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A review of mangrove degradation assessment using remote sensing: advances, challenges, and opportunities

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ABSTRACT

Mangrove ecosystems are essential coastal environments that provide extensive ecological and socioeconomic benefits to both human societies and the natural environment. However, mangrove degradation can lead to significant declines in biodiversity, ecosystem processes, and ecosystem services. Compared to the extensive research focused on documenting mangrove areal changes and deforestation, there is a lack of review on the current status of mangrove degradation identification with the assistance of remote sensing data. This review analyzed 104 papers focusing on remote sensing-based mangrove degradation assessments across tropical and subtropical regions from Web of Science and Google Scholar databases. We summarized the remote sensing approaches employed, the specific proxies or indicators derived from remote sensing data to characterize mangrove degradation, the primary remote sensing datasets utilized and remote sensing image classification methods. We also identified the key challenges (e.g. lack of optimal proxies, confusions between true degradation and natural variability) and emerging opportunities for future research in the remote sensing-based assessment of mangrove degradation. Based on publications, one of the primary challenges lies in the inconsistency of definitions and proxies used to characterize mangrove degradation. Scale effects and the inherent complexity of remote sensing data further compound these challenges. Nonetheless, the increasing availability of advanced multi-source remote sensing data holds promise for more accurate and comprehensive measurement of mangrove degradation, which could ultimately inform and guide sustainable coastal management and restoration efforts.

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Mangrove degradation; degradation and deforestation; remote sensing; review; mangrove health condition; mangrove degradation proxy

1. Introduction

The significance of mangrove ecosystems has been gaining more recognition in recent decades. Mangrove forests, situated in the intertidal regions in tropical and subtropical climate zones, are regarded as unique coastal habitats that play irreplaceable roles and serve invaluable functions. These include carbon sequestration, water purification, and the mitigation of coastal erosion (Alongi 2002; Giri et al. 2011; S. Y. Lee et al. 2014). Located at the land–sea interface, mangroves have been impacted by natural and anthropogenic disturbances (Goldberg et al. 2020). In response to the growing awareness of the ecological significance of mangrove forests, numerous countries have enacted policies and regulations to strengthen the protection and management of these coastal environments (S. Y. Lee et al. 2019). Extensive research attention has been devoted to investigating changes in mangrove areal extent and deforestation at local, regional, and even global scales (Bunting et al. 2018; Giri et al. 2011; Jia et al. 2023). However, compared to the focus on mangrove deforestation and areal change/loss, the issue of mangrove degradation has received relatively less attention from the research community. While mangrove deforestation is well-documented, large-scale degradation patterns remain poorly quantified (Friess et al. 2019), masking hidden ecological declines in standing mangrove forests. A Web of Science topic search using the terms "mangrove degradation" and "mangrove deforestation OR mangrove loss" yielded 1,990 and 2,777 results, respectively. Mangrove degradation reflects the loss of habitat quality (Friess et al. 2019), often characterized by the altered or reduction of functions, attributes, or ecosystem services (Gao et al. 2020; Ghazoul et al. 2015; Vásquez-Grandón, Donoso, and Gerding 2018; Yando et al.

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2021). In addition, degradation is often a gradual process that may eventually lead to deforestation or, alternatively, allow for ecosystem recovery and resilience (Gao et al. 2020). The significance and challenges associated with mangrove degradation have been highlighted by scholars such as Friess et al. (2019), underscoring the need for accurate monitoring and assessment.

Mangrove degradation is driven by complex mix of natural and anthropogenic factors (Yando et al. 2021). Urban development disrupts these ecosystems through construction and other human activities. For instance, road construction alters hydrological conditions, affecting water movement, infiltration patterns, and tidal pumping (Cardenas et al. 2022). Although mangrove root systems are capable of purifying water, pollution from nearby urban areas or aquaculture can severely degrade water quality, leading to altered hydrological conditions that negatively impact the diverse flora and fauna of the ecosystem. While mangrove mudflats can accumulate pollutants, oil deposition from vessels can suffocate the breathing and feeder roots of mangroves, resulting in reduced leaf density and diminished ecological functions and biodiversity (Ishtiaque, Myint, and Wang 2016). Additionally, natural disasters such as typhoons and tsunamis can devastate mangrove areas, disrupting the accumulation of organic matter in sediments and further threatening these vital ecosystems (Ishtiaque, Myint, and Wang 2016). High salinity and low nutrient availability can also contribute to conditions that lead to top-dying disease and further degradation in mangroves (Ishtiaque, Myint, and Wang 2016; Kathiresan 2002). The consequences of mangrove degradation are significant across ecological, economic, and social dimensions (Carugati et al. 2018; Yando et al. 2021). Ecologically, the degradation of mangroves leads to reduced biodiversity, habitat loss, and a decline in ecosystem services, including carbon sequestration, which exacerbates climate change by increasing carbon emissions (Senger et al. 2021; Yando et al. 2021). Economically, degraded mangroves diminish protection for coastal communities and shorelines, raising the risks and costs associated with natural disasters. Additionally, the loss of mangroves reduces access to valuable timber resources and impacts tourism development in coastal areas. On a social level, communities that rely on mangroves for resources and livelihoods face significant challenges, potentially leading to the loss of local cultural heritage and traditions (Carugati et al. 2018). Therefore, it is essential to accurately assess mangrove degradation.

Prior to broadscale access to remotely sensed data, the assessment of degradation in mangrove forests often relied on localized field observations and biological measurements. For example, mangrove degradation in China was assessed based on field investigation and estimation of species extinction and carbon stock decline (W. Wang et al. 2020). Such field-based approaches are valuable for providing evidence on the drivers and mechanisms of ecosystem changes. However, the labor-intensive nature of field measurements and the spatial limitations of localized data often constrained the scalability of these studies. To address this, researchers increasingly turned to remote sensing, a cost-effective and scalable alternative, to complement bioecological approaches. Remote sensing has emerged as an effective technique for mangrove monitoring, enabling spatially continuous and temporally consistent data across extensive geographic regions. By leveraging multi-source remote sensing imagery and advanced methods, remote sensing can map mangrove extent, detect land-cover changes, characterize composition and structural properties, and retrieve key biophysical parameters and ecosystem services, assessing the health condition of mangrove (Kuenzer et al. 2011; Lu and Wang 2022; L. Wang et al. 2019). The integration of fine-scale field data of mangrove habitats with remote sensing information allows for comprehensive monitoring and a deeper understanding of the mechanisms underlying mangrove degradation over broader spatial scales.

Therefore, a thorough understanding of how past studies have utilized remote sensing to monitor and quantify mangrove degradation is critical. Such insights not only highlight the current capabilities and limitations of these approaches but also pinpoint uncertainties, guiding the development of targeted solutions and methodological refinements to enhance accuracy and applicability in future assessments. There are review papers that have examined the broader status of global mangroves (Friess et al. 2019) and ecosystem evaluation. These review articles offer a comprehensive understanding and valuable insights into several aspects, including the functions and services of mangrove ecosystems (Alongi 2014;

Kathiresan 2002; S. Y. Lee et al. 2014; Woodroffe et al. 2016), the drivers and impacts of mangrove change (Bhowmik et al. 2022; Duke 2016; Ilman et al. 2016; Sippo et al. 2018), conservation and restoration strategies (Datta, Chattopadhyay, and Guha 2012; Field 1999), and interdisciplinary perspectives. In addition, the advancements in remote sensing techniques for mangrove monitoring have been adequately reviewed (Kuenzer et al. 2011; Lu and Wang 2022; Pham et al. 2019; Tran, Reef, and Zhu 2022; L. Wang et al. 2019). However, regarding degradation, several review papers summarized the conceptualization and evaluation of forest degradation (Ghazoul et al. 2015; Vásquez-Grandón, Donoso, and Gerding 2018). The challenges associated with defining and measuring degradation based on remote sensing have been reviewed for forests (Gao et al. 2020) and humid tropical forests (Dupuis et al. 2020). To our knowledge, a review focused specifically on the current status of mangrove degradation detection using remote sensing data is lacking. Therefore, we aim to review the current state of remote sensing applications for monitoring and quantifying mangrove degradation. Specifically, we aim to 1) examine the commonly used remote sensing-derived proxies that serve as indicators of mangrove degradation; 2) evaluate the primary remote sensing datasets and classification methodologies that enable mapping mangrove degradation patterns; 3) assess the uncertainties and challenges in these previous publications and explore emerging opportunities to overcome the barriers of accurate mangrove degradation monitoring through advanced technologies.

