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A call for unified definitions and classifications for saltmarshes for accurate mapping of extent: a case study from Sri Lanka

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Abstract

Saltmarshes are increasingly recognised for their ecological value. Their diverse nature, occurrence amongst complex ecological mosaics, and occurrence in both tidal-influenced and isolated inland contexts demand precise delineations and classifications for effective protection. This study classifies tropical saltmarshes in the Indian Ocean region through a literature review to identify the ambiguities. Vegetation based mapping using three approaches (object-based image classification, pixel-based image classification, and satellite embedding dataset with supervised classification) was tested using field survey data collected between 2024 and 2025, covering half of Sri Lanka's coastline. The review revealed a common conflation of inland and coastal saltmarshes, leading to inconsistent extent estimates. Object-based image classification, pixel-based image classification, and satellite embedding dataset with supervised classification yielded saltmarsh extents of 16,406.74 ha, 15,995.50 ha, and 40,410.12 ha, respectively. Field surveys were carried out, focusing on succulent dominated saltmarshes validating 15,807 ha. Object and pixel-based image classification results closely aligned with this data, while satellite embedding dataset with supervised classification overestimated saltmarsh extent. Object-based image classification and pixel-based image classification estimated a coastal saltmarsh coverage of less than 0.25% of Sri Lanka, highlighting the need for greater protection of these ecosystems from further loss. More training data could reduce overestimation by the satellite embedding dataset with supervised classification. The study highlights the need for better definitions and classifications of coastal saltmarshes and urges the need to integrate vegetation, geomorphology, hydrology and climatic data to ensure coastal saltmarshes are segregated from saline inland saltmarshes.

Introduction

Saltmarshes are increasingly recognised as a critical blue carbon ecosystem, yet globally unified action is impeded due to several unresolved issues, compounded by significant barriers in ecosystem access and ease of study. A key unresolved challenge is within the definitions and classifications that are currently applied to saltmarshes (Rogers et al. 2017). This definitional ambiguity arises because the establishment, propagation and existence of saltmarshes are complex processes, influenced by numerous biotic and abiotic factors (Pomeroy and Wiegert 1981). Therefore, the incorporation of all influencing factors and variables results in inherently complex categorisation criteria. Latitude is utilised to distinguish between temperate and tropical saltmarshes within most current classification frameworks (Adame et al. 2024; Galal et al. 2023). Despite limited comparative data, existing literature indicates that temperate saltmarshes exhibit greater floristic diversity than tropical saltmarshes (Doody 2008). However, the adequacy of the binary grouping of saltmarshes into temperate and tropical is contested (Saintilan 2009a).

Further, within coastal and lagoonal regions of the tropics, assemblages of grass, sedge and rush-dominated ecosystems are subject to inconsistent classification, frequently being described using a range of indistinct terminology including, 'coastal marshes', 'tidal marshes', and 'coastal grasslands' (Saintilan 2009a; Adame et al. 2024; Mishra and Farooq 2025). The lack of consensus regarding whether such ecosystems should be classified as saltmarshes, coupled with the application of diverse terminologies leads to a large variance in saltmarsh extent estimates. A notable example is India: positing that their inclusion within saltmarsh ecosystems is debatable, Viswanathan et al. (2020) reported a saltmarsh extent of merely 290 km^2 by excluding halophytic grasses. By contrast, extents in excess of 1600 km^2 were estimated in studies where all halophytic species were included (Banerjee et al. 2017; Gopi et al. 2019). Unlike their temperate counterparts, tropical saltmarshes create consociations and complex ecotones with other associated coastal ecosystems (Bridgewater and Cresswell 1999), frequently co-occurring with one or both of the other blue carbon ecosystems (namely, seagrasses and mangroves) within interconnected local landscapes (Huxham et al. 2018). Although zonation has long been a contested topic in ecology, these overlaps, combined with halophyte presence in diverse geomorphological settings (including in the base of sand dunes, sandy sheets, fertile sandy lands, and lake shorelines) obscures the application of traditional zonation patterns (Mashaly et al. 2008; Rogers et al. 2017; Sayed and Masrahi 2025). Consequently, tropical saltmarshes that coexist with mangroves are frequently classified as 'mangrove associates',

‘mangroves’, or as generalised ‘coastal vegetation’ (Viswanathan et al. 2020). In tropical countries, saltmarshes are consistently misclassified, and their extents are underrepresented (Chanda et al. 2022), due to the persistent absence of unified definitions and a standardised classification system at both the national and global scales (Ramsar Convention Secretariat 2022; Keith et al. 2022).

To prevent over or underestimation of saltmarsh extents, accurate delineation of coastal saltmarsh boundaries from and within their interconnected ecosystems is necessitated. However, porous and ambiguous boundaries of saltmarshes should be taken into account during delineation, due to their ecological complexity and interconnections with other coastal blue carbon ecosystems (Campbell et al. 2022). Rectifying such ambiguities requires immediate attention to enable accurate reporting against the extent-based headline indicators of the Kunming-Montreal Global Biodiversity Framework (KM-GBF) and National Biodiversity Strategic Action Plans (Convention on Wetlands 2022). Accordingly, immediate and robust actions are required to verify national saltmarsh extents and the currently estimated global extent of 5.29 million ha (Convention on Wetlands 2025).

Accurately mapping saltmarsh extent presents considerable methodological challenges: ground surveying is hindered by the sometimes inaccessible, and often physically demanding nature of these ecosystems. Mapping using a remote sensing approach is more complicated than with other canopy-forming vegetation types (Hu et al. 2021), due to spectral confusion with other wetland vegetation, and cyclical environmental factors such as tidal inundation and seasonality (Sun et al. 2018; Correll et al. 2019; Yeo et al. 2020). Nevertheless, advances in satellite telemetry, when integrated with refined classification frameworks and robust ground truthing, offer a promising pathway to improve saltmarsh delineation accuracy.

Sri Lanka, as a tropical island nation, possesses significant saltmarsh ecosystems (Ranawana et al. 2020). However, Sri Lanka’s current classification framework, introduced by Pemadasa et al. (1979) is based on limited field observations within a single dry zone location, where succulent vegetation dominates. This framework vaguely classifies grass, sedge and rush-dominated ecosystems located along Sri Lanka’s wet and intermediate zones, as ‘tidal’ or ‘coastal’ marshes. Thus, such ecosystems might have been excluded in national saltmarsh extent data, which have been reported as: 33,573 ha (Gunatilleke et al. 2008), 27,520 ha (CC & CRMD 2024) and 28,696 ha (Gorman et al. 2022). Further, none of the above-mentioned estimates included classification protocols, definitional criteria or ground truthing methodologies. Therefore, current estimates of the area of saltmarsh in Sri Lanka lack the consistency and methodological rigour required for reliable national or global reporting.

To address the need for the unification of definitions into a standardised classification framework, and the need to distinguish true coastal saltmarshes, both from other coastal ecosystems and from inland saline wetlands, this study has two primary objectives. Firstly, we attempt to systematically compile existing knowledge on saltmarsh classifications and definitions to illustrate the ambiguous and inconsistent application of the term. Subsequently, using the existing classification of Pemadasa et al. (1979) as a baseline and incorporating extensive island-wide ground observations, we develop a satellite-based map of Sri Lanka’s saltmarsh distribution. Three classification approaches are attempted: object-based image classification, pixel-based image classification and a satellite embedding dataset with supervised classification. Model performance is rigorously evaluated through a comprehensive accuracy assessment protocol that utilises the following standard metrics: overall accuracy, the Kappa coefficient, producer’s accuracy and consumer’s accuracy (Stehman and Foody 2019; Foody 2020).

