Studying How Machine Learning Maps Mangroves in Moderate-Resolution Satellite Images

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ABSTRACT
Intertidal mangrove forests are ecosystems that are extremely productive offering diverse socio-economic advantages. Preserving and appropriately using these ecosystems is crucial. However, safeguarding and restoring mangroves present challenges due to their extensive and hard-to-reach areas. Leveraging remote sensing technology and diverse image classification methods has shown promise in accurately mapping and monitoring mangroves. This study reviews the use of machine learning methods in mapping and monitoring mangroves, particularly using moderate-resolution multispectral satellite images. The literature study was conducted by systematically searching and analyzing articles published in Scopus-indexed journals from 2018 and 2023. The primary goals are to uncover methodologies for mapping mangroves with moderate-resolution imagery, identify advancements in machine learning algorithms, and assist researchers in staying updated in this field. The findings reveal that various machine-learning algorithms can be employed to map mangroves. Mangrove mapping with machine learning typically involves stages such as inputting multispectral images, image preprocessing, image classification, and assessing accuracy. Among the techniques, in the case of remote sensing data, ensemble tree-based approaches such as random forest outperform single classifiers. Potential and emerging issues for future research encompass automating the generation of training datasets for specific land cover classification, developing methods to transfer the classification model to different study areas, and making use of cloud-based technologies for processing remote sensing data.

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1. INTRODUCTION

Mangrove forests are a group of salt-tolerant plants that thrive in intertidal zones of the tropics and subtropics [1]. Typically, mangrove plants are found in estuarine areas, along riverbanks, lagoons, and coastlines [2]. As a tropical country, Indonesia has the world’s largest mangrove ecosystem. About 19.5% of the global mangrove ecosystem is situated in Indonesia [3] and this proportion has continued to increase from 2018 to 2020 [4]. The presence of mangrove plants holds significant ecological and economic importance [5], including their role as coastline stabilizers, erosion mitigators, storm protectors, flood regulators, carbon absorbers, water quality maintainers, and breeding grounds for marine species and fauna [1], [6]. Hence, the conservation and wise use of the mangrove ecosystem have garnered global attention [7].

Mangrove mapping that is reliable and precise serves as the foundation and precursor for conservation and restoration efforts. However, mangrove habitats are typically submerged by tidal seawater and are often distributed in hard-to-reach areas [1], [5]. This results in large-scale monitoring through field surveys becoming inefficient [7]. The advent of remote sensing technology, where objects can be observed from a distance without direct contact [1], coupled with geographic information systems (GIS), has become a crucial and convenient tool for regular mangrove ecosystem monitoring [8]. Additionally, with the advancements in remote sensing technology and various classification techniques, ease has been provided in classifying and extracting parameters related to mangroves.

Remote sensing imagery is a valuable data source for Earth observation derived from Earth observation satellites. Remote sensing data comes in various resolutions, such as spatial, spectral, and temporal, and has been extensively utilized across diverse research domains including forestry, agriculture, geology, natural disasters, land use or land cover, etc. [9]. This data requires distinct treatment within the context of land cover classification, such as mangroves. Therefore, specific classification approaches for extracting satellite image data play a significant role in mangrove ecosystem assessment. Classification employing machine learning techniques has recently emerged as a primary focus in remote sensing. The machine learning approach has gained widespread acceptance, as evidenced by its use in land use and land cover classification [10]–[12].

In the past decade, the utilization of remote sensing imagery from open sources, combined with machine learning algorithms, has demonstrated its performance in mapping and monitoring mangroves. Some commonly used open-source satellite images with moderate resolution include Landsat MSS/TM/ETM+/OLI and Sentinel-2 imagery. These images have been employed in conjunction with supervised machine learning algorithms [13]–[17] unsupervised machine learning algorithms [18], [19], and even deep learning techniques [20], [21] for various tasks related to mangrove ecosystems. Moreover, the utilization of cloud-based computer platforms, such as Google Colaboratory and Google Earth Engine, available for free, has also begun to be used for large-scale mangrove forest monitoring [21].