2. Article selection and review

2.1. Article selection criteria

The literature search was conducted to identify and analyze peer-reviewed studies that employ remote-sensing data to monitor or quantify mangrove degradation. We utilized the Web of Science and Google Scholar databases to obtain relevant peer-reviewed journal articles published before November 2024. The keywords employed in the search included ("degraded" OR "degradation") AND ("mangrove" OR "mangroves") AND ("remotely sensed" OR "remote sensing" OR "satellite" OR "earth observation"). A total of 410 papers were initially collected. Further manual screening of the retrieved literature was performed to refine the selection based on the following criteria: 1) the articles must recognize the detection of mangrove degradation as a key research objective and involve quantitative analysis, rather than merely discussing or inferring degradation as a driver of mangrove change; 2) the articles must apply remote sensing techniques or utilize satellite data to detect mangrove degradation; 3) the articles must define the disturbance on mangrove as "degradation," rather than merely labeling it as "disturbance" or "damage." 4) articles that only compared remote sensing-derived biological parameters between selected sites of intact (healthy) and degraded mangroves are excluded from this review, as these studies identified degraded mangrove sites based on expert knowledge during the selection of study areas, rather than employing methodologies grounded in remote sensing technology to detect mangrove degradation over specific spatial extents. Finally, a total of 104 peer-reviewed journal articles were selected to explore the current understanding and practices in remote sensing-based assessment of mangrove degradation. A potential limitation of this review is that our selection criteria may exclude studies utilizing advanced remote sensing techniques to evaluate degradation-related indicators (e.g. biomass or health condition mapping). While such studies can provide valuable insights for refining precision in degradation indicators, they often do not explicitly target quantifying degradation as they lack measurement of indicator decline. Nevertheless, we hope that the selected literature could broadly reveal the current state of remote sensing-based mangrove degradation research, as it prioritizes studies explicitly linking remote sensing-derived proxies to degradation and outcomes.

2.2. Advances of the research

2.2.1. Overview of literature

Prior to 2014, research focused on mangrove degradation using remote sensing was relatively limited, comprising approximately 17% of the total studies on this topic (Figure 1). However, over the past decade, from 2016 up to the present, there has been a marked rise (about 76%) in the number of publications evaluating mangrove degradation using remote sensing techniques. This observed trend aligns with

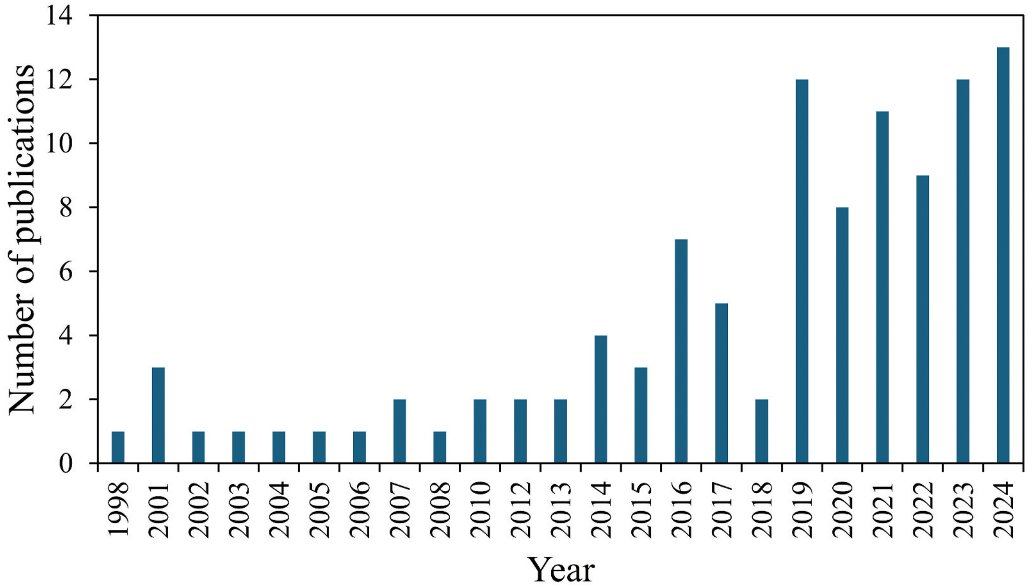

Figure 1. Evolution of studies on remote sensing-based mangrove degradation.

the broader evolution in the publications of remote sensing of mangrove forests (L. Wang et al. 2019). The shift toward a greater emphasis on remote sensing-driven assessments of mangrove degradation over the past decade suggests that researchers and policy-makers have recognized the importance of remote sensing technologies in monitoring the health and status of mangrove ecosystems.

The literature on mangrove degradation appears to exhibit a geographical concentration, with a notable emphasis on research conducted in India (Figure 2). Specifically, over 37 out of 104 publications examined mangrove degradation in India. In addition to India, the research on mangrove degradation has also been concentrated in several other geographical hotspots due to the relatively large mangrove covers, including Bangladesh, Indonesia, Vietnam, and Myanmar. Many studies on mangrove degradation in India and Bangladesh focus on the Sundarbans, which is the largest contiguous mangrove ecosystem in the world. Furthermore, the study area of Florida in the United States has also emerged as a prominent

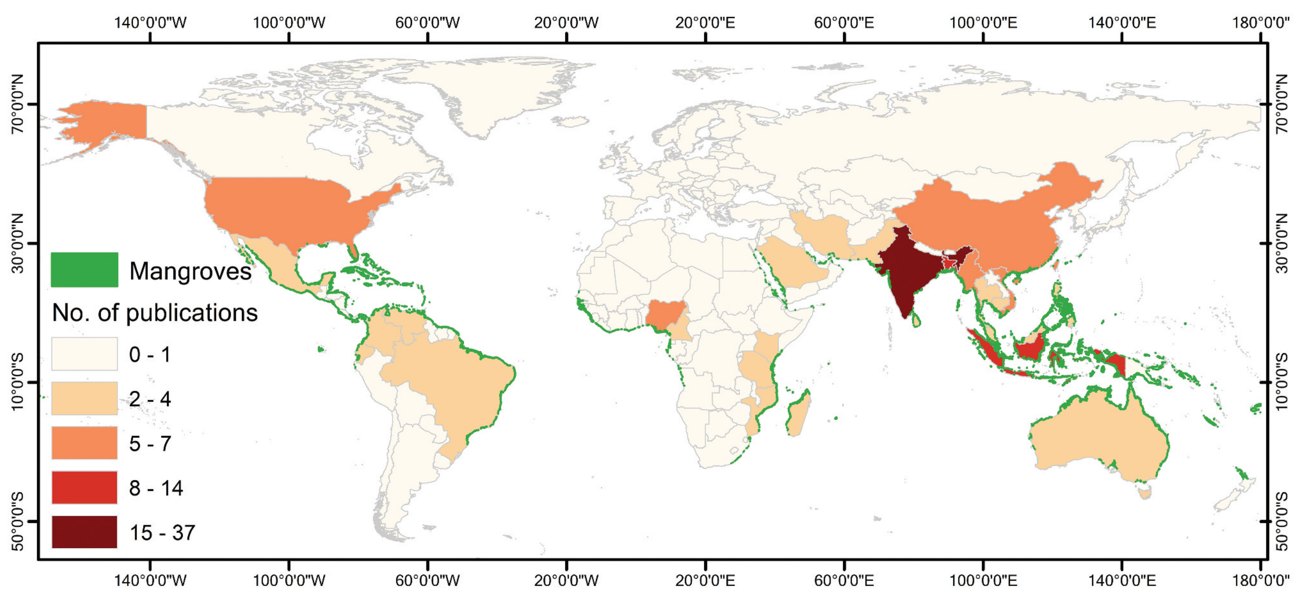

Figure 2. Number of publications on remote sensing-based mangrove degradation by study area.

focus within the literature on mangrove degradation, which is owing to the impact of Hurricane Irma, a major climatic event that occurred in 2017 and posed significant threats to mangrove ecosystems in this region (Jamaluddin et al. 2021; Lee et al. 2021; McCarthy, Jessen, and Barry 2020; McCarthy et al. 2020). The assessment of mangrove degradation based on remote sensing has been conducted at various spatial scales, ranging from large-scale, regional studies to pantropical and global analyses. Several studies have focused on large-scale analysis, such as Southeast Asia (Sakti et al. 2020), tropical continental Asia (Blasco, Aizpuru, and Gers 2001), the pantropical region (Vancutsem et al. 2021), and global mangrove ecosystems (Thomas et al. 2017).

