or recovery of tidal connectivity rather than relying on planting alone where hydrological constraints remain. In this setting, adaptive monitoring is not only for impact accountability, but also for ensuring that future change can be interpreted against the background of an already dynamic and stressed coastal system.

5. Conclusions

This study provides an environmental assessment of mangrove and mangrove-front dynamics in the proposed influence zone of the Kyaukpyu Special Economic Zone and Deep-Sea Port from 2015 to 2024, addressing a significant sub-regional evidence gap in Rakhine State. The key findings are as follows:

1. Mangrove extent declined overall from 15,427.9 ha in 2015 to 12,754.8 ha in 2024, representing a net loss of ~17.3%, with minor interannual variability including a modest increase during 2015–2018. However, losses accelerated after 2021, with ~77% of the total decline occurring from 2022 onward. Meanwhile, within the 3-km CA, mangrove cover decreased from 953.9 ha to 599.9 ha, representing a 37% reduction and an average decline of 39.1 ha/yr.
2. Mangrove change was spatially structured rather than uniform. Losses were concentrated in relatively large, localized patches along tidal channels and fragmented interior margins, while gains were spatially heterogeneous, including relatively coherent local clusters during 2015–2018 and smaller scattered additions elsewhere. The balance shifted from slight net gain in 2015–2018 to net loss in 2018–2021 and the strongest decline in 2021–2024. Within the CA, changes clustered within embankments, with early losses and limited later gains, indicating an intensifying, gradual spatial contraction over time. Overall, the gains represented localized recolonization rather than a continuous landscape-wide expansion process.
3. Shoreline analysis revealed a weak net retreat along both riverbanks (left: -0.2 ± 0.2 m/yr; right: -0.1 ± 0.2 m/yr), although their spatial patterns differed. The left bank contained relatively discrete erosion and accretion clusters, whereas the right bank transitioned from localized downstream accretion through a mixed middle reach to more persistent upstream erosion. Around the proposed deep-sea

port, the shoreline response was asymmetric: the Yanbye margin experienced dominant erosion and net retreat (-0.3 ± 0.5 m/yr), whereas the Made Island margin exhibited more coherent accretion and a slight net advance (0.2 ± 0.6 m/yr). These mangrove-front changes complement, but are not directly equivalent to, the interval-based areal gains and losses.

- Loss patterns are most consistent with land-use and hydrological modification processes associated with embanked coastal farming. Persistent and newly established embankment footprints accounted for the greatest cumulative depletion, whereas abandoned modified areas retained relatively high within-patch mangrove persistence but occupied a shrinking share of the landscape. The observed decline reflects two linked pathways: direct vegetation removal during Kari construction, land enclosure, and agricultural or aquaculture conversion, and indirect habitat degradation associated with restricted tidal exchange and hydrological modification. Abandoned footprints supported localized persistence and recolonization, but these responses were insufficient to offset the wider depletion associated with active and expanding embankment landscapes.
- Hydrometeorological disturbance and governance constraints are best interpreted as contextual modifiers of the persistence and reversibility of gains and losses, rather than as isolated direct drivers. They may have influenced the timing and durability of localized recovery, but the present analysis does not identify them as independent causes of the mapped changes.

Overall, the study provides a quantitative evidence base for future mitigation, adaptation and management provisions by identifying where mangrove loss and limited recovery are concentrated and how these dynamics relate to multiple interacting coastal pressures. Future monitoring should integrate mangrove-area change, tidal connectivity, and movement of the seaward mangrove front so that direct clearance, interior habitat modification, and shoreline adjustment can be evaluated separately. Environmental management should prioritize avoidance of intact mangrove stands, control of new enclosure and tidal-channel blockage, restoration of hydrological connectivity where appropriate, and continued monitoring of both areal and shoreline dynamics.

Because the assessment relies primarily on remote-sensing evidence, the absence of field-based ecological, hydrological, sedimentary, and event-specific observations limits definitive attribution of individual changes to particular mechanisms. Future studies should, therefore, integrate continued remote-sensing analysis with field validation and hydrological monitoring to better resolve the mechanisms of change and strengthen adaptive mangrove management in Kyaukpyu.

CRediT authorship contribution statement

Phyu Phway Thant: Writing – review & editing, Writing – original draft, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Zhijun Dai:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition, Conceptualization. **Saw Nu Sanda Thein:** Writing – review & editing. **Mee Mee Soe:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.marenvres.2026.108378>.

Data availability

Data will be made available on request.

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