There have been numerous studies from various geographical locations worldwide that have employed moderate-resolution satellite imagery and various classification techniques to map and monitor mangrove ecosystems. Maurya et al. (2021) provided a comprehensive summary of the work undertaken in mapping and monitoring mangrove ecosystems using remote sensing techniques, analyzing various digital image classification approaches and satellite image data, and discussing the potential and limitations of these techniques [1]. Kuenzer et al. (2011) discussed the variety of remotely sensed data applied for mangrove ecosystem mapping and the numerous methods and techniques used for data analyses [5]. Thakur et al. (2020) reviewed previous works on mangrove forests using remote sensing techniques, aiming to identify the best combinations of sensors, image processing methods, and vegetation indices for future studies [6]. Wang et al. (2019) reviewed the historical development of remote sensing for mangrove forests from 1956 to 2018, identifying important milestones and research topics related to the emergence of new sensors. The study also compares the evolution of mangrove forest remote sensing with terrestrial forest remote sensing and discusses future research directions in mangrove forest remote sensing [8]. Pham et al. (2019) provided an overview of the techniques currently used to map various mangrove attributes, such as species, biomass, and carbon stocks, using remote sensing approaches [22]. However, these literature studies do not explain in detail the steps in applying machine learning algorithms for mangrove mapping, especially on moderate resolution multispectral satellite imagery. In addition, tools in processing and analyzing remote sensing imagery are not discussed.

In this paper, we summarize these studies, including those related to machine learning approaches for classification, the most relevant spectral band combinations for mangroves, the utilized technologies, and future opportunities or challenges in mapping and monitoring mangroves using available open-access (free) multispectral satellite imagery. The primary objectives of this literature review are as follows:

1. To identify methodologies employed for mapping mangroves using moderate-resolution multispectral satellite imagery.
2. To identify technological advancements and models of machine learning algorithms in the context of tools, utilized technology, and their reliability levels.
3. To analyze key opportunities and obstacles in applying machine learning to satellite imagery for mangrove mapping.

2. RESEARCH METHOD

A systematic search and analysis of articles published in various journals were conducted using the Scopus database, taking into account peer-reviewed journal papers. In this paper, the topics “machine learning” and “mangrove mapping” are the main criterion. To ensure that suitable case studies are identified concerning machine learning for mangrove mapping in moderate-resolution satellite imagery, expressions such as “machine learning”, “landsat”, “sentinel-2,” and “mangrove” were used collectively.

To maintain the currency of literature study results, the search process was confined to the timeframe between 2018 and 2023, “article” as the document type, “final” as the publishing stage, “journal” as the source type, and “English” as the language. In the subsequent stage, various types of information were extracted from each journal article, including algorithms, satellite data, research domain/field, and key findings of the research.

2.1. Remote Sensing Imagery

Remote sensing imagery is acquired from Earth observation satellites (EOS) through the sensors they carry. EOS has two types of sensors, namely active and passive sensors. Active sensors obtain data by emitting energy towards the target object and capturing the resulting reflections. Passive sensors acquire data by capturing the natural reflections or emissions of energy (such as sunlight) from the target object. Each sensor type has distinct uses and characteristics in observing the surface of the Earth. Figure 1 illustrated the types of sensors and remote sensing data [23].