The network visualization from VOSviewer (Figure 3) maps the thematic structure of remote sensing-based mangrove degradation research. Clusters of frequently co-occurring terms reveal dominant interconnected themes, including dataset preferences, study area hotspots, and key drivers. Node sizes reflect term prevalence, with larger nodes representing frequently studied topics (e.g. remote sensing, mangroves, conservation, classification, ecosystem). Landsat satellite data emerged as the most widely used dataset. NDVI, biomass, and leaf area index derived from remote sensing data dominate as proxies for mangrove degradation assessment. Bangladesh and the Sundarbans are hotspots of study area. It also highlights key drivers of mangrove degradation, including tsunamis and erosion.

2.2.2. *Mangrove degradation proxy derived from remote sensing*

The primary proxies for assessing mangrove degradation derived from remote sensing data can be categorized into three main types: health, coverage, and fragmentation indicators (Figure 4). Health indicators mainly indicate biophysical parameters (e.g. greenness, biomass, leaf area index, and net primary productivity). Coverage indicators primarily focus on the spatial extent and distribution of mangrove forests. They provide critical information regarding the presence or absence of mangrove vegetation within specific pixels, as well as quantifying canopy density and fractional coverage.

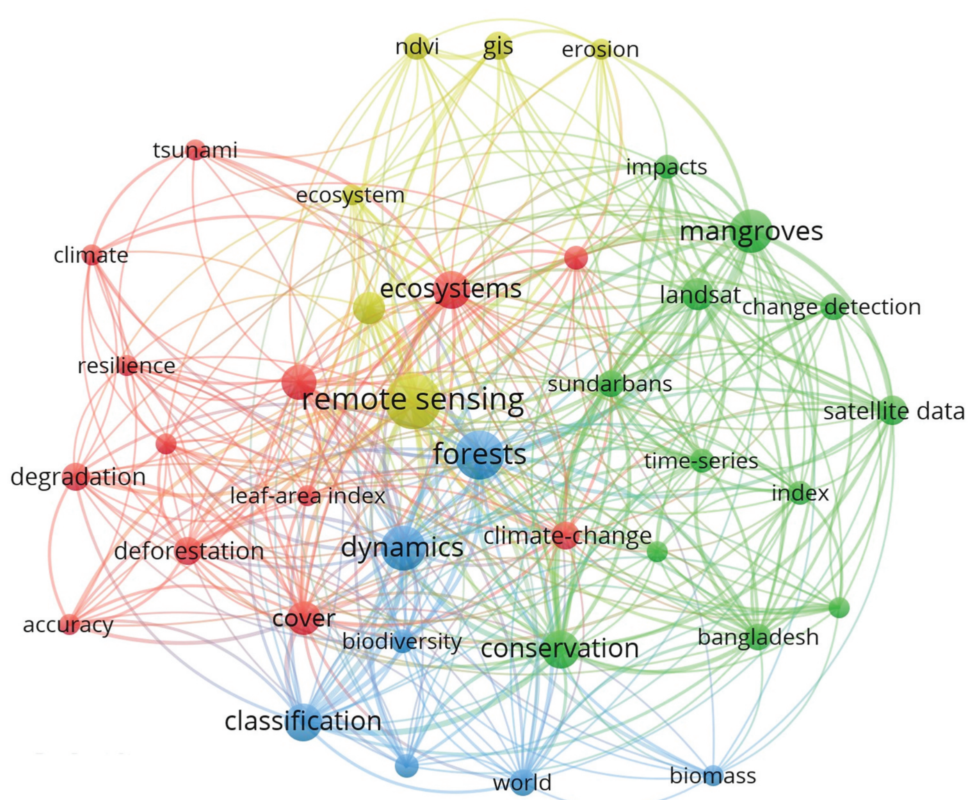

Figure 3. Network visualization (from VOSviewer) on remote sensing-based mangrove degradation studies.

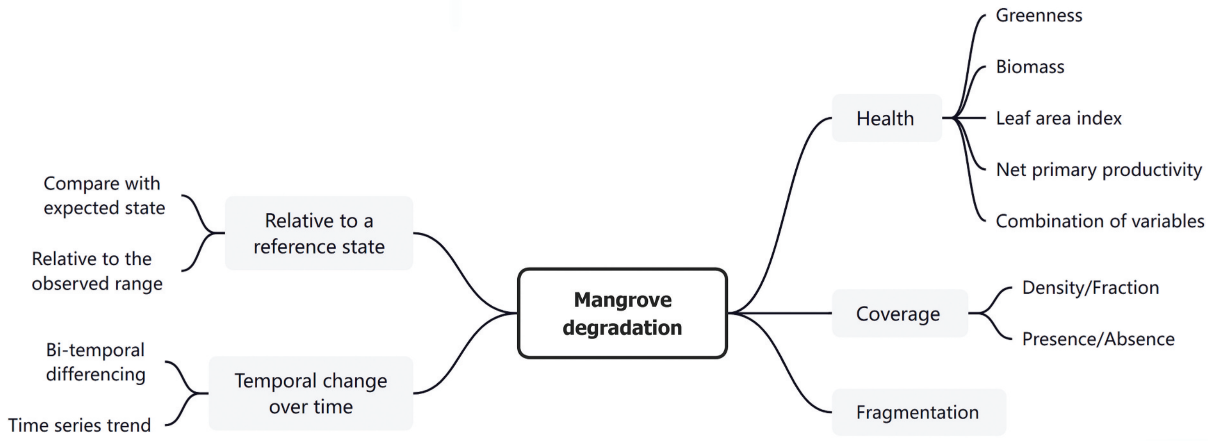

Figure 4. Proxies and space/time reference of mangrove degradation based on remote sensing data.

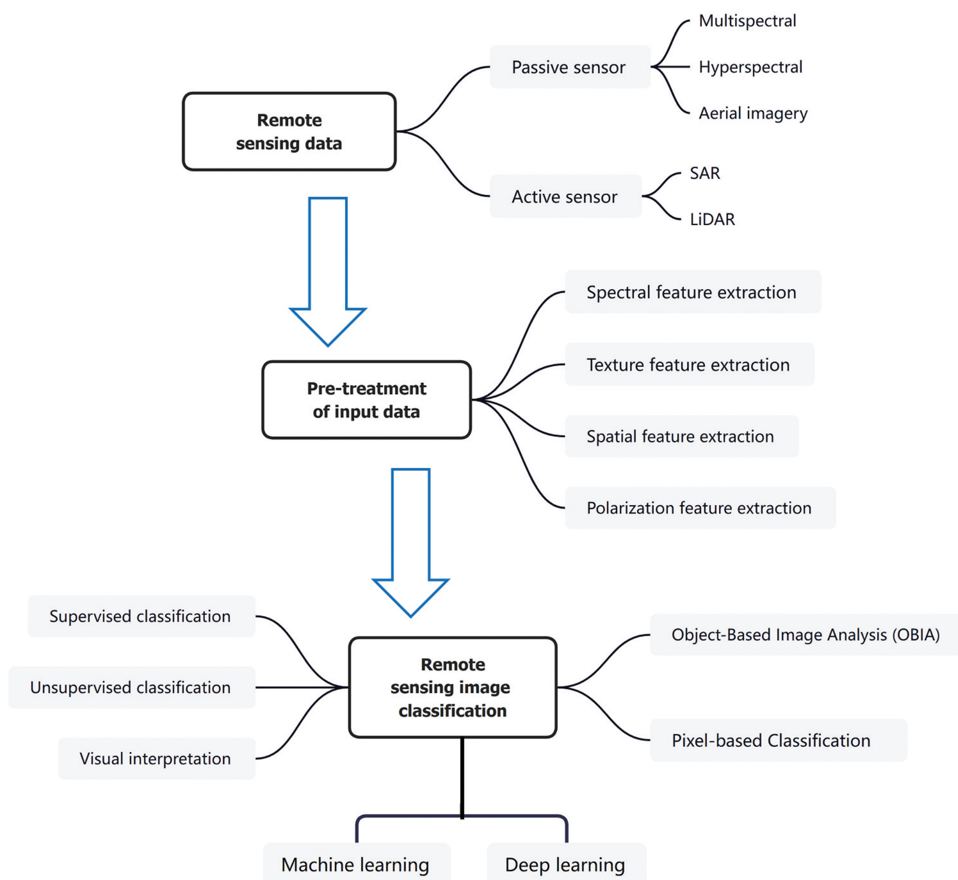

Figure 5. Primary remote sensing data and classification methods.

