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Spatial Analysis of Mangrove Distribution Using Landsat 8 Oli in Badung Regency and Denpasar City, Bali Province, Indonesia

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Abstract
Bali is an island situated among the Indonesian archipelago with huge potential to host mangrove forests. Using remote sensing technology advances, satellite images, such as Landsat images, might be employed to analyse mangrove forest distribution and density. This paper presents an analysis of mangrove distribution in Badung Regency and Denpasar City, Bali, as a basis for the management and conservation of mangrove ecosystems. This study used Landsat 8 OLI images and a vegetation index to analyse the mangrove forest distribution and density in this area. It started by identifying mangrove forests using the RGB 564 band and continued to distinguish between mangrove and non-mangrove objects using unsupervised classification, before analysing mangrove density using the NDVI formula. The results show that the mangrove forest area in 2020 was 1,269.20 ha, with an accuracy rate of 83%. Mangroves were found on the deepest or most curved coastline of the Benoa Bay area, on enclosed waters. This distribution follows the river network in the lower reach, which has thick deposits and is uninfluenced by large currents and waves. Based on the vegetation index analysis results, the mangrove forest area observed mainly had a moderate density, with a total area of 510.85 ha (40%), followed by high density (413.15 ha/ 33%) and low density (340.51 ha/ 27%).

Keywords: density, Landsat 8, mangrove, NDVI.

1. Introduction

Indonesia is an archipelagic country with long-term, tremendously valuable potential coastal and marine resources. One of these is mangroves, which offer high economic and ecological advantages. Mangroves are a unique type of vegetation that can grow in sea water with a high salt concentration (Noor et al., 2015, Sreeranga, 2021). Mangroves also have strong root systems that can withstand waves and prevent abrasion and coastal erosion, a decline far shoreline, thus creating a calm marine habitat (Windusari et al., 2014). Furthermore, mangroves have specific morphological, physiological, and reproductive characteristics that enable them to survive in the presence of critical interfaces, such as salinity and anaerobic soil, as well as in terrestrial, estuarine, and near-shore marine ecosystems within tropical and subtropical regions (Kusmana & Sukristijiono, 2016; Daza et al., 2020). Mangroves also offer other advantages, including their ability to adhere firmly to the edge of the land (at the water-land interface), retain sediment, and protect the surrounding land (Kandasamy, 2012). In shallow coastal environments, mangroves can jut out into the sea, thereby extending the land area and protecting it from erosion and storm damage (Mazda et al., 2006).

The national mangrove area in 2019 was about 3.31 million hectares but this area continues to decrease (Bunting et al., 2018). Healthy mangroves should cover an adequate area in order for them to serve as primary life support systems, which are critical to coastal regions (Febriarta et al., 2018; Febriarta and Oktama, 2020). However, unsustainable resource utilization and the profit orientation of communities have often led to rapid, severe mangrove loss, with serious consequences (Malik et al., 2017). The mangrove ecosystem around the world is characterized as highly threatened, due not only to human interference, but also natural processes which plays a significant role in mangrove vulnerability (Goldberg et al., 2020). Globally, the mangrove areas are declining rapidly as they are cleared for coastal development and aquaculture and logged for timber and fuel production (Polidoro et al., 2020). The declining mangrove area affects not only the environment but also the sustainability of local communities. The sustainability of mangrove forests is important for many reasons, including the prevention of coastal erosion and seawater intrusion; the provision of spawning, nursery, and feeding grounds for diverse marine biota; and also their direct use (such as for firewood, charcoal, and construction material)—all of which benefit the sustainability of local communities (Malik et al., 2017; Untari et al., 2020). Therefore, the need for mangrove distribution monitoring is increasing constantly.

Remote sensing is highly recommended for monitoring mangrove distribution (Xia et al., 2020; Hu et al., 2020; Pham et al., 2019; Duncan et al., 2018; Duke et al., 2017; Purnamasayangsukasih et al., 2016). Remote sensing technology, which produces images of part or all of the Earth's surface, uses a camera or a sensor to record objects from a certain distance or remotely without direct contact, allowing the mapping of resources on a broad swath (Sivakumar et al., 2004; Sowmiya et al., 2017). By taking advantage of this, the mangrove distribution can be identified and classified by applying pixel classification methods to Landsat 8 OLI images. Mangrove and non-mangrove objects can be distinguished by applying the unsupervised pixel classification approach, which relies on composite bands to group pixels systematically using Geographic Information Systems (GIS) (Jia et al., 2014; Maryatika & Lin, 2017; Pham et al., 2019; Islam et al., 2019). GIS is an emerging technology for environmental studies (Kusmiyarti et al., 2018; Hansun et al., 2019; Permatasari et al., 2020; Trigunasih & Wiguna, 2020; Permatasari et al., 2021; Sardiana et al., 2021; Suherningtyas et al., 2021; Wiguna, 2021; Sukraini et al., 2022). The combined supervised-unsupervised approach classifies pixel values through visual interpretation—i.e., based on object characteristics and spatial approaches (Ahmad & Quegan, 2013; Kantakumar, & Neelamsetti, 2015).