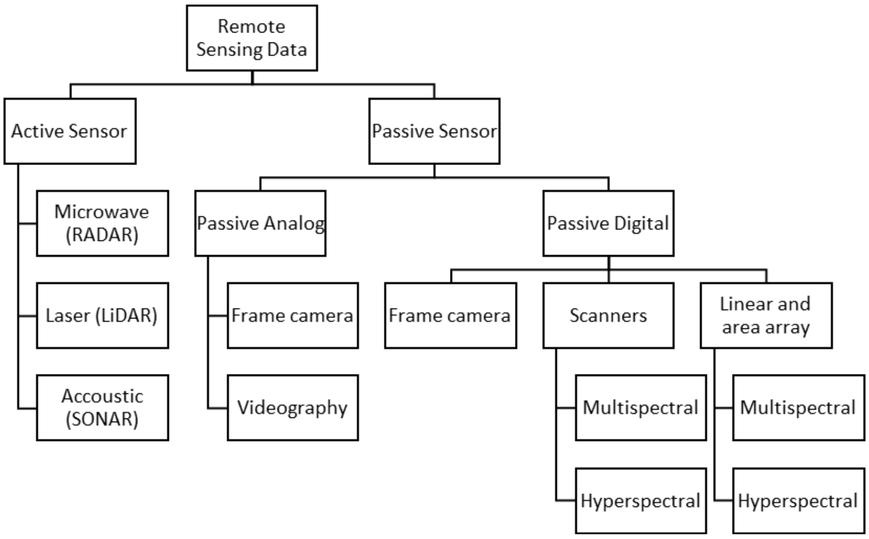

Figure 1. Remote Sensing Data Sources [23]

2.2. Multispectral and Hyperspectral Image

Remote sensing imagery is typically captured by optical, thermal, or Synthetic Aperture Radar (SAR) imaging systems. Optical remote sensing sensors rely on sunlight radiation as an illumination source. This solar radiation traverses the Earth’s atmosphere before being reflected by the surface and returning to the sensor. This process yields Panchromatic, Multispectral, or Hyperspectral images. Multispectral imagery comprises more than 2 to 13 spectral bands, whereas hyperspectral imagery encompasses even more bands than multispectral [11]. A comparison of multispectral and hyperspectral imagery is depicted in Figure 2.

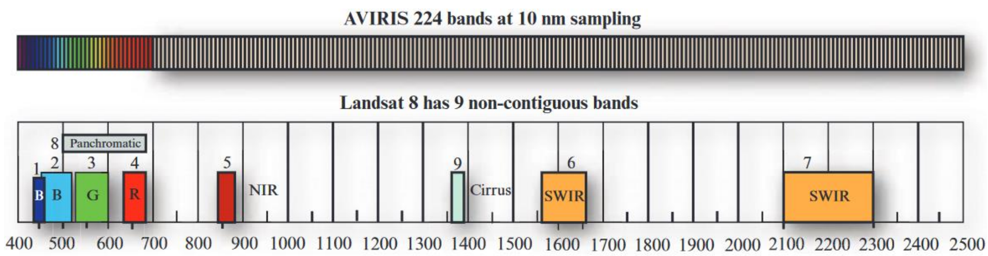

Figure 2. Multispectral (bottom) and hyperspectral (top) imagery

Satellites equipped with multispectral sensors include Landsat/TM, SPOT/HRV, TERRA/ASTER, or IKONOS [24]. Satellite image data with resolutions ranging from low to high are currently widely available to the public. USGS, NASA Earth Data, NEO, NOAA, IPMUS Terra, and Copernicus Open Access Hub are among the most well-known providers of remote sensing data with open access [11].

2.3. Resolution of Satellite Image

Resolution determines the capability to detect, recognize, differentiate distinct objects, and characterize varying object properties over time. There are four types of remote sensing image resolution: spatial, spectral, temporal, and radiometric resolution [25].

1. Spatial resolution relates to the area covered by a sensor. For instance, the spatial resolution of Landsat-8 imagery is 30 meters, meaning each pixel in the image covers an area of 30 square meters on the surface.
2. Spectral resolution involves the width, sensitivity, location, and number of spectral bands. Landsat-8 imagery, for example, includes 11 spectral bands with different purposes.
3. Temporal resolution refers to the time period it takes for a satellite to revisit the identical location on the Earth's surface. Landsat-8 imagery has a 16-day temporal resolution, indicating that the satellite revisits the same location every 16 days.