2.2.3.1. Health indicators. Health indicators (which were the focus of 55.8% of analyzed publications) primarily focus on assessing the biophysical parameters of mangrove ecosystems. The low value or decline of health indicators represents health status or health dynamics and can serve as proxies for mangrove degradation. First, these health indicators can be directly obtained from features of remote sensing imagery, such as spectral, spatial, and textural characteristics. The spectral signatures of mangrove vegetation are closely linked to their biophysical and biochemical properties, which can change significantly due to degradation. Remote sensing images, such as multispectral and hyperspectral imagery, can provide information on the spectral characteristics of mangroves. There are differences in spectral signatures between degraded and healthy mangroves caused by disparity in leaf pigments, water content, and canopy structure. In these studies, degraded mangroves were directly detected from remote sensing images based on spectral characteristics learned from training samples. For example, it is found that degraded mangroves in optical images appear in a grayish tone with coarse and rough texture, whereas dense/healthy mangroves exhibit a red tone due to the presence of chlorophyll and smooth texture (Thakur et al. 2021). Alternatively, health indicators (biophysical parameters) can be indirectly retrieved from the remote sensing data through spectral vegetation indices, radar indices, and composite indices or further estimation.

Spectral vegetation indices have been extensively utilized to identify and assess degraded mangrove areas based on their reduced greenness or moisture content compared to healthy mangroves, with degraded areas exhibiting lower index values. Spectral vegetation indices have been widely applied in mangrove monitoring (Baloloy et al. 2020; Pham et al. 2019; Tran, Reef, and Zhu 2022), which are typically computed by combining reflectance values obtained from different wavelength bands in the electromagnetic spectrum. NDVI is the most commonly adopted spectral vegetation index. Generally, higher NDVI values are indicative of increased vegetation health and greenness. In addition to NDVI, other commonly employed vegetation indices in mangrove degradation studies include EVI, NDM_oI NDWI, transformed difference vegetation index (TDVI), and soil-adjusted vegetation indices (SAVI). In addition, some studies have directly utilized NDVI as a proxy for net primary productivity (NPP) in mangrove ecosystems (Marshall et al. 2018), while others have employed multiple vegetation indices (e.g. EVI, MSAVI, NDVI, NDM_oI) to represent and estimate mangrove biomass (Aljahdali, Munawar, and Khan 2021). This study also compared the performance of four indices, suggesting that NDM_oI performed better in identifying degradation and recovery in sparse mangrove regions (Aljahdali, Munawar, and Khan 2021). The most used vegetation indices as a proxy of biophysical parameters due to previously proved correlation, some studies conducted further estimation on biophysical parameters. For example, some studies estimated the LAI of mangroves using linear regression models with vegetation indices like EVI (Halder and Pereira 2024) and NDVI (Kovacs et al. 2009). These empirical relationships allow for the indirect quantification of this important biophysical parameter, which are closely linked to mangrove productivity and health. Deng et al. (2023) utilized a machine learning regression approach to estimate canopy chlorophyll content (CCC) from vegetation indices derived from unmanned aerial vehicle (UAV) and Gaofen-6 satellite data. The chlorophyll content is a valuable indicator of photosynthetic capacity and can offer insights into the physiological conditions of mangrove canopies.

The sensitivity of radar indices from synthetic aperture radar (SAR) imagery to various biophysical properties, such as mangrove structure and biomass, provides complementary information to the spectral vegetation indices derived from optical sensors (Lucas et al. 2014). Several studies have leveraged the backscatter characteristics of HH and HV polarizations from L-band ALOS PALSAR and ALOS-2 PALSAR-2 data to identify mangrove degradation (Cornforth et al. 2013; Datta et al. 2022; C. K. F. Lee et al. 2021Nababa et al. 2020). Cornforth et al. (2013) and C. K. F. Lee et al. (2021) indicates that HV polarization is better correlated with mangrove structure and aboveground biomass than HH polarization. A study (Zhu, Liao, and Shen 2021) utilizing Sentinel-1 C-band data this study compared the efficacy of four radar indices in depicting mangrove degradation. These indices include the backscattering coefficients of VV and VH polarizations, $\sigma_{VH/VV}$ (polarization ratio), and polarimetric scattering entropy H. The results demonstrated that these SAR-based metrics were consistent in characterizing mangrove degradation patterns (Zhu, Liao, and Shen 2021). Additionally, a study (Cardenas et al. 2022) that employed L-band JERS-1 and ALOS PALSAR data in 1993 and 2006 showed that SAR imagery could effectively identify degraded mangrove areas based on textural differences in the backscattering response. Specifically, the study noted that degraded mangrove areas exhibited a smoother, specular backscattering pattern, in contrast to the rough volume backscattering observed in healthy mangrove stands. These findings collectively highlight the value and complementarity of SAR-based approaches in assessing and monitoring the condition of mangrove ecosystems, offering insights that may not be readily captured by traditional optical remote sensing techniques alone.

2.2.3.2. Coverage. Among the analyzed publications, 42.3% utilized coverage as a proxy for mangrove degradation, with metrics such as canopy density and fractional cover employed to estimate the proportion of each pixel occupied by mangrove canopy. Higher canopy density typically correlates with healthier mangrove ecosystems. For example, Nfotabong-Atheull, Din, and Dahdouh-Guebas (2013) differentiated degraded mangroves based on crown shape and size characteristics. Closed canopies were identified as undisturbed mangroves. The size and frequency of gaps within mangrove forests have also been used to classify degraded mangrove areas into varying disturbance levels. Additionally, ground coverage and density of the mangrove forest have been employed as indicators to distinguish between degraded and healthy mangrove stands, with lower ground coverage (generally less than 80%) associated with degraded mangroves (Blasco, Aizpuru, and Gers 2001; Connette et al. 2016; Nfotabong-Atheull, Din, and Dahdouh-Guebas 2013).

In addition, the observed absence of mangrove pixels has been used as a proxy for mangrove degradation (Eddy et al. 2017). Remote sensing techniques have been widely employed to quantify land use and land cover (LULC) related to mangrove coverage. These spatial analyses often utilize pixel-wise differencing to detect and monitor the loss of mangrove areas, resulting from various drivers, such as deforestation, conversion to other land uses, or coastal erosion. However, it is essential to note that the interpretation of these mangrove absences may not always accurately distinguish between mangrove degradation and deforestation. The pixel-based analysis may not fully capture the complexity of mangrove canopy structure and stand dynamics. The inherent pixel mixture within the remote sensing data can obscure subtle changes in mangrove canopy characteristics that are indicative of degradation, in contrast to the total removal of mangrove cover associated with deforestation.

2.2.3.3. Fragmentation. While literature focusing on using fragmentation as a proxy for assessing mangrove degradation is limited, several studies have explored this approach (Hai et al. 2022; Toosi et al. 2022). Researchers have employed fragmentation indices, such as patch size, shape, and connectivity, to characterize the spatial patterns of mangrove forests and identify areas undergoing degradation. In a notable study, Toosi et al. (2022) developed a spatial disturbance index (SDI) that incorporated various landscape metrics, such as mean patch size, patch density, mean shape index, Euclidean nearest neighbor distance (ENND), total edge, and Shannon's diversity index (SHDI). By applying principal component analysis, it can evaluate the spatial patterns associated with mangrove degradation. Furthermore, Hai et al. (2022) constructed a mangrove health index (MHI) using an analytic hierarchy process. This index comprised indicators related to mangrove canopy width, fragmentation, density, and plant diversity. These studies demonstrate the potential of adopting fragmentation metrics combining various spatial and structural attributes of the mangrove to assess degradation status.

2.2.3. Space/Time references of mangrove degradation from remote sensing

Regarding detecting and identifying mangrove degradation based on remote sensing techniques, the existing literature is broadly categorized into two primary approaches based on space and time reference: relative to a reference state (41.3% of total analyzed papers) and temporal change over time (58.7%) (Figure 4). Mangrove degradation refers to the transition of the mangrove ecosystem from one state to another, often resulting in deteriorated conditions. Remote sensing provides a valuable tool for assessing mangrove degradation by enabling comparisons to both spatial reference (relative to a reference state) and temporal reference (temporal change over time). When assessing mangrove conditions relative to a reference state, remote sensing techniques analyze single scenes to evaluate the current state of mangroves against a reference condition, which was determined using a space for time substitution in a single image. In contrast, assessments based on temporal references focus on analyzing changes in mangrove conditions across multiple time periods. This method involves the use of multiple remote sensing data to monitor how the mangrove ecosystem has altered or deteriorated over time.

2.2.3.1. Relative to a reference state. Around 42% of analyzed publications employed space references for mangrove degradation. Mangrove health conditions are directly detected and mapped from single-date satellite imagery. The mangrove states are typically classified into several distinct classes, such as degraded and healthy/intact mangroves. Some studies compare the current condition of mangroves with an expected healthy condition, which serves as an ideal or baseline state. This reference is typically derived from established knowledge of the spectral and texture characteristics of both degraded and healthy mangroves in specific remote sensing imagery. Such knowledge can then be utilized for unsupervised and supervised classification (Connette et al. 2016), as well as visual interpretation (Nfotabong-Atheull, Din, and Dahdouh-Guebas 2013). For example, in Hayashi et al. (2023) study, degraded mangroves were detected based on rules that identified areas with low development of mangroves, compacted sediments, and low frequency of tidal flooding.