Methods

Literature review on tropical saltmarshes and their current classifications in the Indian Ocean

A systematic literature review was conducted to examine the usage and the definitions of the term ‘tropical saltmarshes’, within countries bordering the Indian Ocean. The review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Fig. 1) (Page et al. 2021b, a). A comprehensive search, using strings such as ‘Saltmarsh’, ‘Tidalmarsh’, ‘Coastal marsh’, ‘Coastal swamp’, ‘Tidal swamp’, combined with country names across five major electronic databases: Web of Science (n = 1,240), Scopus (n = 1,273), Crossref (n = 5,868), PubMed (n = 1,095), and Semantic Scholar (n = 5,287), yielded a total of 14,763 records. During the screening and selection process, duplicates (n = 1,231) were removed. Manual screening of titles (n = 13,532) for relevance, resulted in the exclusion of 11,914 records. A secondary automated screening was then applied to identify records containing the term ‘Marsh’ in the abstract or the titles, which excluded 1,155 further records. Subsequently, after abstract review (n = 463), 321 records were removed. Of the 142 records selected for full-text review, 2 could not be retrieved, leaving a final dataset of 140 records, which were thoroughly assessed to understand regional characterisations of the term ‘tropical saltmarsh’, and regional variations in the term’s definition and features.

Additionally, two major classifications were reviewed to identify their classification approaches, concerning tidal-influenced saltmarshes and other possibly overlapping ecosystems. The two frameworks reviewed were the Global Ecosystem Typology (GET) (Keith et al. 2022) for reporting to KM-GBF and the Ramsar Classification System of Wetland Types (Ramsar Convention Secretariat 2022) for reporting to the Convention on Wetlands.

Case study: Estimating the extent of saltmarshes in Sri Lanka using remote sensing approaches based on a regional definition and classification

To date, Sri Lanka does not report inland saline ecosystems in its national wetland directory (Central Environmental Authority 2006). This absence of inland saline ecosystems, enables the saltmarshes of Sri Lanka to be adopted as a representative model for the heterogeneous coastal saltmarshes characteristic of many similar tropical countries. The efficacy of remote sensing-based mapping approaches was tested under this context. Three approaches using a vegetation characteristics-based definition, independent of geomorphology and hydrology, were utilised to estimate the extent of coastal saltmarshes, limited to those characterised by succulent dominated vegetation.

Collection of ground truth data

To obtain ground truth data for model training and validation, island-wide surveys were conducted covering 1989.40 km out of Sri Lanka’s total coastline of 3929.99 km (50.62%); encompassing Sri Lanka’s North Western, Northern, North Eastern, Southern and parts of the Eastern coasts, together with the adjacent supralittoral zones, between 2024 and 2025.

Initially, a dataset collected and verified by Ranawana et.al (2020), covering selected locations in Sri Lanka’s North Western Province was obtained to serve as a baseline. The characteristics of these verified locations were examined using Google Satellite Imagery to assess key features including colour variations, canopy cover, extent of water logging, and the connectivity and the distance to the broader marine ecosystem. Afterwards, other areas across Sri Lanka showing similar characteristics were identified and marked. Site selection was further refined using digital elevation data, vegetation characteristics and the identification of inland areas likely to experience tidal influence (specifically, those influenced by lagoons, estuaries, coves and bays). Identified areas were visited and their whole perimeters were delineated through GPS points, logged via QField, Google Maps or Epicollect. In locations where access was limited, a sufficient number of random points were marked.

During ground truthing surveys, initial observations specifically targeted saltmarsh plant communities, as described by Pemadasa et al. (1979), i.e. areas dominated by succulent saltmarsh species. This included pure populations or mixed communities of *Tecticornia indica* and *Suaeda* species (*Suaeda maritima, Suaeda monoica* and *Suaeda vermiculata*); areas characterised by seasonal *Salicornia brachiata* stands; and transitional zones where dwarf mangroves co-occur

with *Suaeda* spp., *Salicornia brachiata* or *Tecticornia indica* (Fig. 2). Additionally, secondary saltmarshes associated with aquaculture and salterns were documented and added to the ground truth dataset to be used for training and validation. Afterwards, the collected GPS points were used to digitise polygons and obtain the total ground truth extent.

The spatial extents of directly tidal-influenced grass, sedge and rush-dominated marshes (Fig. 2) (classified in many literatures as 'coastal marshes', 'tidal marshes', 'swamp' or 'barren lands') were documented via GPS, to explore their integration within the ground truth dataset, alongside succulent dominated coastal saltmarshes. However, these areas were excluded from the final dataset due to classification ambiguities specific in tropical contexts. These uncertainties stem from several unresolved factors, including soil and water salinity within these ecosystems, the tolerance and physiological responses of sedge and rush species to varying salinity regimes, and the extent to which such vegetation contributes to ecosystem services typically associated with succulent dominated coastal saltmarshes. Furthermore, the distinction between grass, sedge and rush-dominated ecosystems occurring in coastal settings and those present in inland marshes is not yet well established. Therefore, this study only reports the extent of succulent dominated coastal saltmarshes. When deploying the three remote sensing approaches in this study, only polygons of succulent dominated coastal saltmarshes were used as ground truth data.

Remote sensing approaches for determining the extent of coastal saltmarshes

Two pixel-based classification methods and one object-based classification method were applied to estimate Sri Lanka's saltmarsh extent. The three methods are: object-based image classification, pixel-based image classification, and satellite embedding dataset with supervised classification. The methodological foundations were adapted from protocols established by Navarro et al. (2021), Worthington et al. (2023), and Brown et al. (2025) to identify saltmarshes or tidal marshes. Field-derived observations and data were used to train the classification models and to provide independent validation of their outputs.

Image pre-processing

The Area of Interest was defined within a 10 km inner buffer from the coastal boundary of Sri Lanka. Harmonised Sentinel-2 (S2) Multispectral Instrument (MSI) Level – 2A Surface Reflectance (SR) data for the year 2024 was used. All scenes were filtered to remove cloud-related artefacts through the Scene Classification (SCL) bands. The following spectral indices were calculated: Normalised Difference vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and the Automated Water Extraction Index (AWEI) (Worthington et al., 2023). To capture temporal variability throughout the year, an annual optical composite was generated using 36 covariates derived from the NDVI, EVI and AWEI spectral indices and the Raw Near-Infrared (B8) band. For each input, the median, standard deviation, four percentiles (10th, 25th, 75th, 90th) and three interval means (5th – 95th, 10th – 90th, 25th – 75th) were calculated.

Sentinel-1 Synthetic Aperture Radar (SAR) data was integrated to complement optical imagery and to reduce sensitivity to cloud cover and tidal inundation. Three polarimetric indices: Span, Difference and the ratio of VV (vertical transmit/vertical receive) band for single co-polarisation and VH (vertical transmit/horizontal receive) band for dual-band cross-polarisation were calculated for each image. An annual radar composite was then generated using the final five covariates, consisting of the median values of the two VV and VH bands and the three derived indices. A final multi-band composite was generated by combining the 36 optical covariates derived from Sentinel 2 data and five covariates derived from Sentinel 1 data. An object-based image analysis approach was subsequently implemented.

Object-based image classification

The combined multi-band composite was segmented into spectrally homogeneous clusters using the Simple Non-Iterative Clustering (SNIC) algorithm. As such, the mean spectral values of pixels within each cluster were calculated to create an object-based composite feature dataset. Subsequently, a Random Forest machine learning classifier was trained using the object-based composite features to identify saltmarsh areas. The training dataset was constructed from 211 polygons verified as coastal saltmarshes and 142 non-saltmarsh polygons. From these training polygons 54,895 coastal saltmarsh and 132,667 non-saltmarsh pixel samples were extracted to train the classifier. An elevation mask based on the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data was applied to exclude terrestrial areas with an elevation greater than ten meters above mean sea level. As a post-classification refinement step, a probability threshold of 80% was added to retain only objects whose classification probability is equal to or exceeds this threshold.

Pixel-based image classification

In this approach, the multi-band composite, created by combining the 41 covariates from Sentinel 1 and Sentinel 2 data, was utilised directly for classification without prior segmentation. A Random Forest machine learning classifier was trained using a total of 202, 788 pixels marked during ground truthing (of which 59,239 corresponds to coastal saltmarsh and 143,549 corresponds to non-saltmarsh locations) to predict whether individual pixels are classified as saltmarsh. The probability threshold and elevation mask applied in the previous model remained unchanged.