2.4. Relationship between Image Resolution and Mangrove Features

In their study, Kamal et al. (2015) expounded that the remote sensing sensors' spatial resolution determines the level of generated information. Therefore, remote sensing can furnish information about mangroves at various scales contingent upon users' requirements. By understanding the hierarchical structure of mangroves and the optimal pixel size for extracting mangrove features from satellite imagery, we can build an explicit relationship between mangrove feature spatial and temporal scales and the appropriate spatial resolution of images for mapping these features (refer to Figure 3). Based on this relationship, we may choose the optimal image spatial resolution for correctly mapping certain mangrove features [26].

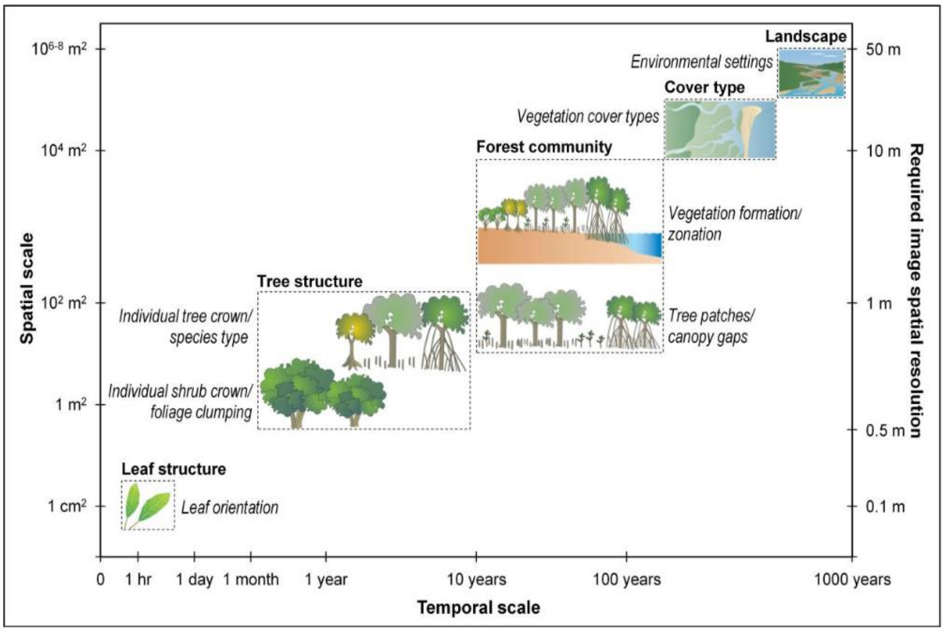

Figure 3. Mangrove characteristics' conceptual hierarchical spatial and temporal relationships with remote sensing imagery, and the pixel resolution of the imagery required to map these features [26]

2.5. Landsat and Sentinel-2 Images

On local, regional, and global scales, many types of remote sensing satellite imagery have been used for mapping and monitoring mangroves. Among the openly available remote sensing satellite images are Landsat (MSS/TM/ETM+/OLI) and Sentinel-2 images. Landsat images can be downloaded from the U.S. Geological Survey's website: U.S. Geological Survey's (https://earthexplorer.usgs.gov), and Sentinel-2 images can be obtained from the ESA Copernicus Data Hub (https://scihub.copernicus.eu).

Landsat images have been available since 1972 until the present. The spatial resolution of Landsat-8 images is 30 meters (visible, NIR, SWIR), 15 meters (panchromatic), and 100 meters (thermal). The temporal resolution of Landsat-8 images is 16 days and consists of 11 multispectral bands (see Table 1).

Table 1. Landsat-8 OLI Image Features

Name	Resolution (m)	Wavelength (μm)	Description
B1	30	0.43 - 0.45	Coastal aerosol
B2	30	0.45 - 0.51	Blue
B3	30	0.53 - 0.59	Green
B4	30	0.64 - 0.67	Red
B5	30	0.85 - 0.88	NIR
B6	30	1.57 - 1.65	SWIR 1
B7	30	2.11 - 2.29	SWIR 2
B8	15	0.50 - 0.68	Panchromatic
B9	30	1.36 - 1.38	Cirrus
B10	100 (30)	10.60 - 11.19	Thermal infrared 1
B11	100 (30)	11.50 - 12.51	Thermal infrared 2

Furthermore, for Sentinel-2 imagery, it is relatively recent. These images have been available since 2015 until the present and possess a spatial resolution of 10 meters to 60 meters. The temporal resolution of Sentinel-2 imagery is 10 days, comprising 13 multispectral bands (refer to Table 2).

