



Determining Changes in Mangrove Cover Using Remote Sensing with Landsat Images: a Review

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Abstract Mangroves are ecosystems within the intertidal zone of tropical and subtropical coasts; they offer ecosystem services such as protection from coastal erosion and storms and flood control, act as carbon sinks and are also sources of income by providing various forest products. However, their cover is rapidly disappearing worldwide, which makes the diagnosis and monitoring of the state of these important ecosystems, as well as their restoration and conservation, a challenge. Remote sensing is a promising technique that provides accurate and efficient results in the mapping and monitoring of these ecosystems. The Landsat sensor provides the most used medium-resolution images for this type of study. The main objective of this article is to provide an updated review of the main remote sensing techniques, specifically Landsat satellite imagery, used in the detection of changes and mapping of mangrove forests, as well as a review of climatic and/or chemical factors related to changes in the spatial distribution of these ecosystems.

Keywords Coastal ecosystem · Estuarine ecosystems · Landscape ecology · GIS · Forest change

Abbreviations/Acronyms

AF	Aerial photography
DT	Decision tree
FCC	False colour composition
GIS	Geographic information systems
ML	Maximum likelihood
MNDWI	Modified normalized difference water index
NDMI	Normalized difference moisture index
NDVI	Normalized difference vegetation index
NDWI	Normalized difference water index
OA	Oriented segmentation
RF	Random forest
SAVI	Soil-adjusted vegetation index
SVM	Support vector machines
VI	Visual interpretation

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1 Introduction

Mangroves can be found in tropical and subtropical climates (Jaelani et al., 2021) and in the intertidal zones and estuaries (Constance et al., 2021). These ecosystems are among the most productive and complex on the planet, growing under extreme environmental conditions (Nguyen et al., 2020a) such as

places with high salinity, high temperatures and the muddy substrates (Gopalakrishnan et al., 2021).

Mangrove forests comprise 73 plant species and cover a total area of 152,000 km² worldwide, across 123 countries (Das & Dhorde, 2021), including notable forested areas of Malaysia, India, Bangladesh, Brazil, Venezuela, Nigeria and Senegal (Saravanan et al., 2018). From this perspective, they provide numerous ecosystem services because they are the habitat of fish communities, flora and benthic fauna, which are crucial in the protection of the coast and for assimilating waste through the purification of marine water and the surrounding air (Nguyen et al., 2020a).

For this reason, mangroves have an important role as carbon sinks because they can store carbon in sediments, reaching up to 22.8 million metric tons of CO₂ per year worldwide (Aljahdali et al., 2021). Supported by this fact, mangroves provide a variety of ecosystem services, generating dynamic ecotourism activities that provide economic benefits and income for fishermen (Abhyankar et al., 2021; Toosi et al., 2019).

Considering the challenges of this ecosystem, mangroves worldwide are experiencing a decline due to their degradation and indiscriminate deforestation (Afiesimama et al., 2021) and conversion to other land uses (Sakti et al., 2020). Thus, there is global evidence that mangrove cover has declined over the last 20 years (FAO, 2023).

Therefore, there is a growing concern about the vulnerability of these strategic ecosystems because some studies project their total disappearance within 100 years (Castillo et al., 2021). That is why monitoring cover changes of these ecosystems is crucial to understand the current risks and future challenges of mangroves and the implementation of effective policies for their conservation. Therefore, the use of remote sensors is an appropriate technology for monitoring and tracking cover changes in mangrove ecosystems, which, together with geographic information systems (GIS), become effective tools for the quantitative analysis of cover extent and cover change studies (Elmahdy & Ali, 2022).

2 Remote Sensing Methods

Remote sensing is a useful tool to assess the extent and spatiotemporal changes in mangrove forests; because this information is usually difficult to obtain

through field monitoring due to the difficult access to this ecosystem, however, it is necessary to validate the remote sensing data to ensure that the identified parameters are set correctly (Maurya et al., 2021).

Over time, specific techniques have been developed to characterize mangrove ecosystems through remote data collection, evolving from traditional to advanced approaches. In the traditional approach, two main techniques were employed (Heenkenda et al., 2014):

1. Aerial photography (AF): the technique involves capturing images from aircraft and at relatively low altitudes above the Earth's surface. Through AF, high-resolution images are obtained that are particularly effective for the characterization of small areas. It also provides precise details that are essential to carry out classification procedures accurately.
2. And the visual interpretation (VI) technique, which allows researchers and professionals to analyse and understand mangrove ecosystems through detailed observation and analysis of captured aerial images. This technique relies on human experience to identify features and classify elements within images.