Additionally, there are also papers that establish space references using known indices and thresholds to determine mangrove degradation. For instance, density and coverage metrics provide quantitative measures of mangrove extent. Known thresholds to determine degradation have been applied, such as canopy density and proportion of coverage (Nayak and Bahuguna 2001). Moreover, indices such as NDVI are commonly used to assess mangrove health, with specific NDVI thresholds indicating the transition from healthy to degraded states (Jones et al. 2015; Valderrama-Landeros et al. 2018).

Another type of reference state is based on the range of observed values, which relies on using index-based rules and thresholds (Sahana et al. 2022; Servino, de Oliveira Gomes, and Bernardino 2018). This method aims to delineate different levels of mangrove degradation, typically categorized into classes such as healthy, moderately degraded, and severely degraded. In this approach, various indices (satellite-derived index, landscape index, and new composite index) are employed as proxy indicators of mangrove degradation. Specifically, Meyer et al. (2019) developed a vegetation index-based composite index, forest degradation index (FDI), which is the sum of three components: top mean canopy height (TCH), large tree canopy area (LCA), and forest percentage cover (PC). Datta et al. (2022) applied a radar forest degradation index (RFDI), which is a normalized ratio of HH and HV backscatter, to assess mangrove degradation. A wetland ecosystem health index (WEHI) based on the pressure-state-response model was developed to assess wetland health across various levels of degradation (Sahana et al. 2022).

2.2.3.2. Temporal change over time. In addition to the static classification approach, an alternative method for mapping mangrove degradation involves using multi-temporal change detection analysis. This approach involves comparing two or more satellite images acquired at different time periods to detect changes in mangrove cover and status, including identifying degraded areas. Temporal information can help identify the underlying causes of mangrove degradation, such as human activities, natural disturbances, or climate-related factors.

(1) Bi-temporal differences

This method is based on bi-temporal differences in LULC or health index. By comparing the index values or LULC between two time periods, it is possible to highlight areas where mangrove cover has changed, including areas that have experienced degradation. Tracking the changes derived from satellite images over time can offer insights into the temporal patterns and dynamics of mangrove conditions. The LULC dynamic-based change detection methodology involves the classification of mangrove cover in two satellite images acquired at different time periods, commonly referred to as the “from” and “to” images. This approach effectively captures the disappearance or conversion of mangrove areas as an indicator of degradation. Following the classification of mangrove cover for the two time periods, a pixel-wise differencing operation is performed to detect mangrove changes. Specifically, the identification of mangrove degradation can be approached through two specific schemes based on classification results from two distinct periods. First, pixels that exhibit a change from “dense” to “sparse” mangrove (Hauser et al. 2020) or a decrease in dense mangrove coverage alongside an increase in sparse mangrove coverage (Kanjin and Alam 2024) are classified as areas of mangrove degradation. Second, pixels that were classified as mangrove in the "from" image but not in the "to" image are also recognized as areas of mangrove degradation (Jia et al. 2014; Liman Harou et al. 2023). However, it is crucial to note that this conversion in the second scheme is sometimes perceived as mangrove deforestation rather than degradation.

In addition to the LULC dynamic-based change detection approach, some of the studies on mangrove degradation employ a change detection analysis based on mangrove health indices. These studies involve the classification of mangrove health conditions using various indices in two different time periods. The decrease in the health condition indices between the two time periods is used as an indicator of mangrove degradation. The health condition is typically assessed using vegetation index (e.g. NDVI, enhanced vegetation index (EVI), leaf area index (LAI), gross primary productivity (GPP)) (Akhand et al. 2017; Ayanlade and Drake 2016; Ayanlade and Howard 2016; Etemadi, Smoak, and Abbasi 2021; Hasan et al. 2024; Rajitha et al. 2010; Samanta et al. 2021; Singh and Schoenmakers 2023; Solanki et al. 2022; Toor, Tater, and Chandra 2024), radar indices (e.g. backscatter, polarimetric features) (Cornforth et al. 2013), landscape index (e.g. fragmentation, connectivity) (Hai et al. 2022) and composite index (mangrove health index (MHI)) (Hai et al. 2022; Halder and Pereira 2024) to infer the greenness, biomass, and fragmentation of the mangrove ecosystem. This approach focuses on the mangrove environment's ecological health and functional aspects, rather than solely on the areal extent or land cover changes.

(2) Time series trend

Utilizing time series satellite images to detect the long-term trends in mangrove conditions provides valuable insights into the degradation and recovery processes. By analyzing the temporal patterns and trajectories of mangrove-related indices or spectral characteristics, researchers can identify areas that have experienced gradual or abrupt changes, indicating degradation or recovery. Trend analysis can help distinguish between temporary disturbances and persistent degradation of the mangroves. Some research has applied trend analysis to detect mangrove degradation (Aljahdali, Munawar, and Khan 2021; Hong, Avtar, and Fujii 2019; Thakur et al. 2021; Vancutsem et al. 2021; Wu et al. 2022; Zhu, Liao, and Shen 2021). For instance, in some studies (Aljahdali, Munawar, and Khan 2021; Vancutsem et al. 2021; Zhu, Liao, and Shen 2021), trend analysis (e.g. Theil-Sen, Mann–Kendall test, Hurst exponent) or linear regression (least square regression) was used to analyze long-time series satellite images. The significant decreasing trends in vegetation indices (NDVI, EVI, MSAVI (modified soil-adjusted vegetation index), and NDM_oI) represent the occurrence of mangrove degradation over this period. The integration of time series analysis and trend detection methods can offer a more thorough and holistic understanding of the temporal patterns, dynamics and trajectories of mangrove ecosystems, thereby enhancing the detection and characterization of mangrove degradation processes. Vancutsem et al. (2021) achieved a high overall accuracy of 91.4% for its disturbance mapping, encompassing both deforestation and degradation classes. This underscores the potential of integrating trend analysis to produce accurate degradation maps. Trend analysis techniques are primarily employed to detect changes in mangrove distribution or proxies like NDVI over various time periods, the observed decline trends are indicative of degradation. However, most trend analysis studies tend to only report classification accuracy for individual time points (Hong, Avtar, and Fujii 2019) or do not report accuracy as degradation was measured by the decreasing trend of NDVI (Aljahdali, Munawar, and Khan 2021), rather than the accuracy of the final degradation maps derived from trend analysis.

2.2.4. *Primary remote sensing data*

Remote sensing data utilized in mangrove degradation research encompasses a diverse range of sensor platforms (Figure 5), including passive sensors (multispectral and hyperspectral optical imagery, aerial imagery) and active sensors (SAR, light detection and ranging (LiDAR)).

2.2.4.1. Passive and active sensors. Among the commonly employed optical data sources are the Landsat series (TM, ETM+, OLI), Sentinel-2, and MODIS, with Landsat data accounting for about 60% of the total publications in the field. The availability of high-resolution satellite sensors allows high accuracy mangrove mapping and improved discrimination between healthy and degraded vegetation. High-resolution optical such as SPOT, WorldView-2, QuickBird, GaoFen-6, RapidEye, PlanetScope, RESURS, ALOS-1 AVNIR-2, CORONA, Resourcesat-2A LISS, and KeyHole-9, have been employed in local-scale analyses (Blasco and Aizpuru 2002; Blasco, Aizpuru, and Gers 2001; Deng et al. 2023; Dev Roy and Trivedi 2023; Giri et al. 2007; Kovacs et al. 2009; McCarthy, Jessen, and Barry 2020; McCarthy et al. 2020; Toosi et al. 2022; Valderrama-Landeros et al. 2018; Veettil 2022; Walcker et al. 2019). For example, Deng et al. (2023) utilized image from the Chinese civilian remote sensing satellite GaoFen-6, with a spatial resolution of 8 m, to estimate species-level canopy chlorophyll content and infer the degradation status of mangroves in the Beibu Gulf region of Guangxi, China. Furthermore, Valderrama-Landeros et al. (2018) showed that WorldView-2 imagery (1.6 m spatial resolution), achieved the highest accuracy in differentiating dead mangrove and various mangrove species compared to SPOT-5 (10 m), Landsat-8 (30 m), and Sentinel-2 (10 m) data.