Satellite Embedding dataset with supervised classification

Rather than relying on conventional spectral indices from a single source, high-dimensional deep learning features were incorporated through the Google Satellite Embeddings (V1) annual collection, which obtains data from multiple sources and satellite systems and generated using AlphaEarth Foundations. An annual composite was generated by mosaicking these embeddings to capture temporal variability and the complex semantic patterns of the landscape. The resulting covariates consisted of 64-dimensional feature vectors derived from a pre-trained deep neural network. An elevation mask was applied based on the SRTM DEM to exclude terrestrial areas with an elevation greater than 10 meters above mean sea level. A binary classification scheme (saltmarsh vs non-saltmarsh) was adopted, to predict whether the individual pixels were classified as saltmarsh using a K-Nearest Neighbours (KNN) machine learning classifier (k = 5) trained using a total of 104, 781 pixels (6,864 verified as coastal saltmarsh and 97,917 verified as non-saltmarsh).

Accuracy assessment

The ground truth dataset was split to obtain an independent validation subset, in all three classification approaches. For object-based image classification, the validation dataset was constructed from 89 coastal saltmarsh polygons and 63 non-saltmarsh polygons, yielding 12,799 coastal saltmarsh and 48,356 non-saltmarsh pixels, respectively. Pixel-based image classification, was validated using 8,456 coastal saltmarsh and 38,015 non-saltmarsh pixels. Finally, the satellite embedding dataset with supervised classification was evaluated using 2,488 coastal saltmarsh pixels and 21,600 non-saltmarsh pixels. To evaluate model performance, accuracy was calculated using a confusion matrix, from which the Overall Accuracy, Kappa coefficient, Producer’s Accuracy (PA), and Consumer’s Accuracy (CA) were derived (Foody 2002).

Spatial distribution maps were generated for each classification approach and subsequently compared to assess relative performance and consistency using the above-mentioned evaluation metrics. The accuracy of the classification approaches was also visually evaluated based on the collected knowledge and expertise from the ground surveys.

Results

Existing classifications in tropical saltmarshes in the Indian Ocean

A comprehensive, internationally accepted framework for classifying Earth's ecosystems has been developed under several United Nations conventions and published as the GET (Keith et al. 2022). This framework classifies the saltmarsh ecosystems considered in this study, as MFT1.3 Coastal saltmarshes and reedbeds, which fall under the MFT1 Brackish tidal biome within the MFT Marine-Freshwater-Terrestrial transitional realm. According to the GET, coastal saltmarshes are characterised as tidally influenced ecosystems with vegetation composed of salt-tolerant grasses and typically low-growing, succulent shrubs, possessing strong salinity gradients. Additionally, the Ramsar Classification System for Wetland Types (Convention on Wetlands 2025) groups all wetlands into marine/coastal, inland, or human-made categories. This classification includes coastal saltmarshes, in the same category as other habitats such as salt meadows, saltings, raised saltmarshes, and tidal brackish and freshwater marshes, within the marine/coastal categorisation.

The GET and Ramsar classifications do not provide a comprehensive definition to differentiate between coastal saltmarshes, that encompasses their origins, vegetation characteristics, physio-chemical properties of their abiotic environment, and their occurrence in relation to marine proximity and influence. The literature review identified some inland saline wetlands lacking direct connections to the ocean are classified as saltmarshes within the Indian Ocean region. These ecosystems are primarily confined to dry and cold deserts, areas with intense evaporation, depressions below sea level, sandstone aquifers with intensive agriculture and inland highlands (Table 1). In contrast, ecosystems with tidal influences, which were classified as saltmarshes were predominantly located within intertidal and supratidal zones. In some cases, these direct tidal-influenced saltmarshes extended further inland when low-relief terrain facilitates saline intrusion (Saintilan 2009b) (Table 1).

The synthesis of the literature review indicates that within the Indian Ocean region, inland saline ecosystems might be included in coastal saltmarsh extent estimates if they are not explicitly distinguished and reported separately from coastal saltmarsh ecosystems. Such misclassification has important implications for the accuracy of regional and global assessments of coastal saltmarsh distribution.

Table 1
Literature derived saltmarsh classification through marine influence and geographic location

Marine influence	Locations of occurrence	Type	Description/ Reason for inclusion in current literature survey	Country	Reference
Absent	Inland	Desert wet salt marshes	Found in areas where intensive aquaculture has formed salt affected soils with poor drainage and where sandstone aquifers are located. Areas impacted by seasonal water-level fluctuations; characterised by surface deposits of quartz grains cemented by salt originating from lake water evaporation. Lacustrine environments where the water source is the lateral infiltration or discharge of groundwater. Further, within inland spring-fed regions characterised by a shallow water-table, where intense evaporation drives upward migration of soil water, leading to progressive salt accumulation in the upper soil horizons through evaporative concentration.	Egypt	(Elkhouly and Negm 2021)
		Desert dry salt marshes	Topographic depressions below sea level in extremely arid areas.		
		Inland saline lake marshes	Form around the margins of inland saline lakes, with seasonal-precipitation pattern-governed hydraulics, that frequently result in the formation of saline crusts.	Iran	(Ghorbanalizadeh et al. 2020; Matinzadeh et al. 2022)
		Inland saline areas/ Inland saltmarshes	Certain habitats are interpreted as the geomorphological remains of formerly shallow seas. Some plant species found in inland saline areas also occur in coastal saltmarshes.	Australia	(Saintilan 2009a, b)
		Inland saltmarshes/ Sabkhas/ Sabkhat	Found around lakes, springs and wells within topographic depressions, and are classified as secondary saltmarshes; formed due to the evaporation of spillover from flooding in adjacent plains connected to shallow groundwater tables in severe arid	Egypt, Saudi Arabia	(El-Ghani 2000) (El-sheikh et al. 1985; Hassan 2021; Sayed and Masrahi 2023)

Marine influence	Locations of occurrence	Type	Description/ Reason for inclusion in current literature survey	Country	Reference
			conditions resulting in elevated salinity levels.		
		Saltmarsh-grass swamp	Formed in inundation regions containing saltmarsh vegetation. These regions are dominated by Australian saltmarsh-grass *Puccinellia stricta*, with *Puccinellia perlaxa* also prevalent at inland sites. These ecosystems develop on very heavy saline soils that experience cyclical hydraulic regimes characterised by intermittent freshwater inundation, followed by prolonged dry periods, during which hypersaline conditions develop.	Australia	(Boon et al. 2015)
		Mountain (High-Altitude) Saltmarshes	These communities occur at high-elevation sites, typically establishing in valley bottoms, along the banks of brackish lakes and by mineral springs within high-altitude cold deserts.	India	(Dvorský et al. 2011)
		Inland salt pans and playas	Occurring in temperate and subtropical latitudes where halophytes such as *Sarcocornia decumbens* grow in both sandy and clay soils; around inland saltpans and dried brackish lakes.	South Africa, Namibia and Mozambique	(Steffen et al. 2010)
Present	Coastal	Estuarine saltmarshes	Occurs in very heavy saline soils, in marine-connected locations protected from the surf, such as at river mouths and estuaries.	Australia	(Laegdsgaard 2006; Boon et al. 2015)
		Estuarine saltmarshes	Occurs within estuarine mixing zones, where saltwater and freshwater hydraulic regimes converge.	India	(Paul et al. 2021; Mishra and Farooq 2022)
		Arid estuarine saltmarshes	Occurs in temperate regions characterised by a mean annual temperature of 18°C and a mean annual precipitation of 45–150 mm.	South Africa	(Tabot and Adams 2019)
		Cape estuarine saltmarshes	Found in regions with greater variability in rainfall and climate, when		