Several studies of mangrove distribution using remote sensing exist (Darmo et al., 2018; Pratama et al., 2019). Darmo et al. (2018) used Landsat 8 imagery to estimate the change in mangrove density and identify the best vegetation index for estimating mangrove canopy density. Similar studies employ other satellite products, such as Sentinel-2A (Pratama et al., 2019). However, studies which employ spatial distribution and density as a basis for the management and conservation of mangrove ecosystems are lacking in the literature. This paper presents an analysis of mangrove distribution in Badung Regency and Denpasar City as a basis for the management and conservation of the mangrove ecosystem.

2. Research Method

Mangrove ecosystems grow in the northern and southern parts of Bali Island. This research focuses on the south mangrove habitat, spanning from 8°43'20.40" to 8°48'1.39"S and from 115°10'55.10" to 115°14'16.99"E, and administratively located on the coastlines of Badung Regency and Denpasar City (Giri et al., 2000). Mangroves grow on sheltered beaches, in tidal areas and onmuddy sands (Geurhaneu & Kamiludin, 2013; Lee et al., 2014). In the tropics, the climatic conditions and coastal geomorphological zones determine the mangroves' characteristics (Gupta et al., 2018). Figure 1 shows the research location.

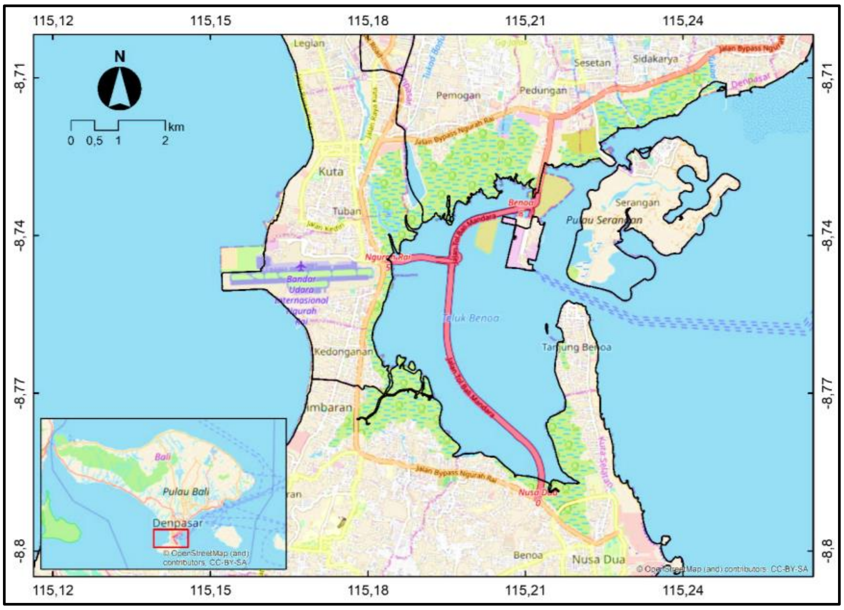

Figure 1. Research Area.

The mangrove identification and vegetation density index was calculated using the Landsat 8 OLI/TRIS 116/Row 66 image product acquired on November 06, 2020. This product was selected because Landsat imagery is widely accredited for its advantages: a large aerial extent, reliable data availability and high image accessibility (Mathieu & Aubrecht, 2018; Warnasuriya et al., 2020). The mangrove identification involved a pixel-based interpretation and image analysis (Heenkenda et al., 2014; Dezhi et al., 2018). A pixel value is a point containing a numerical value and, in remote sensing, refers to the band emission value. Landsat interpretation and image analysis use the 564 band (color composite) with a 30m resolution. Band 5 or near-infrared (NIR) band has a wavelength of 0.85–0.88 μm and high sensitivity to biomass content and shorelines. Band 6 is short-wave infrared (SWIR 1) with a wavelength of 1.57–1.65 μm and can discriminate moisture contents, soils, and vegetation species, and also penetrate thin clouds. Meanwhile, band 4 or the red band has a wavelength of 0.64–0.67 μm and can distinguish between vegetation species (Olsen et al., 2013; Stark et al., 2015; Misbari & Hashim, 2016; Roy et al., 2016; Lee et al., 2018). The 564 band produces a false color composite that accentuates objects located in the land-sea transitional zone, thus enhancing mangrove tree visibility on the image.