Table 2. Sentinel-2 Image Features

Name	Resolution (m)	Wavelength (μm)		Description
		S2-A	S2-B	
B1	60	443.9	442.3	Aerosols
B2	10	496.6	492.1	Blue
B3	10	560	559	Green
B4	10	664.5	665	Red
B5	20	703.9	703.8	Red Edge 1
B6	20	740.2	739.1	Red Edge 2
B7	20	782.5	779.7	Red Edge 3
B8	10	835.1	833	NIR
B8A	20	864.8	864	Red Edge 4
B9	60	945	943.2	Water vapor
B10	60	1373.5	1376.9	Cirrus
B11	20	1613.7	1610.4	SWIR 1
B12	20	2202.4	2185.7	SWIR 2

3. RESULTS AND DISCUSSION

Image analysis via remote sensing is a critical and difficult task. Thanks to digital image processing techniques and machine learning, this task becomes more manageable. Various combinations of image processing approaches and machine learning can be employed to extract and analyze a range of spectral, spatial, and textural features in remote sensing images [1]. In general, the stages involved in mangrove mapping using moderate-resolution multispectral satellite images are illustrated in Figure 4.

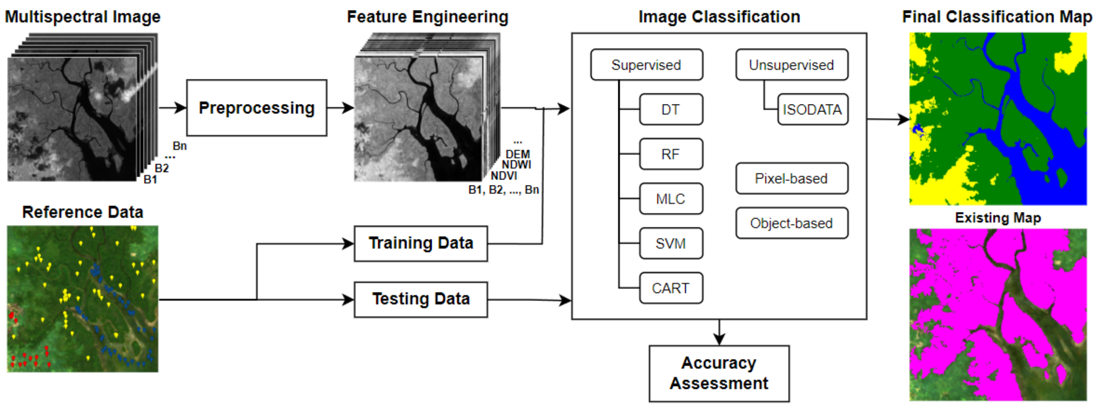

Figure 4. The general stages of monitoring and mapping mangroves using moderate-resolution multispectral satellite images (adapted from [1])

3.1. Preprocessing

Preprocessing of image is the initial stage in remote sensing image processing. Image preprocessing encompasses sub-tasks where input data is prepared for subsequent stages (i.e., feature extraction and training). The goal of image preprocessing is to generate an improved version of the image and enhance the overall process performance by rectifying distorted or degraded image data or fusing image data with other data, thereby enhancing the image's utility for further processing [11], [27]. Various methods of satellite image preprocessing exist, tailored to the available data. Generally, satellite image preprocessing consists of geometric, radiometric, and atmospheric correction [13]–[15], [17], [19]. These methods are typically integrated into satellite image processing software like ArcGIS and are commonly applied to images obtained from data providers (USGS and ESA Copernicus Data Hub). In the case of satellite images provided by Google Earth Engine (GEE), these three methods are often optional due to GEE also offering images that have undergone geometric, radiometric, and atmospheric correction [28]. Another frequently employed preprocessing step is cloud and cloud cover removal. This method is typically used when the research area is extensive and situated in tropical or subtropical climates. Commonly used techniques for cloud and cloud cover removal include median pixel and fmask algorithm [21], [29].