It should be noted that more advanced and accurate approaches have been developed to characterize mangroves through remote sensing. These advanced methods typically use satellite imagery, such as Landsat and ETM+, which are subjected to image processing and machine learning algorithms for a more objective and accurate characterization of mangrove ecosystems. These advanced techniques complement and enhance the capabilities of AF and VI, allowing for a more rigorous analysis of mangroves and their evolution over time (Heumann, 2011).

Since its launch in 1986, SPOT has played a significant role in Earth observation, offering strong spatial and spectral resolution for various applications (Almeida et al., 2015). However, unlike Landsat, SPOT imagery is not freely available on publicly accessible platforms, which can be limiting for users seeking free and broad access to satellite information.

The ASTER satellite, launched in 1999, has become a valuable source of Earth observation data since it became freely available in 2016. This increased accessibility has expanded its utility for

researchers and practitioners across various fields (Abrams & Yamaguchi, 2019).

Sentinel, launched in 2014, is another key player in Earth observation (EoPortal Directory, 2020, as cited in Hu et al., 2020), offering similar sensor capabilities. However, it is important to note that Sentinel data is only available from that year onward. Like ASTER, this underscores the need for careful consideration of data consistency in study periods when using Sentinel images.

In addition to the satellite missions mentioned, there are other alternatives available. However, most of these options require a payment to access the data, although over the years, their costs have decreased (Zhao et al., 2022). The choice between these different sources of satellite imagery should be based on specific project requirements, data availability, financial resources and time considerations.

Landsat, with its free high-quality imagery available since 1972, plays a pivotal role. Its long history of continuity and accessibility has made Landsat an irreplaceable resource for scientists, planners and decision-makers worldwide. Landsat's extensive data history offers an unparalleled view of Earth's changes over time, contributing significantly to research and natural resource management. Landsat stands out not only for its extended history of free data but also for its spectral and spatial resolution, making it a versatile and indispensable tool for various Earth observation applications (Pasquarella et al., 2018).

Landsat images are emerging as one of the most employable tools in the mapping of these ecosystems (Islam et al., 2021). These data are frequently used to classify land use features in an area of interest. The above is because they can be easily downloaded for free and have an optimal spatiotemporal resolution, which allows choosing a wide variety of options to perform these studies (Purwanto et al., 2021).

The diversity of existing methods used for the identification or extraction of mangrove forests with Landsat imagery mainly includes VI, supervised classification, unsupervised classification, neural network classification, spectral indices and object-based methods (Roy et al., 2019). Several studies carried out at different latitudes around the world use varying techniques (Findi & Wantim, 2022), which supports the suitability of using satellite imagery and their spectral indices. However, there are few review articles that are focused

on determining mangrove cover using Landsat satellite imagery (Budi et al., 2022). That is why the objective of this article is to provide an updated review of the main techniques used in change detection and mapping of mangrove forests, using remote sensors, specifically Landsat satellite images, as well as a review of climatic and/or chemical factors related to changes in the spatial distribution of these ecosystems.

3 Literature Search Strategies

Through a literature review, the methodologies used to study the detection of changes in mangrove cover using GIS and Remote Sensing were identified in the Google Scholar and SCOPUS databases. The queries were performed using the following keywords both in the titles and abstracts of the articles in the consulted databases: 'MANGROVES', 'CHANGE DETECTION', 'REMOTE SENSING' and 'LANDSAT'. Articles published from 2018 to August 2023 were selected as sources of information for the review to have updated and relevant information about the methodologies used to study mangrove cover change detection using GIS and remote sensing.

Also, manual searches were performed to obtain important information that search engines could ignore; 60 articles met the described criteria.

For the writing of this article, it is imperative to indicate the inclusion and exclusion criteria; therefore, each of the articles consulted and used in the development of this document was reviewed. These criteria included topics related to changes in mangrove cover using Landsat imagery; irrelevant and duplicate articles that did not contain quantitative information on change detection in the cover of these ecosystems were excluded.

4 Results and Discussion

Of the 165 articles found in the computer-assisted search, 60 were selected for analysis, published between 2018 and 2023 with information from 47 mangrove ecosystems.