The use of supervised pixel classification in the mangrove identification process aimed to characterize each pixel value for both mangrove and non-mangrove objects. To obtain the optimum results, an image sharpening technique called pan sharpening was applied. Then, the objects on the pan-sharpened image were classified using interpretation keys, such as hue, texture, pattern, and association.

The vegetation density index was computed using a transformation equation of the image pixel values. The NDVI is the ratio of the difference between the measured red (R) and near-infrared (NIR) band reflectance values, divided by their sum (Naser et al., 2020). It is presented in the equation (1).

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)} \qquad (1)$$

NDVI	:	Normalized Difference Vegetation Index
NIR	:	Near-infrared (band 5) reflectance value
Red	:	Red (band 4) reflectance value

The NDVI values obtained from the equation above were then categorized into classes of canopy density according to the provision set in Table 1. After the Mangrove identification and vegetation density index calculation had been performed in several stages, a field check was made to determine the area and density of the mangroves qualitatively. The various stages of the research methodology are shown in the research diagram in Figure 2.

Table 1. Vegetation Index Values.

NDVI value ranges	Canopy density classes
$0.43 \leq NDVI \leq 1$	High/Dense
$0.33 \leq NDVI \leq 0.42$	Moderate
$-1 \leq NDVI \leq 0.32$	Low/Sparse

Source: Department of Forestry, 2005

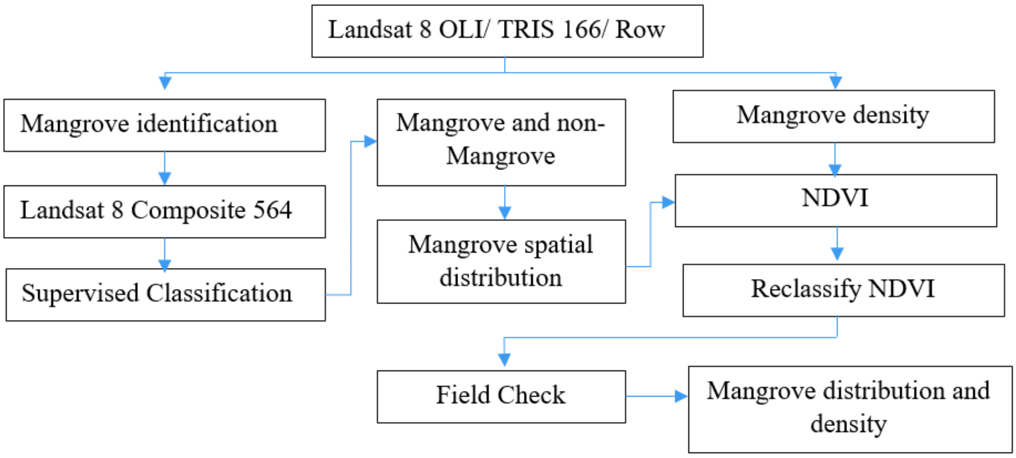

Figure 2. Flowchart of the Primary Research Process.

3. Results and Discussion

3.1. Monitoring the Mangrove Distribution

Mangroves grow along the coastlines of Badung Regency and the eastern part of Denpasar City, where fluvial depositional landforms like alluvial plains develop. The Telaga Waja River deposits sediment at its mouth, which is surrounded by land and water protruding into the land (Benoa Bay). Low-lying lands with elevations ranging from 0 to 4 m asl and a flat morphology (0–4%) are the precursors to the process. In regional geology, these forms are built on the Alluvium Formation. Seafloor sediments consist of muddy sands with a small amount of gravel (KESDM, 2018; Lacerda, 2002).