Marine influence	Locations of occurrence	Type	Description/ Reason for inclusion in current literature survey	Country	Reference
			compared to arid estuarine saltmarshes.		
		Open coast back barrier marshes	Occurs in lees behind barrier spits or islands, shielded from direct wave action.	India	(Paul et al. 2021)
		Lagoonal saltmarshes	Occurs along the shores of coastal lagoons	Australia	(Saintilan 2009a)
		Littoral saltmarshes	Ecosystems are characterised by distinct zonal patterns driven by environmental gradients such as local ground elevation variance, horizontal distance from shoreline, vertical position relative to the saline water table, salinity gradient, soil textural properties, aridity regimes and local competitive interactions. These environmental filters collectively determine the distribution patterns, structural organisation, and vegetation composition.	Saudi Arabia	(Mahmoud et al. 1982)
		Coastal Littoral saltmarshes/ Sabkhas	Occurs in association with coastal dunes and sandy plains; that experience periodic inundation events. These periodic inundations are followed by evaporative drying, facilitate the accumulation of soluble salts at the soil surface, resulting in the formation of crystalline salt crusts.	Yemen	(Zahran and Al-Kaf 1996; Kürschner et al. 1998)
		Temperate mid to upper-zone estuarine salt marshes	Occurs within the supratidal (splash-zone) terraces of arid estuarine, cape estuarine and seashore locations within temperate and subtropical latitudes where halophytes such as *Sarcocornia decumbens* grow in both sandy and clay soils.	South Africa, Namibia and Mozambique	(Steffen et al. 2010)
Present except in the case of inland Sabkhas and saline flats	Coastal and immediately adjoining inland areas as well as inland areas with no direct connection to sea	Hypersaline flats/ Coastal hypersaline saltmarsh	Occurs in the upper intertidal zone, where inundation is infrequent. During extended periods of exposure, evaporative processes concentrate salts to hypersaline levels. Vegetation is extremely sparse or entirely absent.	Australia	(Saintilan 2009a; Boon et al. 2015)
		Freshwater tidal marshes	Occur towards the upper - reaches of estuaries, where some tidal influence	Australia	(Saintilan 2009a)

Marine influence	Locations of occurrence	Type	Description/ Reason for inclusion in current literature survey	Country	Reference
			persists, but hydraulic conditions are characterised as slightly brackish or freshwater. These ecosystems are predominantly characterised by dense fringing vegetation communities dominated by reeds and tall sedges.		
		Saline flats /Sabkhahs	Occurs in both coastal and inland playas. The centre of the playa is unvegetated, while the peripheries contain halophytes and psammophytes.	Egypt	(El-Bana et al. 2002)

Case study: Estimating the extent of coastal saltmarshes in Sri Lanka using remote-sensing approaches based on a regional definition and classification

Based on collected ground truth data, this study estimated Sri Lanka's succulent dominated coastal saltmarsh extent along its North Western, Northern, North Eastern, Southern coasts and parts of its Eastern coast, as 15,807 ha. Significant variations were observed in the estimated island-wide coastal saltmarsh extent, across the three remote-sensing approaches. Object-based image classification, pixel-based image classification, satellite embedding dataset with supervised classification, yielded estimates of 16,406.74 ha, 15,995.50 ha, and 40,410.12 ha, respectively (Fig. 3 and Table 2). All three estimates indicated that coastal saltmarshes are primarily dispersed in the North Western and Northern coastlines of the country (≈ 80%), where field observations confirmed succulent dominated communities as the predominant ecosystem type. In contrast, observations on the southern coast, together with limited observations on the eastern coast, showed that most coastal marshes are dominated by sedges and rushes. While the producer's and consumer's accuracy is high in the map derived from the satellite embedding dataset, there was significant misclassification, resulting in an overestimation of saltmarsh area, despite an overall accuracy of 0.98 (Table 2).

Table 2
Results of the accuracy assessment of the extent of saltmarshes from the three remote-sensing approaches: object-based classification, pixel-based classification and satellite embedding dataset with supervised classification. (PA – Producer's Accuracy, CA – Consumer's Accuracy)

Classification	Overall Accuracy	Kappa coefficient	PA Saltmarsh	PA Non_Saltmarsh	CA Saltmarsh	CA Non_Saltmarsh	Extent of coastal saltmarsh (ha)
Object-based image classification	0.91	0.74	0.85	0.92	0.74	0.96	16,406.74
Pixel-based image classification	0.88	0.65	0.81	0.89	0.64	0.96	15,995.50
Satellite Embedding dataset with supervised classification	0.98	0.92	0.93	0.99	0.92	0.99	40,410.12

The grid based spatial agreement analysis (Fig. 4) revealed significant variations in the saltmarsh extents obtained by the three classification methods. Despite these disparities, high agreement was consistently observed in core-saltmarsh zones, indicating that dominant saltmarsh areas were robustly detected regardless of the classifier used. Conversely, areas of moderate and low agreement were primarily concentrated in areas with overlapping spectral signatures, such as: ecotones, sand dunes, mudflats and other waterlogged areas including paddy fields.

As indicated by Table 3, the satellite embedding dataset with supervised classification approach resulted in a proportionately higher extent calculation in both the surveyed and non-surveyed areas, when compared to the object and pixel-based image classifications.

Table 3
Classified coastal saltmarsh extent from the three remote-sensing approaches: object-based image classification, pixel-based image classification and Satellite embedding dataset with supervised classification, within surveyed and non-surveyed regions

	Object-based image classification	Pixel-based image classification	Satellite embedding dataset with supervised classification
Classified coastal saltmarsh area within the surveyed region for ground truthing	14,576.20 ha	14,237.12 ha	33,702.97 ha
Classified coastal saltmarsh area within the non-surveyed region for ground truthing	1,830.54 ha	1,758.38 ha	6,707.15 ha

As indicated in Fig. 5 the satellite embedding dataset with supervised classification failed to differentiate coastal saltmarshes from adjacent or co-occurring ecosystems with similar vegetation structures. In Vidattaltivu Nature Reserve (VNR), for example, adjacent paddy fields and mudflats were misclassified as coastal saltmarshes, thereby providing a higher estimate of 4,658.47 ha compared to the lower estimates of 3,828.80 ha and 3,348.76 ha provided by the two other tested classification methods. Similarly, in Chundikulum Nature Reserve (CNR), sand dunes and dry-thorny shrubs were misclassified as coastal saltmarshes, which yielded an overestimation of 6,806.66 ha, compared to 1,889.05 ha and 1,895.20 ha provided by the two other methods.

Discussion

Coastal saltmarsh extents that were provided by the object-based image classification (16,406.74 ha), and pixel-based image classification (15,995.50 ha) approaches, closely approximated the succulent dominated saltmarsh extent obtained from the final ground truth dataset (15,807 ha). In contrast, the satellite embedding dataset with supervised classification substantially overestimated saltmarsh extent (40,410.12 ha). Spatial agreement analysis in Fig. 4, revealed that saltmarsh areas identified during the ground truthing were congruently identified by all three classification approaches. This agreement demonstrates the robust detection of primary spectral signatures irrespective of classification approach, however significant discrepancies between methods occur at habitat boundaries.

This congruence between ground truth data and estimates from the object and pixel-based image classification approaches should be interpreted cautiously, as ground surveys covered ≈ 50% of Sri Lanka's coastline. These findings suggest the following: firstly, many non-surveyed areas might not support the same extent of coastal saltmarshes as the surveyed areas do, which aligns with the projected distribution of coastal saltmarshes in Australia, which is a scattered distribution with some coastlines lacking them altogether (Navarro et al. 2023). Secondly, certain saltmarshes with vegetation structures that were not adequately characterised in the training dataset might have been overlooked. Notably, there are extensive tidal influenced, grass, sedge and rush-dominated coastal wetlands along Sri Lanka's Eastern coastline, which are labelled as 'brackish/saline marshes' within the National Wetland Directory (Central Environmental Authority 2006).