Moreover, hyperspectral remote sensing, which collects data in hundreds of narrow spectral bands, has shown potential for a more accurate classification of mangrove health status by detecting subtle differences in leaf chemistry and structure (Hati et al. 2022; Vidhya et al. 2014). For example, Vidhya et al. (2014) suggested the effectiveness of hyperspectral data in monitoring mangrove health and distinguishing between degraded, healthy, and sparse mangrove areas. Hati et al. (2022) used airborne hyperspectral AVIRIS-NG data and the SAM method to separate healthy and degraded mangroves in India based on various vegetation indices.

In addition, aerial images have also been used for visual interpretation of degraded mangroves in Cameroon (Nfotabong-Atheull, Din, and Dahdouh-Guebas 2013) and Kenya (Dahdouh-Guebas et al. 2004) during the 1970s, 1990s, and 2000s. These aerial images were scanned and enlarged to very high resolution, around half-meter pixel resolution, to enable better identification of degraded mangrove areas. In recent years, UAV imagery has become available and has been utilized to complement satellite data. Studies have used UAV images from DJI Phantom 4 (Cardenas et al. 2022) and Matrice 200 (Deng et al. 2023) platforms to assist in estimating mangrove canopy height and chlorophyll content information, which can provide additional details not easily captured by satellite imagery alone.

Among active sensors, SAR data has proven effective in retrieving various biophysical properties of mangrove vegetation, such as structure and biomass. SAR data used in mangrove studies includes ALOS PALSAR, ALOS-2 PALSAR-2, Sentinel-1, and JERS-1 (Cardenas et al. 2022; Cornforth et al. 2013; Datta et al. 2022; C. K. F. Lee et al. 2021; Nababa et al. 2020; Thomas et al. 2017; Zhu, Liao, and Shen 2021). The unique capabilities of SAR sensors, which can collect data without being hindered by cloud cover and time, make them invaluable for monitoring dynamic coastal environments like mangrove forests. For example, Datta et al. (2022) has utilized SAR data (ALOS PALSAR and ALOS-2 PALSAR-2) to identify mangrove degradation based on RFDI, which is a normalized ratio of HH and HV polarizations (Datta et al. 2022; Zhu, Liao, and Shen 2021). Several research have also shown the effectiveness of using the backscatter characteristics of HH and HV polarizations from SAR data to assess mangrove degradation (Cornforth et al. 2013; Datta et al. 2022; Lee et al. 2021; Nababa et al. 2020).

The use of LiDAR can provide additional insights into mangrove structure attributes (e.g. height) and biomass, which are essential for understanding degradation processes and ecosystem health (Salum et al. 2020; Yin and Wang 2019). In a LiDAR-based study (Meyer et al. 2019), a forest degradation index (FDI) was constructed using LiDAR-derived height and biomass models, along with a Random Forest prediction approach. The FDI enabled the classification of mangrove areas into intact and degraded categories, demonstrating the potential of integrating LiDAR data for a more comprehensive assessment of mangrove conditions. Similarly, Cardenas et al. (2022) utilized drone-generated point cloud data combined with Digital Surface Models to estimate mangrove canopy height, achieving high-resolution vertical structure mapping for mangrove degradation assessment.

Integrating diverse remote sensing datasets could enable more comprehensive characterization and monitoring of mangrove ecosystems. The most common integration involves combining optical data (e.g. Sentinel-2, Landsat) with SAR data (e.g. Sentinel-1, ALOS PALSAR), where SAR complements optical imagery in cloud-prone regions (Cardenas et al. 2022) or is fused with optical features in Random Forest models for degradation classification (Halder and Pereira 2024; Lee et al. 2021). Additionally, LiDAR is frequently paired with optical data to refine mangrove extent mapping and provide precise height and biomass estimates (Meyer et al. 2019).

2.2.4.2. Pre-treatment of input data. Existing literature extracted spectral, texture, spatial, and polarization features of input remote sensing data. Spectral signatures in different bands can be used to assess healthy versus degraded mangrove areas (L. Wang et al. 2019). As stated in Dev Roy and Trivedi (2023), the feature of degraded mangroves in optical images is irregular and smooth. In the panchromatic band, the tone of degraded mangroves is typically white or light gray, in contrast to the black or dark gray tone of healthy mangroves. In the false-color composite, the tone of degraded mangroves is pale red, compared to the bright red representation of healthy mangroves.

The modification of bands plays a critical role by emphasizing specific spectral or polarization characters that are essential for accurately assessing mangrove health and condition. Spectral vegetation indices, which are mathematical combinations of multiple spectral bands, are effective in enhancing vegetation signal, such as EVI, NDVI, NDMI, and NDWI. In the context of mangrove degradation detection, Datta et al. (2022) applied RFDI to assess mangrove degradation, which is a normalized ratio of HH and HV polarizations. Moreover, C. K. F. Lee et al. (2021) and Nababa et al. (2020) used a combination of radar indices (HV, HH) and vegetation indices (NDVI, normalized difference moisture index (NDMoI), and normalized difference water index (NDWI)) as input features for RF classification to map mangrove degradation.

2.2.5. Remote sensing image classification

2.2.5.1. Object-based and pixel-based classification. Object-based classification involves dividing the image into homogeneous objects based on their properties (such as spectral, spatial, and textural features), and then classifying these objects into mangrove classes (Kuenzer et al. 2011), including the degraded mangrove class. Several studies have demonstrated that this approach can provide more accurate results than traditional pixel-based classification, particularly in heterogeneous mangrove environments (Wang et al. 2018). The commonly used algorithm in mangrove degradation studies is the multi-resolution segmentation algorithm in mangrove degradation studies (Cardenas et al. 2022; Dev Roy and Trivedi 2023; Hayashi et al. 2023). It is an object-oriented image classification based on scale, shape, and compactness (Wang et al. 2018). This method considers both the spatial and spectral characteristics of groups of pixels, capturing the inherent heterogeneity and structure of the mangrove landscape.

In contrast, pixel-based classification combined with various classifiers can accurately differentiate between healthy and degraded mangrove classes due to the subtle spectral differences (Blasco, Aizpuru, and Gers 2001; Connette et al. 2016; Nfotabong-Atheull, Din, and Dahdouh-Guebas 2013). This method treats each pixel as an independent unit, analyzing its spectral information to determine whether it corresponds to healthy mangroves, degraded areas, or other land cover types. However, pixel-based classification may encounter mixed pixel issues, where a single pixel contains a combination of healthy and degraded mangroves.

2.2.5.2. Approaches to training classes and classifiers. Some studies have manually identified and digitized degraded mangroves based on features such as size, color, and texture (Eddy et al. 2017, 2021; Khairuddin et al. 2016; Thomas et al. 2017). The texture and spatial patterns of the canopy can vary considerably between healthy and disturbed mangrove areas. For example, Ramachandran et al. (1998) characterized the features of degraded mangroves in SPOT, IRS LISS II, and Landsat 5 imagery as having a grayish tone, coarse, and rough texture, in contrast to the dense mangrove stands, which exhibits a red tone due to the presence of chlorophyll and smooth texture.

Beyond visual interpretation, there are a variety of supervised and unsupervised classification approaches that have been employed to map degraded mangroves from satellite imagery. The unsupervised classification methods include ISODATA and K-means (Beitl et al. 2019; Bosire et al. 2014). Supervise classification mainly relies on machine learning methods, such as, random forest (RF) (Connette et al. 2016; Senger et al. 2021), maximum likelihood (ML) (Majumdar et al. 2019; Salami, Akinyede, and De Gier 2010), gaussian maximum likelihood (Connette et al. 2016), support vector machine (SVM) (McCarthy et al. 2020), Neural Network (McCarthy et al. 2020), and decision tree (Kuenzer et al. 2014; McCarthy, Jessen, and Barry 2020; McCarthy et al. 2020). Machine learning has been widely used for mangrove degradation, using advanced algorithms to classify pixels or objects based on training data. These methods rely on the distinctive spectral signatures of different mangrove cover types, learned from training data, to differentiate between healthy and degraded mangrove areas.