3.2. Feature Engineering

The next stage is feature engineering or also known as feature extraction, feature selection, and feature transformation. Feature engineering aims to eliminate excessive information from the input data, reduce its dimensionality, and define a well-suited set of representations (called features) as input, where a classifier can build a model and then predict the target class [11]. Features used in satellite imagery to observe the Earth include spectral bands. In Landsat-8 imagery, bands B1 to B7 contribute to the accuracy of mangrove classification [17]. In Sentinel-2 imagery, the spectral bands that significantly contribute to mangrove classification accuracy are bands B5, B6, and B12, while bands B2, B3, B4, and B8 are the least beneficial [30]. Besides using spectral bands, combinations and calculations of these bands can result in new features known as spectral indices. Spectral indices provide valuable information about the environment. In mangroves, key indices are those that offer information about green vegetation (Red and near-infrared) and water reflectance (Green and middle infrared) [16]. Integrating characteristics of water and vegetation can help differentiate between land vegetation and mangrove vegetation [20]. Hickey and Radford (2022) discovered that the Modified Normalized Water Index (MNDWI) and Green Chlorophyll Vegetation Index (GCVI) in Landsat-8 imagery are the best predictors for mangroves [16], Meanwhile, in Sentinel-2 imagery, it was discovered that MNDWI and Mangrove Discrimination Index (MDI) significantly enhance mangrove extraction performance [20]. Other relevant spectral indices for mangrove classification include the Normalized Difference Moisture Index (NDMI) [13], Normalized Difference Soil Index (NDSI) [17], and Mangrove Vegetation Index (MVI) [31]. In addition to spectral bands and spectral indices, the use of Digital Elevation Models (DEMs) can enhance mangrove classification accuracy [17], [30]. Feature assessments show that DEM is the most important variable for forest type classification [30].

3.3. Image Classification

The core of machine learning involves the training phase, during which machine learning algorithms construct mathematical models on the basis of training samples and grasp the correlations between features or the training dataset's representations and the pre-defined classes. After training, testing, and validation of the model, it is employed to predict and classify new data [11]. Various types of machine learning algorithms are categorized based on their learning strategies for mangrove mapping tasks, namely supervised learning and unsupervised learning. In supervised classification, learning is performed on labeled training datasets, where the output i.e. the variable to be classified or predicted is already known [32]. For land cover classification, training datasets are typically collected through field surveys or ground truth. Supervised machine learning techniques used for mangrove mapping include decision tree (DT) [13], random forest (RF) [33], maximum likelihood classification (MLC) [19], support vector machine (SVM) [34], and classification and regression trees (CART) [14]. In unsupervised classification, learning is conducted on training datasets that have not been labeled, where the output variable is unidentified [32]. Unsupervised classification is particularly useful when prior knowledge of field data is not available or when there are no experienced analysts. For land cover classification, satellite images can be analyzed by grouping pixels or objects with similar characteristics based on statistical or mathematical relationships [1]. The unsupervised machine learning algorithm utilized for mangrove mapping is ISODATA [18], [19].

Another approach involves pixel-based classification and object-based classification. Pixel-based classification is a method of analyzing pixels based on their spectral and reflective characteristics. The main goal of this method is to assign all pixels in an image to land cover classes like forest, water, or soil. Depending on the classification technique employed, the number and kind of classifications assigned might vary. Unlike pixel-based classification, which depends simply on a pixel's spectral properties, object-based classification uses both spectral and spatial information for classification. This approach analyzes a group of pixels based on comparable spectral features [1]. In mangrove mapping studies, these two approaches are combined with supervised [31], [33] or unsupervised machine learning methods [18], [19].