This study did not include grass, sedge and rush-dominated coastal marshes within the final ground truth training dataset, due to ambiguities about their classification within the 'coastal saltmarshes' category in a tropical context. This ambiguity stem from several unresolved factors, including the soil and water salinity within these ecosystems, the tolerance and physiological responses of sedge and rush species to varying salinity regimes, and the extent to which such vegetation contributes to ecosystem services typically associated with saltmarshes (Keith et al. 2022). Furthermore, the distinction between grass, sedge and rush-dominated ecosystems occurring in coastal settings and those present in inland marshes is not yet well established (Banerjee et.al 2017). Further, while many literature sources contextual of tropical countries (Hurst and Boon 2016; Gedan and Fernández-Pascual 2019; Viswanathan et al. 2020; Mishra and Farooq 2025), classify grass, sedge and rush-dominated coastal marshes as 'coastal saltmarshes', their similarities and differences with the standard succulent dominated saltmarshes, have not been presented. These knowledge gaps highlight the need for further investigation before such ecosystems can be confidently classified as coastal saltmarshes. However, the exclusion of such marshes from the ground truth training data might have resulted in them not being detected by object-based image classification and pixel-based image classification.

A visual and qualitative comparison with ground truth validation data revealed that the pixel-based classification approach produced extent maps with a 'speckled effect', with scattered misclassified pixels appearing even in adjacent non-coastal saltmarsh ecosystems such as paddy fields, sand dunes, sand flats and mudflats, which is confirmed by a low consumer's accuracy value of 0.64 (Table 2). The low consumer's accuracy indicates that analysing single pixels introduces significant classification noise (Yuh et al. 2023). It is evident from the visual comparative analysis that the speckled effect has been effectively addressed in the extent map produced by the object-based image classification approach, which eliminated the misclassification of individual pixels through a SNIC algorithm that groups pixels into homogeneous clusters prior to classification. Further, the calculated extent using object-based image classification (16,406.74 ha; Table 2) closely aligns with the extent captured during ground truthing (15,807 ha). Therefore, object-based image classification is a more robust approach than the pixel-based image classification approach in identifying and mapping coastal saltmarsh ecosystems and their extent.

The limitations of automated classification were further shown by the extent derived from the satellite embedding dataset with supervised classification approach (40, 410.12 ha). Although this approach achieved higher accuracy metrics than the previous two approaches, visual inspection revealed significant over classification through misidentification of adjacent sand dunes, mudflats, and agricultural areas as saltmarsh ecosystems (Fig. 3).

This classification approach employs the KNN supervised machine learning algorithm, which assigns classes by identifying the nearest pixel values with similar spectral features (Yuh et al. 2023). Additionally, because the deep learning model used to generate the satellite embedding dataset was trained to recognise broad landscape patterns, all intertidal coastal wetlands were aggregated into a single category and the specific spectral characteristics of saltmarshes were made indistinguishable (Brown et al. 2025). Although, this aggregation yielded high accuracy metrics, it might reflect oversmoothing effects rather than genuine classification precision. Consequently, in its current form, the supervised classification methodology applied here is not suitable for the identification and delineation of ecosystems characterised by complex spectral signatures and pronounced seasonal variability, such as coastal saltmarshes.

The satellite embedding dataset with supervised classification approach estimated a coastal saltmarsh extent of 6,707.15 ha along coastlines that were unverified during ground truthing (Table 3). This further highlights the well-established need for extensive ground truthing data stated in literature (Toosi et al. 2019; Maurya et al. 2021). Additionally, training data must capture vegetation heterogeneity (Mcowen et al. 2017; Murray et al. 2022) to obtain reliable map outputs. Future research should prioritise a comprehensive ground truth survey of the remaining coastline to enhance classification accuracy.

Methodological constraints further complicated classification efforts with the satellite embedding dataset. Notably, persistent processing errors in the open-source version of Google Earth Engine necessitated a substantial reduction in training data volume. Ultimately, only 25 polygons for the saltmarsh class and 60 polygons for non-saltmarsh classes were retained, with all pixels within these polygons incorporated into the training set. This data limitation compromised the independence of observations, potentially biasing model performance: the classifier might exhibit high accuracy in areas covered by training polygons but generalise poorly in unrepresented regions. A similar issue arose with the validation dataset, which may have inflated accuracy estimates, as previously noted by Hammond and Verbyla (1996). Because of the above-mentioned limitations, the object-based image classification emerged as the most robust approach to identify and map coastal saltmarsh ecosystems, out of the three tested approaches.

To mitigate these limitations in future research, two improvements are recommended. Firstly, to increase the number of training polygons in data deficient areas to obtain better spatial representation, and secondly, to reduce the number of points per polygon, while maintaining a balanced distribution across all training polygons to improve model generalisability. Additionally, as emphasised by Millard and Richardson (2015), training datasets should reflect the actual proportional distribution of classes across the landscape. Consequently, future studies should prioritise collecting polygons or points in a manner that captures the proportion of non-saltmarsh areas relative to coastal saltmarsh areas in a selected region of interest. This will prevent models from disproportionately emphasising the rarer ‘coastal saltmarsh’ class. These methodological refinements are essential to minimise potential overestimation of saltmarsh extent, particularly when employing satellite embedding dataset with supervised classification approaches, as observed in the current study. Further, the ecological adaptivity of succulents, which exhibit high seasonal variability and the ability to establish and propagate in both coastal and inland locations, creates complex ambiguities in the classification and delineation of saltmarshes in the Indian Ocean region (Lugendo 2016; Chanda et al. 2022). This ambiguity necessitates the urgent need to distinguish, define and separately report coastal saltmarshes, given their vital role as a blue carbon ecosystem; their long-term carbon sequestration ability; and their relevance to carbon credit systems (Maxwell et al. 2024).

A call for a clear segregation in defining and reporting coastal saltmarshes and inland saline wetlands.

The literature review’s outcomes present important implications for saltmarsh research in tropical regions, clearly highlighting the need for improved and harmonised classification frameworks with evidence-based definitions for coastal saltmarshes.

While the existing recognised GET and the Ramsar Wetland Classifications provide a broadscale framework, they require further narrative development to yield useful and precise definitions for coastal saltmarshes (Brook et al. 2025). However, as globally defined classifications may not always align acceptably with regional contexts, it is essential for countries to develop their own regional definitions that incorporate local terminology. For comparability, these regional definitions should be developed from global classifications, enabling countries to adhere to international standards while accurately reporting on their unique national ecosystems (Serrano et al. 2019; Gorman et al. 2022; Campbell et al. 2022; Veettil et al. 2024).

The diverse classification practices of many studies within the Indian Ocean region present a dual challenge for accurately assessing coastal saltmarsh extent. As highlighted by the review, the broad categorisation of both tidal influenced coastal saltmarshes, and inland saline ecosystems simply as 'saltmarshes' can lead to a significant overestimation of the true coastal saltmarsh extent unless reported data contains explicit contextual details. This inconsistency stems in part from a vegetation-centric approach, where the presence of halophytic plants (categorised by salinity tolerance as extreme halophytes, mesohalophytes, or xerohalophytes) often leads to the application of the generalised 'saltmarsh' label, irrespective of a site's connections to the ocean (Zahran and Al -Kaf 1996; Kürschner et al. 1998; Elkhouly and Negm 2021; Al-Taisan 2022; Galal et al. 2023). The inconsistent practice of reporting tidal-influenced ecosystems dominated by

sedges or rushes, either as 'saltmarshes', or as 'tidal coastal marshes', increases ambiguity. While further studies are required, it is possible that the exclusion of grass, sedge and rush-dominated ecosystems leads to underrepresentation of actual coastal saltmarsh extent.

To resolve this, a two-pronged approach is recommended. First, regional classifications must be developed that clearly distinguish between inland saline ecosystems and coastal saltmarshes by describing the distinct biotic and abiotic factors, particularly in terms of hydrology and geomorphology, that define each. Second, there is a critical need to investigate the scientific suitability of amalgamating all tidal-influenced coastal marshes under a unified coastal saltmarsh category, moving beyond classifications based solely on dominant vegetation type. This is especially urgent for tropical regions like the Indian Ocean, where grass, sedge and rush-dominated saltmarshes are frequently excluded from national saltmarsh inventories (Hurst and Boon 2016). While nations may continue to use local terminologies for finer-scale management, a concerted regional or global dialogue is needed to establish clear, functional definitions for coastal saltmarshes. These definitions should integrate multiple characteristics: hydrology, geomorphology, climatic responses and biota, rather than relying solely on vegetation. The employment of a multi-parameter definition allows for the functional equivalence of grass, sedge and rush-dominant coastal marshes, and succulent dominated tropical coastal saltmarshes to be investigated. Their potential taxonomic unification, may reduce the underestimation of certain ecosystem services in national and global inventories. It is a priority for further studies to assist in establishing such a coherent framework for advancing saltmarsh science, and fundamental to accurately recognising, studying, and conserving these ecosystems. Such a framework allows for the collection of more extensive ground truth delineations, that can be used in machine learning classifiers based on refined spectral signatures. Further-tuned classifiers will be able to identify tropical coastal saltmarshes irrespective of the presence or absence of vegetation. This is imperative as vegetation appears only seasonally in some tropical coastal saltmarshes.