The mangrove and non-mangrove vegetation identification was based on data extracted from the 564-composite Landsat 8 OLI images, which produced a pseudo color composite with contrast in the pixel values around mangrove plants. Under this color scheme, mangroves appear in a relatively coarse texture, in a brighter hue than the dense vegetation clusters, and with site-association to the sea-land interface. The 564-colored image was pan-sharpened to produce a pseudo-color sharpness, thus allowing straightforward mangrove area identification and accurate interpretation. In this research, supervised classification was applied to interpret and group the mangrove pixel values, then compare these with the true-color RGB image to produce more accurate results. The classification results showed that the image pixel values ranged from 1 to 89. Based on this segmentation, pixel values of 73–75 represented mangrove features, and those lying outside this range reflect non-mangrove objects. Mangroves were associated with objects like rivers (pixels values = 20–21) and the sea (pixel values = 11–12). The supervised classification produced raster data containing mangrove and non-mangrove pixel/grid values and revealed that mangroves were located in the land-sea transitional zones along Benoa Bay. Figure 3 shows the segmentation with the 564-Composite Landsat 8 OLI Image of the Benoa Bay area, in Denpasar City and Badung Regency, distinguishing mangrove from non-mangrove vegetation.

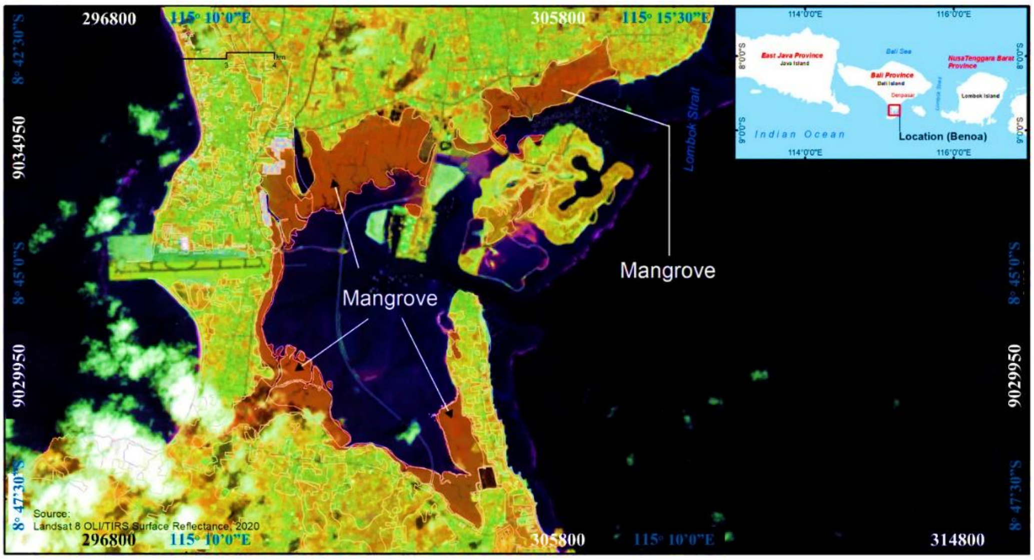

Figure 2. Segmentation using the 564-Composite Landsat 8 OLI Image of the Benoa Bay Area.

The landward and seaward boundaries of the mangrove areas in 2010 were approximately 10–100 m and 1–22 m from the coastline, respectively. In the northern part of the study area, mangroves protruded into the coastline as far as 3 m. As stated by the Indonesian Institute of Aeronautics and Space (LAPAN) (2017), despite the areal expansion and shrinkage that occurred from 2010 through 2016, the mangrove area generally increased from 1,015.23 ha to 1,245.96 ha, or by 203.73 ha (18.51%). The most extensive change in mangrove distribution was detected in the northern part of Kuta District (the Denpasar Mangrove Zone), where the landward boundary of the mangrove area shifted from ±470 m to 310 m from the coastline, potentially due to land-use conversion. However, mangroves grew closer to the coastline, increasing the total mangrove area in the west (Kelan Mangrove Zone), east (Tahura Ngurah Rai Mangrove Zone), and south (Taman Sari Mangrove Zone).

As seen in the 546-composite image (Figure 3), mangroves had a site-association with the downstream drainage network of Telaga Waja River, which was adjacent to the Taman Sari Mangrove Zone. Fluvial deposits, i.e., sand and mud substrates, create an ideal habitat for mangrove ecosystems (Vannucci, 2004). The river downstream had a darker hue, as found in the Denpasar Mangrove Zone in the north, where the Nusa Dua Reservoir's outlet system is situated. In coastal regions with flat topography, such as the Benoa Bay area, there is little influence by sea current and wave dynamics, and this bay is thereby categorized as a closed sea.