4.1 Criteria for Selecting Satellite Images

Among the important characteristics to consider when selecting remote sensing imagery for mapping mangroves are the tidal cycle, tidal flooding and cloud cover (Kamaruddin & Shigeo, 2018). These factors can significantly skew the change detection results (Nguyen et al., 2020b) because, to contrast temporal changes, it is necessary to compare changes in the boundary between land and sea at the same tide level, resulting in complexity (Das & Dhorde, 2021).

Based on the above, one of the main limitations of these studies is the lack of satellite imagery with matching tide levels, which they attempted to resolve in the most appropriate way by using the MNDWI method for satellite images taken during the dry season (Haider & Hossain, 2021).

Another alternative for the limitation described is that optical remotely sensed data such as Landsat and Sentinel provide time series images that provide more options for avoiding these effects, such as their temporal resolution which allows selecting images in seasons where tide levels are similar (Chamberlain et al., 2020) (Das & Dhorde, 2021).

However, it is important to know the sea level in the study area at the time of image acquisition (Nguyen et al., 2020b). The Landsat and Sentinel-1 and Sentinel-2 sensors, as well as high-resolution data, for example, Quick Bird and Worldview-2, have been used to quantify mangrove cover worldwide (Quang et al., 2020). With respect to aerial hyperspectral images, these have narrow bands (<10 nm), which provide new opportunities to map mangrove forests. These data have been used to distinguish mangroves at the species level (Toosi et al., 2019).

Therefore, this review article focuses on Landsat satellite imagery, as they are the main source of remotely sensed images used due to their sampling frequency and data availability and because they are free (Saravanan et al., 2018). The images were obtained from the Earth Resources Observation and Science (EROS) Center through the Global Visualization Viewer of the United States Geological Survey (USGS) (Haider & Hossain, 2021). To illustrate is one particular case with Landsat 7 ETM+ imagery with errors in the scan line from 2003 due to a malfunctioning sensor (Chen et al., 2017). However, these images can be repaired with the space-filling tool of ENVI software (Nguyen et al., 2019).

4.2 Preprocessing

For change detection, the satellite images must be preprocessed to eliminate factors such as atmospheric influences and satellite errors (Saravanan et al., 2018). For this, radiometric, geometric and atmospheric corrections are performed (Hapsari and Permatasari., 2020). In addition, these adjustments include orthorectification, image visualization enhancement and cloud masking (Diniz et al., 2019). The goal of atmospheric correction is to produce a new image that is free of atmospheric noise (Constance et al., 2021).

The most common method for performing atmospheric correction was FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes), an advanced atmospheric correction module available in the ENVI software. This module is initially based on the standard spectral radiance equation for each pixel of the sensor (L), which is applied to the solar wavelength range and flat Lambertian surfaces or their equivalents (Purwanto et al., 2021). When using ArcGIS software, the DOS method (subtraction of dark objects) is the most used.

The subtraction of black objects is a simple empirical atmospheric adjustment method for satellite imaging, which assumes that the reflectance of dark objects includes an important component of atmospheric scattering (Toosi et al., 2019).

After atmospheric correction, image cropping is performed in the area of interest (Purwanto et al., 2021); the images are converted to reflectance values at the top of the atmosphere; this is known as radiometric correction, and it is performed so that the images acquired on different dates can be compared radiometrically (Roy et al., 2019).

4.3 Change Detection

The basic concept for identifying mangrove cover using remote sensors is based on two basic properties: first, mangroves have green leaves (chlorophyll), and second, mangroves grow on the coast. Chlorophyll can focus sunlight so that it can be interpreted using remote sensing techniques (Purwanto et al., 2021).

After preprocessing and cropping the area of interest for the satellite images, composite images are generated by combing multiple bands (Mayunga & Uhinga, 2018). Among these, the false colour composite (NIR, SWIR, RED) is considered the best

combination to identify mangroves using Landsat satellite imagery (Nguyen et al., 2021b).

Subsequently, in the analysis of the band combinations, there are several methods for the identification of mangrove forests. These methods mainly include VI (Nguyen et al., 2021a) spectral indices, unsupervised and supervised classification, neural network classification, object-based methods, etc. (Roy et al., 2019). The following paragraph describes the most common techniques.