Conclusions

This study highlights the robustness of satellite-based saltmarsh mapping when validated against ground truth data, while emphasising the computational limitations inherent in those approaches. Sri Lanka’s coastal saltmarsh ecosystems remain understudied; this research estimates that saltmarshes constitute approximately less than 0.25% of the nation's land area, based on the characterisations from both the object-based and pixel-based image classification approaches. This figure contrasts with the lower estimate of 0.11% reported within the GET. The rarity of these ecosystems, together with the disproportionate services they supply illustrates the critical need for enhanced governance to protect these vital, yet vulnerable habitats.

A key recommendation of this study is to develop more precise, yet representative definitions and classifications of coastal saltmarshes. To achieve this, future research must integrate geomorphological, hydrological, and climatic variables, in addition to vegetation, to ensure accurate segregation of coastal saltmarshes from inland saline wetlands.

Declarations

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Authors' contributions: Contributions to the study conception and design were made by all authors. Data collection design and data collection were performed by Gavindya Kawshani and Astha Fernando, and Sevvandi Jayakody. The literature review for the study was conducted by Gavindya Kawshani under the supervision of Mathew A. Vanderklift and Sevvandi Jayakody under the Early-Career Ocean Professionals programmes. All relevant algorithms and codes were generated by Gavindya Kawshani, with guidance from Tom Worthington, Alejandro Navarro, and Emma Deeks. Further inputs were provided by Chaturangi Wickramaratne. Field coordination and relevant study logistics were managed by DSM de Silva, Kelum Wijenayake, Chaturangi Wickramaratne and Tilak Premakantha. The first draft of the manuscript was written by Gavindya Kawshani and Sevvandi Jayakody and was reviewed by Astha Fernando. Previous versions of the manuscript were commented on by all authors. The final manuscript was read and approved by all authors.

Data availability: The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Google Earth Engine code availability: The Google Earth Engine scripts for mapping saltmarshes in Sri Lanka using object-based image classification, pixel-based image classification and Satellite embedding dataset-supervised classification are available in the following publicly accessible GitHub repository:https://github.com/gavindya-kawshani/gee_codes_to_saltmarsh_mapping_lk

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation Process: The large language model Claude Sonnet 4.5 was used to debug and review the generated code for mapping by Gavindya Kawshani. After using these tools, Gavindya Kawshani reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Figures

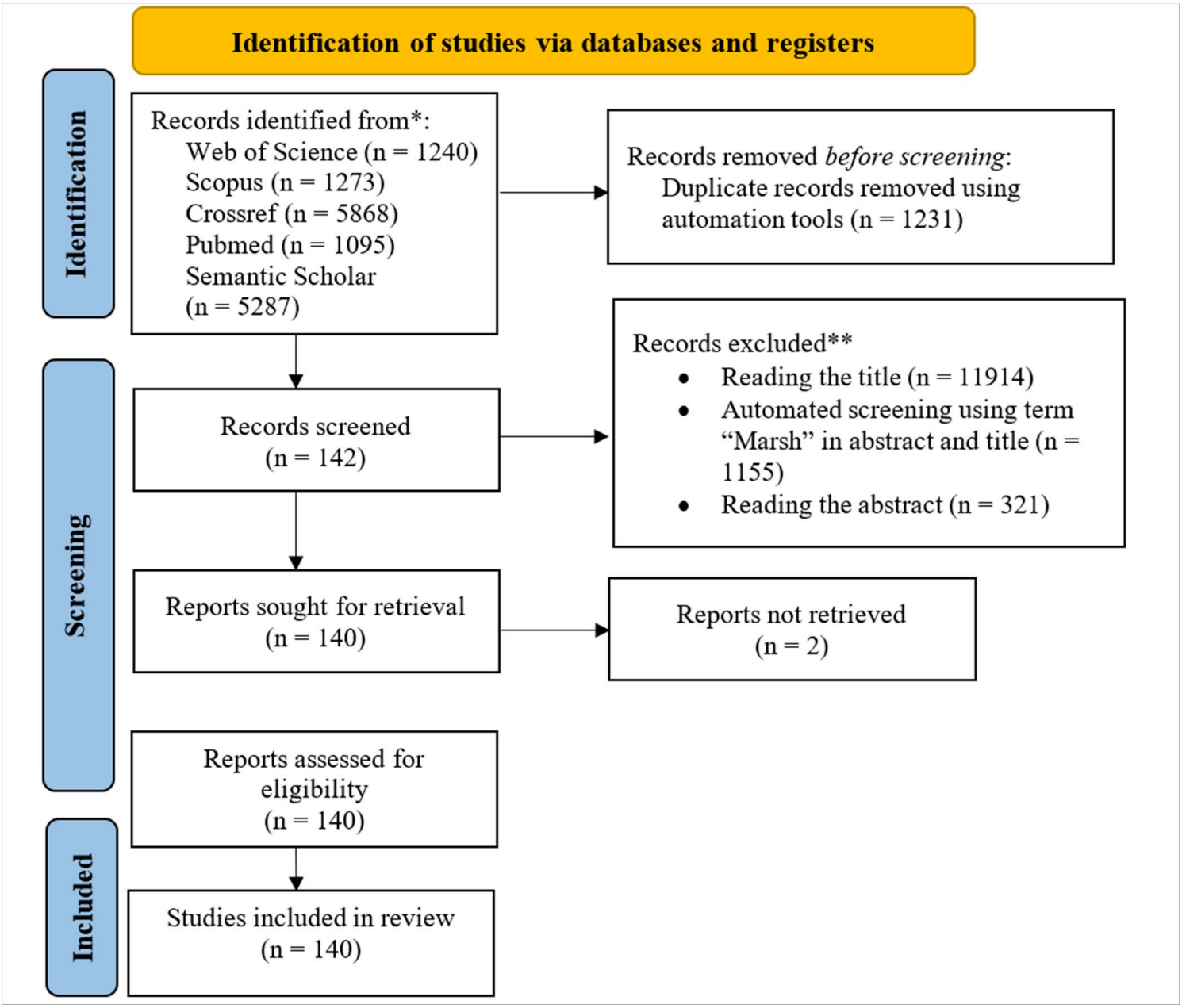


Figure 1

PRISMA flow diagram illustrating the search and selection criteria used in the systematic review