Based on the literature review, various machine learning algorithms have been employed and demonstrated their performance in mangrove mapping tasks. The accuracy obtained from these algorithms ranges from 87% to 99%. Among these methods, the RF algorithm has been the most extensively utilized, with an overall average accuracy above 92%. Nevertheless, when compared to SVM, RF's performance needs further investigation. According to a study [35], it was found that SVM outperforms RF and vice versa. The SVM classifier exhibits better performance than RF when applying object-based image analysis (OBIA), but it is more sensitive to feature selection and requires the setting of numerous parameters to achieve optimal results. On the other hand, RF can achieve better classification results when multidimensional data, such as hyperspectral or multisource data, is used. Additionally, RF requires fewer parameter adjustments and is faster than SVM or other ensemble classifiers like AdaBoost [35]. In cases of poor spatial resolution images, RF regularly outperforms SVM [36].

3.4. Accuracy Assessment

In general, four measurement criteria are used to compare anticipated mangrove mapping findings to reference sample points. User accuracy (UA), producer accuracy (PA), Overall accuracy (OA), and the Kappa coefficient (K) are among these measurements. Additionally, some also utilize the F1-score (F1). The accuracy measurement metrics are shown in Table 3.

Table 3. Accuracy Measurement Metrics

		Reference Data				
		Mangrove	NonMangrove	RowTotal	UA	ChanceAgree
Predicted Data	Mangrove	X1	Y1	X1+Y1	X1/RowTotal1	RowTotal1 / TotalSample
	NonMangrove	X2	Y2	X2+Y2	Y2/RowTotal2	RowTotal2 / TotalSample
	ColumnTotal	X1+X2	Y1+Y2	TotalSample		
	PA	X1/CT1	Y2/CT2	OA	K	
	ChanceAgree	ColumnTotal1 / TotalSample	ColumnTotal2 / TotalSample			ChanceAgree Total

UA quantifies commission errors, which are the proportion of pixels misclassified into the evaluated class. PA measures omission errors, which are the proportion of pixels in a specific class misclassified into another class and omitted from the actual class [14]. PA calculates the likelihood that identified samples in the field represent that category. UA determines the probability of samples being correctly classified [21]. OA computes all validation points correctly classified (Equation 1). The harmonic mean of PA and UA is represented by the F1-score, reflecting the classification capability of each class [29], [31]. The overall classification accuracy is determined by the Kappa coefficient (K) [21]. It is calculated from the confusion matrix by comparing the values achieved in the classification process and the ground truth values (Equation 2). Models with Kappa > 0.8 have strong predictive power, models with Kappa between 0.6 and 0.8 are adequate, and models with Kappa < 0.5 lack discrimination capability [16].

$$OA = \frac{X1 + Y2}{TotalSample} \tag{1}$$

$$K = \frac{OA - ChanceAgreeTotal}{1 - ChanceAgreeTotal} \tag{2}$$

3.5. Reference Data

Image classification using a supervised machine learning approach requires training and validation data in order to train and test the algorithm's accuracy [37]. In existing research on mangrove classification, training and validation data are obtained through various methods, including field surveys (using GPS), sourced from local authorities, and interpreted visually from high-resolution images such as Google Earth, aerial photographs/UAV, SPOT 6/7, and WorldView-2, supported or supervised by the knowledge of researchers and experts. These data are then used to label datasets using specific software such as ArcGIS, ArcMap, ENVI, eCognition, and Quantum GIS. Furthermore, the availability of open-source datasets like Global Mangrove Watch (GMW) [3], tidal flat datasets [38], GlobCover 2009, and Global Forest Watch is also used to support the interpretation of these images [29], [30].