VI Techniques Simple principles for interpreting photographs are used to detect and demarcate the growth of mangroves in the study areas, and the most relevant identification criteria are tone/colour, texture and association with coastal waters (Nguyen et al., 2021a).

Spectral Indices Changes in vegetation, water and soil are often detected using indices such as vegetation indices or relationships (Sakti et al., 2020) such as the normalized difference vegetation index (NDVI) (Wang et al., 2018), the soil-adjusted vegetation index (SAVI) (Islam et al., 2021) and the normalized difference water index (NDWI) (Roy et al., 2019).

The NDVI is the most used vegetation index derived from a combination of red and near-infrared bands, which indicate the presence of vegetation and its greenness. This index has been applied in many ecological studies to monitor the spatial trends of forest degradation and detect abrupt changes in ecosystems (Sakti et al., 2020).

NDVI-based vegetation indices are able to monitor health and identify the variation in the structure of mangroves over time (Das & Dhorde, 2021). Their values are divided such that negative values to 0 refer to water; values lower than 0.1 usually represent soil, rock, sand or snow; approximate values of 0.2 to 0.5 are shrubs, pastures or dry fields; and values from 0.6 to 0.9 or close to 1.0 are trees and plants. Therefore, the NDVI is regarded and selected as a useful tool to determine the presence of mangroves (Nguyen et al., 2020a). However, using NDVI by itself can significantly underestimate the biomass of some woody mangroves (Nguyen et al., 2019).

Similarly, the NDWI is a measure of reflectance that is sensitive to changes in the water content of plant canopies (Diniz et al., 2019). The water content is important because a higher water content indicates healthier vegetation that will probably grow faster

and be more resistant to fire. Applications include agricultural crop management, forest cover monitoring and vegetation stress detection (Sakti et al., 2020).

SAVI is similar to NDVI but suppresses the effect of pixels containing bare soil (Roy et al., 2019). The SAVI index is more adapted to studies analysing vegetation in the early stages of growth or sparse vegetation. In short, SAVI can be a good alternative to any soil where there is a low plant density and exposed soil surfaces (Sakti et al., 2020).

These three indices are the most used for studies on change detection in mangroves; however, several studies complement them with other indices, such as the enhanced vegetation index (EVI) (Aljahdali et al., 2021). EVI is based on NDVI, but with the addition of a blue band to improve the vegetation signal, it corrects the impacts of the soil bottom and the dispersion of atmospheric aerosols and is also a solution for the problem of NDVI index saturation under high vegetation cover.

The EVI was selected as the optimal index for the mangrove time series analysis (Zhu et al., 2021). The normalized difference moisture index (NDMI) has been used to detect disturbance and recovery of the forest since it detects the variation in the moisture content of the vegetation (Aljahdali et al., 2021). The MNDWI index is a modified version of the NDWI method that can improve the features of open water while efficiently suppressing and even eliminating terrestrial noise, as well as the noise of vegetation and soil (Haider & Hossain, 2021).

4.4 Classification Algorithms

The most used algorithmic methods are ISODATA, support vector machines (SVM), random forest (RF), decision tree (DT), maximum likelihood (ML) and oriented segmentation (OA). These are used for mapping mangrove covers, and the choice of the most appropriate classification method can influence the final outcome (Toosi et al., 2019). Supervised classification is significantly based on the knowledge of the domain or the experience of an analyst, through which the relationship between different data and classes can be established. The resulting classification can be further validated through real field data, and the accuracy of the classification can be evaluated (Maurya et al., 2021).

Supervised classification is the most used classification method with remotely detected mangrove areas, and the ML algorithm, based on Bayes's theorem, is one of the most used techniques in this type of study (Faye et al., 2022). The ML classifier assumes that the samples of each class follow a normal distribution and calculates the probabilities of all classes for each sample (Findi & Wantim, 2022). Then, the class with the highest probability is assigned to that sample.

In this method, the unknown measurement vector is assigned to the class in which it is most likely to belong. The advantage of the ML classifier is that for normally distributed data, it works better than the other known classifiers with data of a nonnormal distribution, where the results may be unsatisfactory (Haider & Hossain, 2021). The SVM classifier is another of the algorithms used in the detection of changes in mangrove cover; it aims to find the support vectors and the separation hyperplane of each pair of classes to extend the margin between the classes (Quang et al., 2020). It provides a modern and efficient supervised classification method that requires many fewer samples than the ML classifier, and it is not necessary for the data to follow the normal distribution.