In addition to machine learning, deep learning methods have been applied to mangrove degradation detection, due to their ability to learn complex information and require few samples for effective performance. For example, Jamaluddin et al. (2021) applied the MDPrePost-Net deep learning method with vegetation indices using Sentinel-2 data to separate intact or degraded mangroves due to Hurricane Irma in Florida. The study demonstrated that indices such as NDVI, normalized difference mangrove index (NDMaI), combined mangrove recognition index (CMRI), and modular mangrove recognition index (MMRI) could improve the accuracy of distinguishing degraded mangroves from intact mangroves. Panuntun et al. (2024) proposed a LinkNet-Spectral-Spatial-Temporal Transformer model, demonstrating a better and more effective performance compared to existing deep learning and machine learning models. While the proposed novel deep learning model achieved the highest accuracy, all other deep learning models evaluated in the comparison (e.g. U-Net, LinkNet, MDPrePost-Net, SST-Former) demonstrated superior performance over traditional machine learning approaches (RF and SVM) in terms of overall accuracy, mean IoU, and F1-score (Panuntun et al. 2024). By comparing the overall accuracies of selected studies that detected degraded mangroves as a distinct class across different classification methods (Figure 6), most classifiers performed well, with a mean overall accuracy exceeding 85%. Deep learning models achieved the highest accuracy, outperforming other machine learning approaches (e.g. RF, SVM) and object-based classification methods. In contrast,

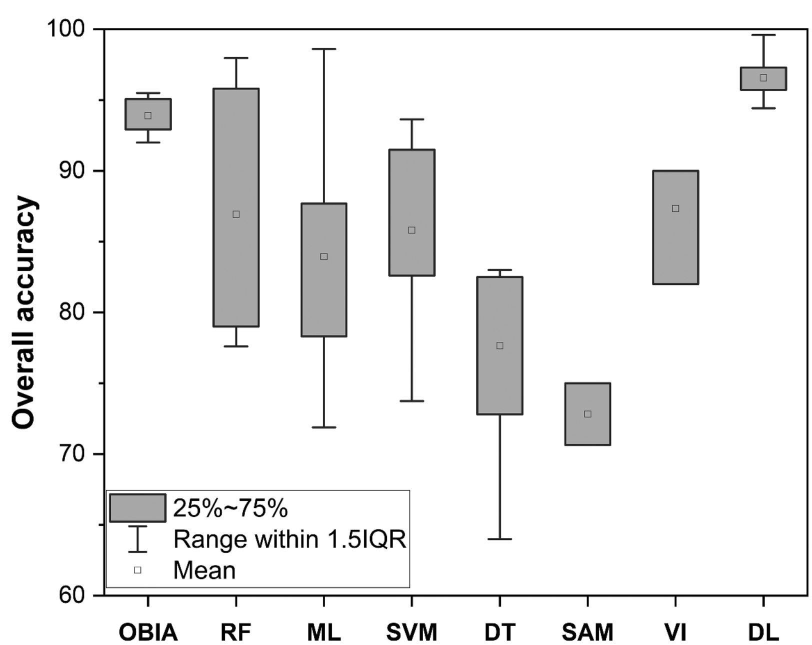

Figure 6. Box plot of overall accuracies of selected studies that detected degraded mangroves as a class based on different classification methods. (OBIA- Object-based image analysis; RF- Random forest; ML- Maximum likelihood; SVM- Support vector machine; DT- Decision tree; SAM- Spectral angle mapper; VI- visual interpretation; DL-Deep learning).

decision tree-based classifiers and the Spectral Angle Mapper exhibited relatively lower performance, with accuracies around 80%. However, due to the variability in proxies and criteria used to define mangrove degradation across studies, it is challenging to determine which data or methodological approach represents a better practice based solely on direct comparisons of mapping accuracy.

3. Challenges

3.1. Difficulty in selecting optimal proxies for mangrove degradation

Mangrove degradation is frequently assessed using proxy indicators derived from remote sensing, such as vegetation indices (e.g. NDVI, EVI), canopy cover, and biomass estimates. As reviewed above, mangrove health conditions (Etemadi, Smoak, and Abbasi 2021; Thakur et al. 2021), often quantified through spectral vegetation indices like NDVI, are the most widely adopted (Marshall et al. 2018). For instance, NDVI is commonly used as the proxy of greenness, biomass, or NPP, which is then interpreted as a measure of mangrove degradation. However, selecting the most appropriate proxy remains a challenge, as each indicator captures only one aspect of degradation (e.g. vegetation health, structural changes, or ecosystem functions), leading to incomplete or biased assessments. For example, NDVI may indicate greenness but fail to capture structural degradation. Similarly, biomass proxies may overlook functional declines, such as reduced carbon sequestration capacity. Overreliance on single proxies may oversimplify degradation, leading to incomplete or misleading conclusions about mangrove health (Hai et al. 2022). In addition, variability in proxy selection complicates cross-regional comparisons and validation, which may hinder policy standardization, and reliable baseline establishment for restoration.

3.2. Confusion between degradation and deforestation

Deforestation and degradation are distinct ecological processes but are often confused in remote-sensing studies. Deforestation refers to the complete removal of mangrove cover, often associated with land-use conversion (e.g. to aquaculture or urban areas), whereas degradation means a reduction of mangrove attributes, function, or ecosystem services without full removal of mangrove areas (Friess et al. 2019). For example, some articles define degradation as the complete conversion of mangrove ecosystems to other land covers, which closely resembles the definition of deforestation (Liman Harou et al. 2023). Actually, it is difficult to distinguish deforestation and degradation, especially in coarse-resolution remote sensing imagery. Pixels containing thinning mangrove canopies or decreased greenness might be classified as deforested mangroves in coarse-resolution imagery due to spectral averaging. Misclassification between degradation and deforestation (Souza et al. 2013) can lead to over- or underestimation of the extent of mangrove degradation.

3.3. Differentiating true degradation from natural variability

Distinguishing true degradation from the natural variability of mangroves remains a critical challenge in remote sensing assessment. Mangroves exhibit inherent variability due to factors such as stand age, seasonal changes, environmental differences or tidal fluctuations, all of which can mimic degradation signals in spectral or structural data. For example, young mangrove stands in early growth stages or naturally sparse stands (e.g. species like *Avicennia* or *Sonneratia*) (Taureau et al. 2019) often exhibit lower canopy density or height. These traits may be misinterpreted as degraded vegetation, despite being healthy. In addition, tidal inundation may alter the spectral properties of mangroves (Wang et al. 2019), leading to inaccurate assessments. Existing literature has often relied on single-date imagery or long-term (e.g. decadal) change detection approaches to identify and quantify mangrove degradation (Datta et al. 2022; Hamuna, Kalor, and Tablaseray 2019). However, some commonly used indicators of mangrove health, such as greenness and biomass, are sensitive to the natural phenological cycles of these ecosystems and can exhibit regular fluctuations over time (Pastor-Guzman, Dash, and Atkinson 2018). Relying on these indicators without sufficient temporal frequency can confound the distinction between seasonal changes and degradation trends. Remote sensing assessments require a sufficiently high temporal frequency of observations to accurately differentiate between mangrove phenological changes and degradation. This allows for the detection of short-term changes and the separation of seasonal/cyclical variations from long-term degradation trends.

3.4. Uncertainty from varied resolutions and mixed pixel

The choice of spatial resolution of remote sensing data significantly influences mangrove degradation assessment, introducing uncertainties that stem from mixed pixels and scale-dependent misclassification. Sensors with coarse-resolution data often aggregate spectral signals from heterogeneous surfaces and lead to mixed pixels (Kuenzer et al. 2011). A single pixel contains a combination of both degraded and healthy mangroves, as well as non-mangrove features (L. Wang et al. 2019), obscuring fine-scale degradation patterns. This can introduce uncertainty in the classification of degraded mangrove areas. Coarse spatial resolution satellite data may average spectral signals and limit the ability to capture the fine-scale details and heterogeneity within mangrove ecosystems, hindering the detection of early stages of degradation or small patches of degradation. Mangrove forests often exhibit high species diversity and structural complexity (Datta et al. 2022). Optical sensors struggle to differentiate spectrally similar but ecologically distinct classes, such as stressed *Avicennia* vs. healthy *Sonneratia*. In addition, partial degradation in a single pixel may be mislabeled as deforestation in coarse-resolution data due to dominant spectral signals from water or bare soil.

4. Opportunities

4.1. Integrating multi-source datasets for holistic insights

Mangrove degradation monitoring is hindered by environmental and technical challenges as discussed in Section 3. Factors such as tidal cycles, cloud cover, and atmospheric conditions can significantly impact the spectral response of mangrove canopies, making it challenging to obtain reliable and consistent observations over time from optical sensors. Emerging remote sensing technologies, including hyperspectral sensors, UAV, SAR, and LiDAR, offer synergistic solutions when integrated, enabling robust, multi-dimensional assessments of mangrove degradation.