3.6. Opportunities and Challenges

Mapping mangroves on a wide scale is still a difficult endeavor. Remote sensing techniques have been widely employed for monitoring the Earth's surface, including mangroves, and have proven effective in effectively mapping mangroves in expansive regions. However, as far as the author is aware, there has been no nationwide mangrove mapping conducted in Indonesia. One reason for this is that Indonesia has a vast national boundary, making image processing and class identification intricate [21]. Large-scale mangrove mapping demands a substantial number of training samples, which are time-consuming to gather. Moreover, mapping specific land cover classes, such as mangroves alone, necessitates incorporating all classes (other land covers) within the study area into the training data. Failure to do so could lead to misclassification [34]. In their research, [34] found that a binary classification approach outperforms one-class classification. However, one of the challenges is the imbalance in training data. Furthermore, both binary and multi-class classification require the inclusion of data from other classes that are not the focus. Thus, the development of entirely automated methods for collecting and augmenting training samples is imperative [29].

In the existing mangrove-related research, reference data was collected manually through field surveys and interpretation of very high-resolution images. Studies [39] and [40] explored automated methods for collecting training samples but required existing products as references, making them inapplicable to land cover types lacking specific available products. Murray et al. (2022) developed a global reference dataset from seven coastal ecosystems (coastTrain: https://www.coasttrain.org), including mangroves, to support current and future remote sensing classification models [41].

Classification techniques using machine learning play a crucial role in processing remote sensing data. Various machine learning techniques and their combinations have demonstrated successful performance in land cover classification, including mangroves. Among these methods, Random Forest (RF) outperformed other machine learning methods [15]. RF is an ensemble learning technique utilizing bagging. Besides RF, another ensemble learning technique, XGBoost, showed promising performance for mangrove mapping [42]. Moreover, object-based approaches (OBIA) were found to outperform pixel-based methods, particularly for high-resolution images [33]. OBIA classification generates more suitable spatial units than pixel-based methods for land cover mapping due to increased consistency [31]. The combination of OBIA with ensemble learning algorithms such as RF and XGBoost warrants further exploration. Regardless of the machine learning method used, models should maintain at least the same performance when applied to different study areas. Waśniewski et al. (2020) found that transferring classification models for forest types is complex because of the diversity of forest types and climatic circumstances between research areas. However, models succeed when both images share the same land cover classes [30].

Validation of mangrove mapping results is crucial. Hence, existing mangrove maps should be used to avoid underestimation or overestimation risks [14]. Validation can be conducted using locally owned mangrove maps. Additionally, global mangrove maps such as the Global Distribution of Mangroves USGS [43] and Global Mangrove Watch [4] can serve as references for validating produced mangrove maps.

Regarding technology or software for satellite image analysis and processing, most researchers use paid software installed on personal computers. This approach is inefficient considering the large data size of satellite images and the need for extensive storage capacity. Furthermore, the process is time-consuming, involving downloading and then processing the data. Therefore, cloud-based technologies for processing and analyzing satellite images, such as Google Colaboratory (GC) and Google Earth Engine (GEE), should be maximally utilized in the future. GC and GEE have demonstrated efficient remote sensing data processing capabilities [21], [29].

4. CONCLUSION

Machine learning techniques and remote sensing technologies have proven successful in monitoring and mapping mangrove ecosystems. This paper presents the findings of a study related to mangrove mapping using machine learning on open-source satellite images, Landsat (MSS/TM/ETM+/OLI) and Sentinel-2. The mapping stages of mangroves and the utilized techniques are comprehensively explained, spanning from image preprocessing to accuracy assessment. The advancements in remote sensing technology and machine learning algorithm models are also outlined, encompassing tools, technologies employed, and their reliability levels. Furthermore, the main opportunities and challenges in applying machine learning methods to satellite imagery for mangrove mapping are discussed.

Based on the conducted literature study, it can be concluded that all machine learning techniques can be employed for mangrove mapping. Among the various categories, frequently utilized techniques include RF, SVM, CART, and MLC. Nevertheless, the exploration of diverse and novel machine learning developments and implementations is warranted, along with comparative studies of object-based and pixel-based approaches. Furthermore, as cloud-based platforms for open-source satellite image analysis, such as Google Colaboratory and Google Earth Engine, emerge, it is critical to maximize their use.

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