In the case of the DT learning technique, a recent study has shown that this method is one of the most popular machine learning approaches and can be accurate and efficient for the classification of land cover based on remotely sensed data. The DT learning technique is capable of producing classification rules directly from the training data without human intervention. In addition, the method does not depend on assumptions of distribution of values or independence of variables (Kamaruddin & Shigeo, 2018).

The RF classifier creates hundreds of trees, known as a set of decision trees, which are used to build a model that can be used for prediction. Each DT is created by randomly generated parts of the original training data. Each tree generates its own prediction and votes on the result. The forest model considers the votes of all decision trees to predict or classify the outcome of an unknown sample (Jamaluddin et al., 2022).

Similar to the SVM, the random tree classifier does not need many reference samples, nor does it assume a normal distribution; it is a relatively new classification method that is widely used among researchers.

DT learning technique can provide more advantages than using traditional methods to monitor changes in mangroves from remotely sensed time series data (Kamaruddin & Shigeo, 2018).

When it is difficult to obtain a sufficiently complete set of training sites to apply a supervised classification approach, unsupervised classifications could be adequate options to deliver acceptable results (Quang et al., 2020). The unsupervised classification is useful when prior knowledge of the field data is not available or there is no experienced analyst. In this method, the data can be analysed by grouping a similar set of data according to some statistical or mathematical relationship. Therefore, this method is ideally known as learning without a teacher (Maurya et al., 2021).

Among the unsupervised methods, the ISO Cluster tool is frequently used, which uses a modified iterative optimization clustering procedure, also known as the migrating means technique. The algorithm separates all cells from the number of distinct unimodal groups specified by the user in the multidimensional space of the input bands; this tool is generally used in preparation for unsupervised classification.

The ISODATA algorithm is considered an excellent clustering algorithm if and only if the required input parameters are correctly defined since being an iterative algorithm depends largely on the a priori knowledge of the dataset and its experience to be able to efficiently provide the parameters needed by the algorithm (Zuhairi et al., 2019). In most cases, unsupervised classification is mainly used to perform a preliminary analysis of the data before applying supervised classification (Maurya et al., 2021).

With the classification methods described above, it is difficult to identify mangroves using a moderate spatial resolution, such as 30 m for satellite data, because these may not be adequate for a detailed analysis of mangrove forests and their species composition (Ai et al., 2022). That is why, lately, a new type of object-oriented classification is increasingly used for the classification of high-resolution imagery (Mokhtar et al., 2022). This method is able to extract an object from satellite images to differentiate the trees of the canopy according to their shape and species and to map the land cover of mangroves (Shi et al., 2022).

However, studies focused on testing the appropriate value segmentation parameters to extract the area and features of mangroves (young and mature) are

still limited (Mokhtar et al., 2022) since most applications based on remotely sensed data still use basic image processing concepts developed in the early 1970s (Ai et al., 2022).

4.5 Changes in Mangrove Cover

The change in land cover for each type of land use (including mangrove cover) is calculated as an increase or decrease in mangrove cover (areas) of the previous period for each type of land use. The annual change rate is obtained by dividing the change in land use observed in the area by the number of years necessary for the change to occur (Afiesimama et al., 2021).

4.6 Correlation of Changes in Mangrove Cover with Other Variables

Changes in the spatial distribution of mangrove ecosystems are multidimensional, so describing their causes is a complex task where geophysical, geomorphic, biological and anthropogenic influences must be considered. The geophysical component refers to sea level, tidal properties and weather conditions.

The geomorphic component refers to sedimentation and topographic influences along with the geomorphic process of the area, such as river or tidal influences (Constance et al., 2021). The biological component refers to the competition between species in a particular area in different plant communities (Emch & Peterson, 2006). Finally, anthropogenic factors are caused by human activities that have influenced the change in the spatial distribution of mangroves.

Some researchers explain the distribution of mangroves through the analysis of gradients, salinity and pH, finding that mangroves are tolerant to salinity (Faye et al., 2022), so that the increase in saline intrusion acts as a feeder (Asmara et al., 2021) and will have a positive impact on the health of mangroves (Sakti et al., 2020).