UAV-based remote sensing can generate data with very high spatial resolution images, enabling the detailed mapping of mangrove species, canopy structure, and condition at the individual tree or stand level (Cardenas et al. 2022; Deng et al. 2023). It is useful to distinguish deforestation and degradation caused by coarse-resolution remote sensing data. UAV-mounted sensors, such as RGB, multispectral, or thermal cameras, have been used to assess multiple mangrove health indicators. In addition, hyperspectral sensors can capture detailed spectral information, facilitating the differentiation of individual mangrove species and the detection of subtle changes in canopy chemistry associated with degradation. Studies have demonstrated hyperspectral data can effectively map mangrove species composition, biomass, and stress indicators, such as changes in chlorophyll content or water content (Hati et al. 2022; Vidhya et al. 2014).

Furthermore, SAR data, which uses microwave radiation to penetrate cloud cover and dense canopies, effectively maps mangrove extent, structure, and biomass. SAR data allows for consistent monitoring in tropical and cloudy regions. Researchers have utilized multi-temporal SAR data to detect changes in mangrove canopy structure and infer degradation (Cornforth et al. 2013; Datta et al. 2022), especially in regions with frequent cloud cover that restricts the use of optical satellite imagery. Advancements in LiDAR technologies can provide detailed information on mangrove canopy structure, biomass, and even belowground carbon stocks (Meyer et al. 2019).

Importantly, integrating multiple sources of remote sensing images is a vital step in achieving comprehensive and accurate monitoring of mangrove ecosystems (Cardenas et al. 2022; Giri et al. 2007). By fusing data from various satellite platforms, sensors, and spatial resolutions, researchers can overcome the limitations of individual data sources and capture the spatial, temporal, and spectral complexities of mangrove habitats. It is possible to reduce reliance on single proxies and improve the accuracy of mangrove degradation monitoring. In addition, multi-source integration with ancillary spatial data (e.g. aquaculture development, natural disaster, pollution sources, and coastline erosion) could enhance the accuracy of mangrove condition assessment (Aljahdali, Munawar, and Khan 2021).

4.2. Leveraging advanced techniques for accurate degradation monitoring

Recent advancements in technology, open philosophies, and statistical validity could enhance mangrove degradation monitoring, allowing researchers to address longstanding challenges with greater precision and transparency. These advancements facilitate the differentiation of true degradation from natural variability, improve proxy-based analyses, and enhance the decomposition of mixed-pixel scenarios.

4.2.1. Technological advancements in remote sensing

Previous studies mainly relied on biological parameters such as greenness and biomass as a proxy for mangrove degradation to achieve robust and comprehensive monitoring (Aljahdali, Munawar, and Khan 2021; Etemadi, Smoak, and Abbasi 2021). Incorporating ecosystem service indicators is also crucial for comprehensive mangrove degradation assessment. By linking the biophysical parameters extracted from remote sensing data to the ecosystem services offered by mangrove forests, such as coastal protection and carbon sequestration, a nuanced evaluation of mangrove conditions would be achieved. Deep learning models are capable of handling complex datasets and identifying subtle patterns that traditional methods may overlook (Jamaluddin et al. 2021). Furthermore, artificial intelligence-driven models can integrate mangrove conditions with environmental data, effectively resolving the confusion between degradation and natural variability. These approaches enhance classification accuracy by identifying patterns across multiple dimensions.

Platforms like Google Earth Engine store and organize petabytes of satellite data into spatially aligned and analysis-ready formats, enabling large-scale mangrove extent mapping (Jia et al. 2023). Data cubes (Chen, Wang, and Gong 2023) enable the seamless integration of multi-temporal, multi-sensor datasets. These platforms could facilitate large-scale monitoring of mangrove degradation, making it more feasible and cost-effective. Additionally, advancements in cloud computing and computational capacity allow for real-time processing of dense time series data (Binh et al. 2024), facilitating rapid alerts for mangrove disturbances.

4.4.2. Transition to open philosophies

Collaborative code-sharing forums (e.g. GitHub) enable researchers to share open-source scripts for mangrove estimation (Simard et al. 2025), deep learning classification algorithms, and time series analysis. This promotes technical exchange, accelerates methodological improvements, and ensures reproducibility across studies. Access to free data is gradually increasing. The GEE platform provides free, high-quality, and global-scale satellite imagery, enabling cost-effective monitoring in resource-limited regions (Yang et al. 2022; Zhao et al. 2021). Local open data initiatives, such as those by the Hong Kong government, which provide free aerial imagery covering the entire territory, have demonstrated the effectiveness of estimating accurate mangrove cover (Zhang et al. 2025).

Collaborative initiatives, such as the Global Mangrove Alliance and the International Blue Carbon Initiative (Herr et al. 2017) of the United Nations Environment Programme (UNEP), could facilitate harmonized monitoring protocols and share best practices across borders. The Global Mangrove Alliance has launched the Global Mangrove Watch platform (https://www.globalmangrovewatch.org/), which displays interactive maps and statistics on mangrove cover, species distribution, height, and dynamics, serving as a critical baseline for policymakers. For some local initiatives, integrating indigenous knowledge with remote sensing data could enable local communities to both contribute to and benefit from degradation assessments.

4.2.3. Improvements in statistical validity

Integrating time series analysis techniques is crucial for monitoring mangrove degradation (Vancutsem et al. 2021; X. Yang et al. 2024; Zhu, Liao, and Shen 2021). By examining the temporal dynamics of mangrove ecosystems using high-frequency remote sensing data, researchers can better differentiate between seasonal fluctuations, disturbance-driven changes, and persistent degradation trends. Analyzing mangrove changes over multiple time steps to identify persistent losses (deforestation) versus cyclic or fluctuating changes (degradation) enables a more detailed and precise representation of mangrove conditions across different time periods.

Approximately 59% of the studies examined or discussed the drivers of mangrove degradation, encompassing both natural (e.g. climate change, natural disasters, coastal erosion) and anthropogenic factors (e.g. land use change, pollution, overexploitation, infrastructure development). Driver analysis of mangrove degradation could consider geographical, ecological, climatic, and social perspectives to develop a comprehensive understanding of the underlying causes (Yando et al. 2021). By investigating the interactions between factors such as land use changes, climate change, and socioeconomic pressures, researchers can better evaluate the complex drivers of mangrove degradation. This holistic approach is crucial for informing sustainable development strategies that address the coupled human-nature dynamics in mangrove-dependent regions. By bridging the biophysical and social dimensions, researchers can gain a more nuanced understanding of how human activities, policies, and institutional arrangements interact with and influence the condition of mangrove forests (Beitl et al. 2019). Statistical advancements also enhance the ability to quantify uncertainties in degradation assessments, improving the scientific validity and reliability of results.

4.3. *Implications of accurate mangrove degradation monitoring*

Accurate mangrove degradation monitoring could offer actionable insights for conservation, climate policy, and sustainable development. First, it strengthens evidence-based conservation and restoration strategies by enabling policymakers to prioritize high-risk areas and allocate resources efficiently (Dabalà et al. 2023). Early detection of degradation allows timely interventions that reduce long-term restoration costs (Zimmer et al. 2022). This will bridge remote sensing data with actionable management strategies, ensuring degraded ecosystems are restored before reaching ecological tipping points and safeguarding biodiversity and coastal resilience.

In addition, the implications of mangrove degradation monitoring extend beyond the immediate ecological consequences to support Environmental-Economic Accounting (Ramesh et al. 2023) and climate action (Donato et al. 2011). Mangroves are critical carbon sinks, storing more carbon per hectare than terrestrial forests (Donato et al. 2011). Precise monitoring quantification of degradation-driven carbon emissions can inform blue carbon projects and international commitments related to mitigating and adapting to climate change (Senger et al. 2021). Accurate monitoring thus transforms ecological data into economic and policy tools, advancing equitable climate resilience and sustainable development, which is aligned with the UN Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action) and SDG 14 (Life Below Water) (Eyzaguirre, Iwama, and Fernandes 2023).

5. Conclusions

This review provided an overview of mangrove degradation studies that utilized remote sensing techniques. We found that the specific proxies of mangrove degradation derived from remote sensing data to assess mangrove degradation predominantly fall into three broad categories: health indicators (e.g. canopy condition, biomass, and productivity), coverage and fragmentation. Remote sensing enables comparisons to both spatial reference (relative to a reference state) and temporal reference (temporal change over time). Based on previous publications, we detected some key challenges, including difficulty in selecting optimal proxy, confusions between degradation and deforestation, confusions between true degradation and natural variability, and uncertainty caused by coarse resolution. Nonetheless, the growing accessibility of advanced remote sensing technologies and data sources offers significant opportunities. Accurate and comprehensive monitoring of mangrove degradation could significantly inform and guide sustainable coastal management and restoration efforts, helping to preserve the invaluable ecological and socioeconomic benefits provided by these critical ecosystems.

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Data availability statement

The data that support the findings of this study are available in Figshare https://doi.org/10.6084/m9.figshare.27125385.v1.

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