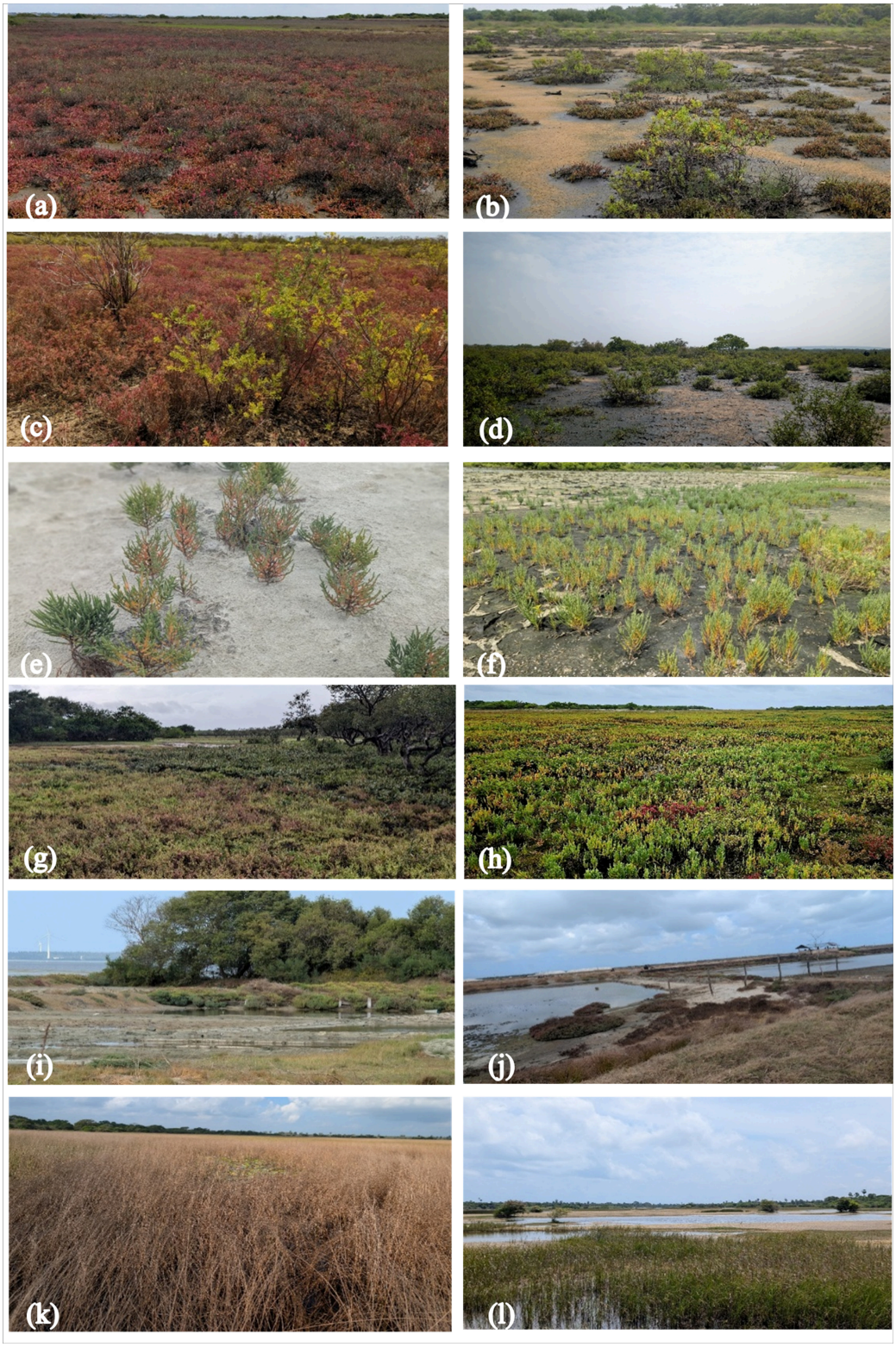


Figure 2

Heterogeneous coastal saltmarsh vegetation types considered during the ground truthing survey across Sri Lanka (a)(b) Pure or mixed communities of *Tecticornia indica,* (c)(d) Pure or mixed communities of *Suaeda* spp.,(e)(f) Seasonal

Salicornia brachiata dominated communities, (g)(h) Saltmarshes mixed with dwarf mangroves, (i)(j) Secondary saltmarshes associated with shrimp farms and salterns, (e)(f) Grass, sedge and rush-dominated coastal wetlands

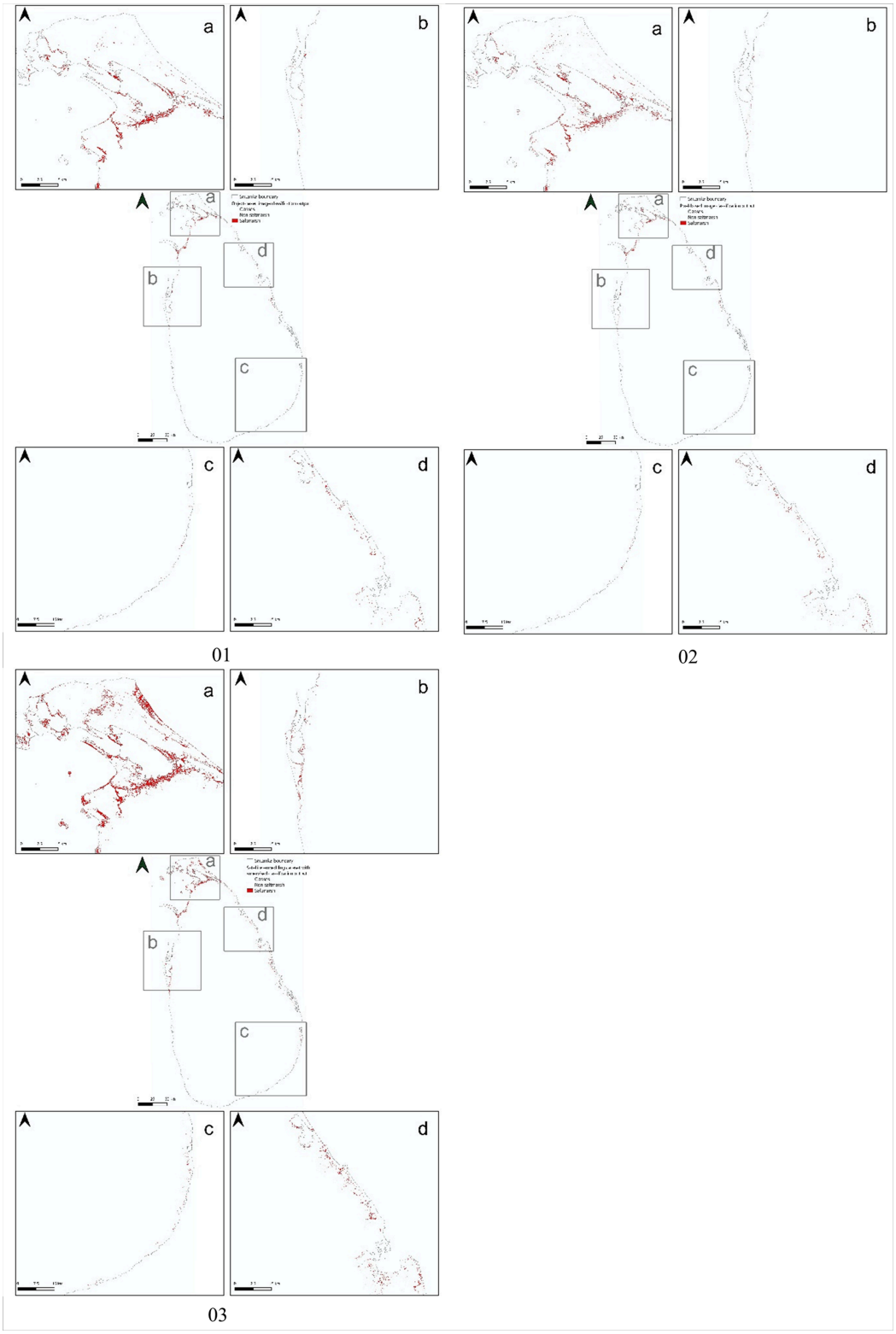


Figure 3

Comparison of classification results of saltmarsh distribution from (01) object-based image classification, (02) pixel-based image classification and (03) Satellite embedding dataset with supervised classification. The four enlarged areas depict the Northern, North Western, Southern and Eastern coastlines of Sri Lanka respectively as a,b,c,d