Dissolved oxygen is an important factor for the life of an aquatic ecosystem, which functions as a regulator of the organism's metabolism to grow and reproduce. The pH greatly affects the growth of mangrove ecosystems and the condition of aquatic organisms in general, and waters that are very acidic and alkaline will endanger the life of the organism because

they will cause metabolic and respiratory disorders (Suciani et al., 2020). The altered levels of salinity, dissolved oxygen and pH are also related to degradation and recovery patterns in response to the obstruction of water recharge. These parameters can affect the productivity of mangroves. An example of this is that in conditions of high salinity and low nutrient content, mangroves increase the transpiration process, which leads to less flow and less productivity (Suciani et al., 2020).

On the other hand, temperature and rainfall are also factors used to evaluate the impact on the degradation and regeneration patterns of mangroves (Aljahdali et al., 2021). An increase in temperature will result in water loss during the evapotranspiration process, which in turn affects the availability of water for plants (Sakti et al., 2020). Studies indicate that an increase in temperature and extreme rainfall could be one of the reasons for the occurrence of deforestation. However, studies related to water balance to determine the effect of climate change on water content in mangrove vegetation are useful to evaluate this occurrence (Sakti et al., 2020).

Nonetheless, the analysis of these factors influencing the spatial distribution of mangroves should be performed with extreme caution, since it is common for data from monitoring stations to present errors or for remotely sensed data to have a very low spatial resolution. Therefore, it must be ensured that the pixel-by-pixel correlation of the climate data and spectral indices have the same spatial resolution. Another limitation of correlating climatic factors with changes in mangrove distribution is that although the dataset may be useful for monitoring impacts and trend patterns at the global level, it is possible that they are not always useful in reflecting a specific spatial and temporal situation (Aljahdali et al., 2021).

The tidal level factor has a direct impact on the expansion of mangrove colonies (Aljahdali et al., 2021) since it is assumed that changes in mangrove extent (gain or loss) can occur in areas with greater wave power due to the changing dynamics of the sediments. Research has been conducted that shows that exposure to waves plays an important role in the stability of mangrove distribution along protected coasts around the world (Constance et al., 2021). The correlation of this factor with mangrove cover extent can be valuable for assessing threats and sites with the greatest potential for restoring these ecosystems.

Table 1 (continued)

Source	Country	Study period	Annual rate of increase or decrease in mangrove area	Change detection				Classification algorithm				Correlation factors						
				Other		Spectral Indices		Type	Algorithm			Oth-ers	ML	OA	Geo-physi-cal	Geo-mor-phic	Bio-logi-cal	Anthro-pogenic
				VI	FCC	NDVI	SAVI	NDWI	EVI	NDMI	Oth-ers							
Simarmata et al., (2021)	Indonesia	1991–2019	2,14%									X						X
Kumar et al., (2021)	Bangladesh	1989–2019	-0,03%															X
Jaelani et al., (2021)	Indonesia	1997–2018	-0,16%	X	X													X
Purwanto et al., (2021)	Indonesia	1995–2015	0,08%	X	X													
Long et al., (2021)	Vietnam	1986–2019	2,36%															X
Castillo et al., (2021)	Panama	1987–2019	0,15%			X												X
Nguyen et al., (2021a)	Vietnam	2015–2020	-18,23%	X														X
Constance et al., (2021)	Seychelles	1997–2018	0,25%															X
Haider and Hossain, (2021)	Bangladesh	1990–2015	-0,97%							X								X
Nguyen et al., (2020a)	Vietnam	2000–2018	28,73%	X														X
Hamzah et al., (2020)	Malaysia	2006–2014	-1,05%	X														X
Quang et al., (2020)	Vietnam	1975–2019	37,49%														X	X
Sakti et al., (2020)	Southeast Asia	2001–2012	-			X	X	X	X	X								X

Table 1 (continued)

Source	Country	Study period	Annual rate of increase or decrease in mangrove area	Change detection				Classification algorithm				Correlation factors						
				Spectral Indices		Other		Type		Algorithm		Others	ML	OA	Geo-physi- cal	Geo-mor- phic	Bio- logi- cal	Anthro- pogenic
				FCC	NDVI	SAVI	NDWI	EVI	NDMI	Others	NDMI							
Mia et al., (2019)	China	1985–2015	0,56%	X	X				X					X	X	X	X	X
Awty-Carroll et al., (2019)	Bangladesh, India	1988–2017	0,13%	X	X				X					X				X
Roy et al., (2019)	India	1990–2015	1,14%	X	X	X	X		X									X
Saravanan et al., (2018)	India	1999–2016	0,21%	X	X				X					X				X
Monga et al., (2018)	Tanzania	1991–2015	–0,52%						X					X				X
Kamaruddin and Shigeo, (2018)	Malaysia	1990–2013	0,15%			X			X					X				X
Mayunga and Uhinga, (2018)	Tanzania	1985–2013	–0,50%			X			X					X				X
Wang et al., (2018)	China	1995–2014	9,94%	X	X				X					X				X

VI means visual interpretation; *FCC*, false colour composite; *NDVI*, normalized difference vegetation index; *SAVI*, soil-adjusted vegetation index; normalized difference water index; *EVI*, enhanced vegetation index; *NDMI*, normalized difference moisture index; *SVM*, support vector machines; *RF*, random forest; *DT*, decision tree; *ML*, maximum likelihood; *OA*, oriented segmentation

Table 1 shows the titles of the articles reviewed in this study along with the year of publication, study period and area of change in Ha.

4.7 Accuracy Assessment

Data validation is an important step in change detection studies since the maps or results derived from the study may contain errors. This is why the accuracy of the maps produced on each date usually includes an error matrix and the Kappa coefficient (Zuhairi et al., 2019). This matrix indicates the relationship between the predictions made by a supervised learning algorithm and the correct results that it should have shown (Findi & Wantim, 2022).

As such, the performance of the algorithm can be measured, determining the type of errors and successes of each model when going through a learning process on proposed data and deriving a Kappa agreement index (Hamzah et al., 2020).

Essentially, the Kappa values are classified into different groups whereby if they are less than zero, it indicates that there is no agreement; from 0 to 0.20 refers to a slight agreement; from 0.21 to 0.40 indicates a fair agreement; from 0.41 to 0.60 is a moderate correspondence; from 0.61 to 0.80 is a substantial correlation; and finally from 0.81 to 1.0 is considered an almost perfect agreement (Rahman et al., 2021).

5 Conclusions

For mapping and monitoring the cover of mangrove ecosystems, remote sensing is necessary, which is a promising tool that provides more accurate and efficient results. However, one of the main limitations of these studies is that the lack of satellite imagery with equal tide levels can significantly skew the results. To address this limitation, using the Landsat sensor has an advantage because its time series images provide more options for mitigating these effects; for example, its temporal resolution allows selecting images in seasons where tide levels are similar, and there is also a good availability of free data. In this article, the methodologies of publications that used this type of imagery were reviewed, finding that bands are usually combined, highlighting the false colour for identifying mangrove covers.

After analysing the band combinations, several methods are available for identifying mangrove forests. These methods primarily encompass vegetation indices, spectral indices, unsupervised and supervised classification, neural network-based classification and object-based techniques, among others.

The inclusion criteria revealed that the most common techniques for supervised or unsupervised classification are algorithms and spectral indices; among all, the most used is the ML-supervised classification algorithm, used together with indices such as NDVI, SAVI and NDWI. Additionally, unsupervised classification is generally used to perform a preliminary analysis of the data before applying supervised classification. In addition, in recent years, some studies have used an object-oriented type of classification; however, being new, their study has been very limited.

Therefore, few studies have been carried out correlating the changes in mangrove cover with climatic and chemical factors; in the studies consulted, it was shown that the variables with which these changes can be correlated are salinity, pH and oxygen as chemical parameters, while other climatic parameters, such as temperature, precipitation and tidal levels, can also be correlated with the spatial distribution of these ecosystems.

It should be noted that the analysis of these factors, especially climatic factors, influences the spatial distribution of mangroves. Therefore, extreme caution should be taken, given that it is common for data from monitoring stations to present errors or for remotely sensed data to have a very low spatial resolution.

Finally, data validation is an important step in change detection studies since the maps and results derived from the study may contain errors, which is why the accuracy of the maps produced for each date usually includes an error matrix and the Kappa coefficient.

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Author Contribution All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by JV. RA-B, WM-C, MG and LM-O reviewed and commented on the previous versions of the manuscript. All authors read and approved the final manuscript.

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Data Availability All data generated or analysed during this study are included in this published article.

Declarations

Conflict of Interest The authors declare no competing interests.

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