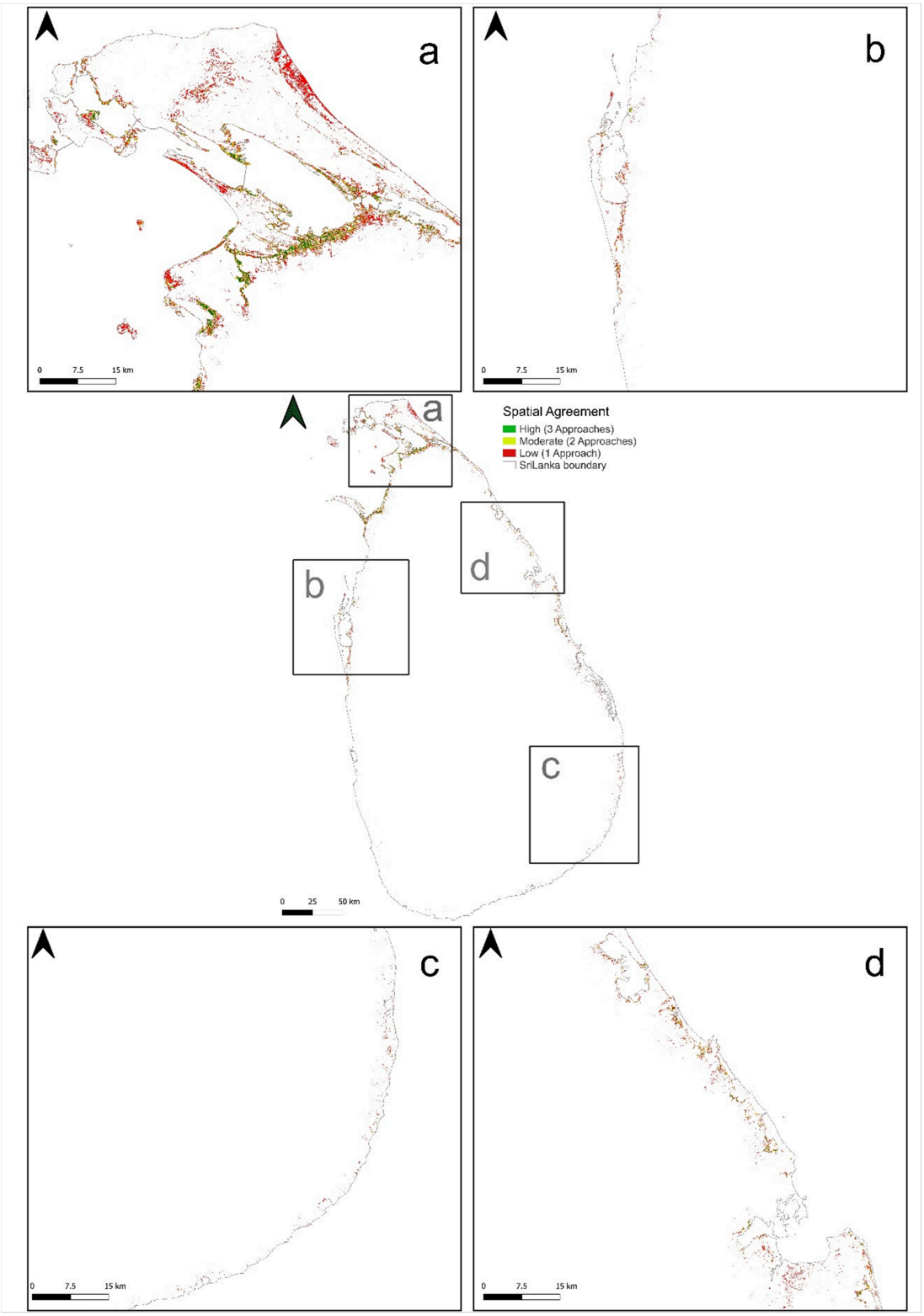


Figure 4

Spatial agreement map derived from (01) object-based image classification, (02) pixel-based image classification and (03) Satellite embedding dataset with supervised classification. Green indicates areas where all three remote sensing approaches identified saltmarshes. Yellow indicates agreement between two approaches and red depicts areas identified by only one approach. The four enlarged areas depict the Northern, North Western, Southern and Eastern coastlines of Sri Lanka respectively as a,b,c,d

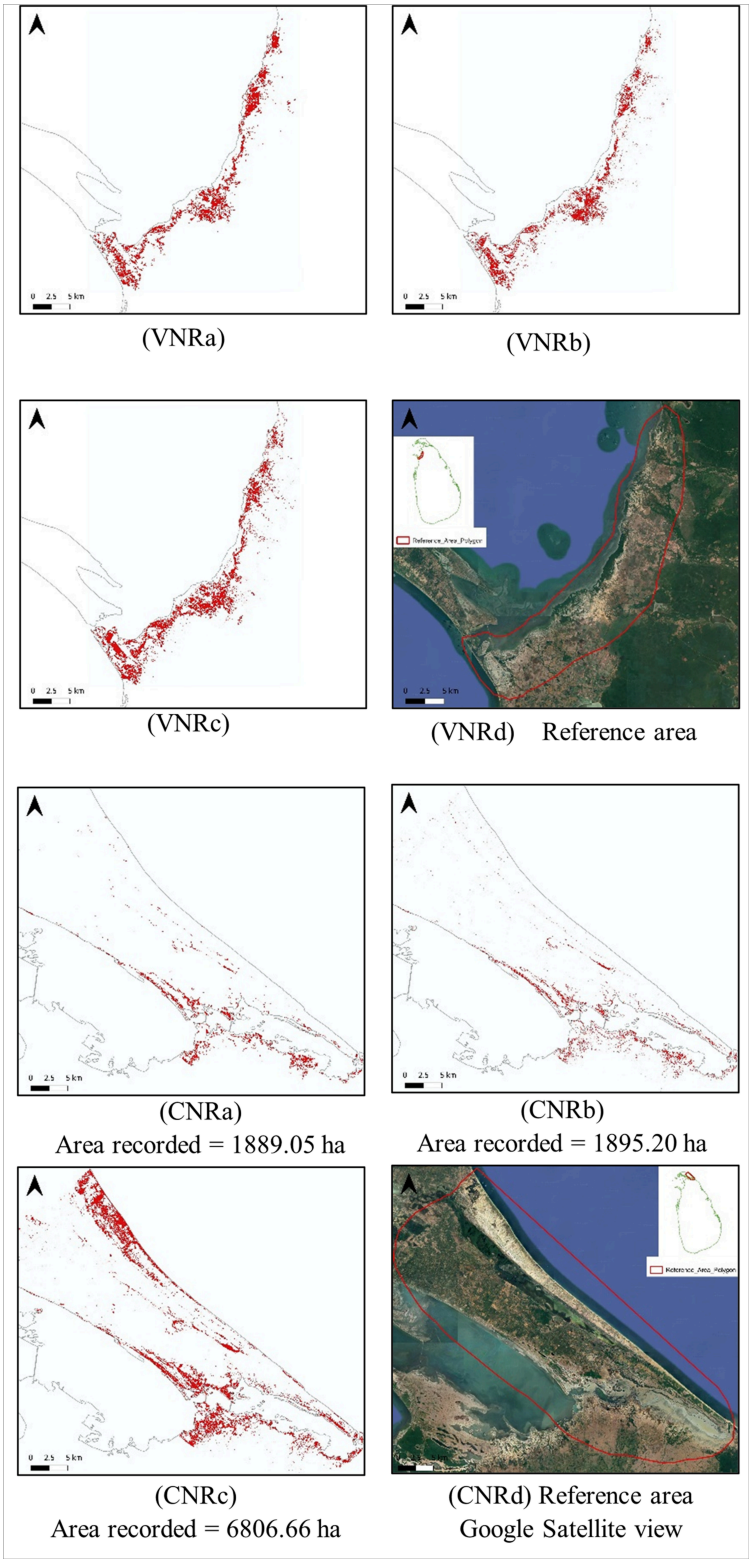


Figure 5

A comparison of discrepancies in the mapping and extent calculations observed between three remote sensing approaches in Vidattaltivu Nature Reserve (VNR) (VNRa: results from object-based image classification 1, VNRb: results from pixel-based image classification 02, VNRc: results from satellite embedding dataset with supervised classification 3, VNRd: original Google Satellite image of the selected region for reference) and Chundiculum Nature Reserve (CNR) (CNRa: results from object-based image classification 1, CNRb: results from pixel-based image classification 02, CNRc: results

from satellite embedding dataset with supervised classification 3 CNRd: original Google Satellite image of the selected region for reference)