Based on the supervised classification of the 564-composite image acquired on November 06, 2020, mangroves covered 1,269.20 ha of land and had a similar distribution pattern to the condition in 2016 (1,245.96 ha), except for in the Denpasar Mangrove Zone in the north. Here, the landward boundary shifted 170 m or closer to the coastline, but an additional area jutted out as far as 2 m into the sea. On the contrary, in the south (Taman Sari Mangrove Zone), the mangrove seaward boundary had receded inland and was 30 m from the coastline. The landward shift and areal shrinkage of the mangrove ecosystem on the sea-land interface are believed to be the result of fluvial currents from adjacent rivers (He and Siliman, 2019). Figure 4 shows the result regarding the distribution of mangroves in Denpasar City and Badung Regency as well as the previous mangrove distribution as stated by the Indonesian Institute of Aeronautics and Space (LAPAN) (2017).

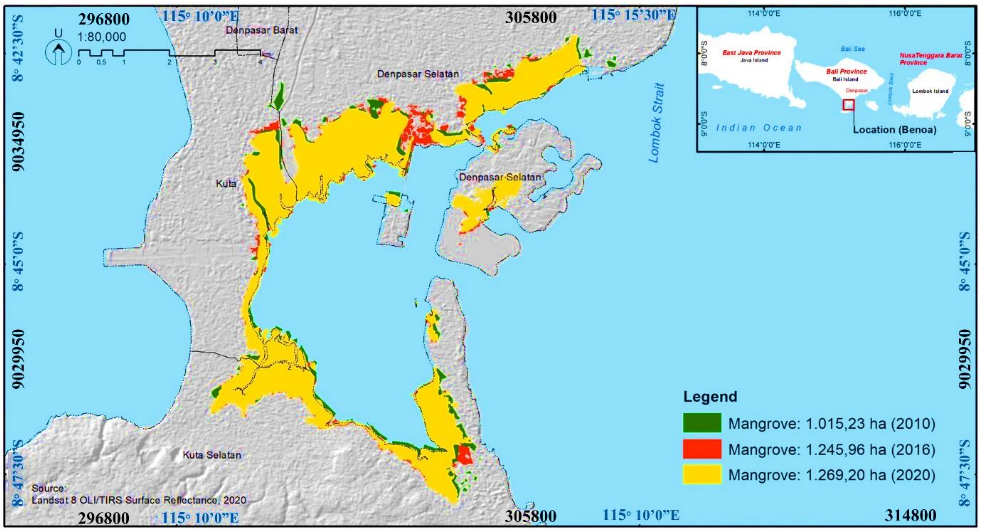

Figure 4. Mangrove Distribution in the Benoa Bay Area.

The leaf area or canopy width reflects the relationship between mangrove distribution and vegetation density (Monsef and Smith, 2017). The high vegetation density or wide canopy show the broad leaves of the true (main) mangroves. Based on the transformation equation of the red (band 4) and near-infrared (NIR/band 5) reflectance values, there were 413.15 hectares of mangrove with a high density or wide canopy, i.e., an indicator of true mangroves. True mangrove trees refer to the major or dominant stands within the mangrove ecosystems in intertidal environments. Based on these characteristics, the true mangroves in Badung Regency and Denpasar City were associated with the downstream river network. Tide-affected mangroves tend to have high density, such as in the Denpasar Mangrove Zone in the north, the Taman Sari Mangrove Zone in the west, and the Tahura Ngurah Rai Mangrove Zone in the southeast. Mangroves with low density (sparse distribution) were mostly located on the outermost coastline, indicating young mangroves or shoots. Mangroves with moderate density surrounded those with high density. Combined with the additional area jutting out into the sea, this indicates healthy mangrove growth. Mangroves with moderate density covered an extent of 510.85, and this density level was found to be dominant (40.39%), followed by high density (413,15 ha/ 33%) and low density (340,51 ha/ 27%). Figure 5 shows a map of the mangrove vegetation density class in the Benoa Bay area. An accuracy test for the distribution and density of mangroves was conducted qualitatively through field observations and compared with the mangrove distribution map produced by the National Aeronautics and Space Agency of the Republic of Indonesia (LAPAN), with similar results. Table 2 shows the area of each vegetation density class.

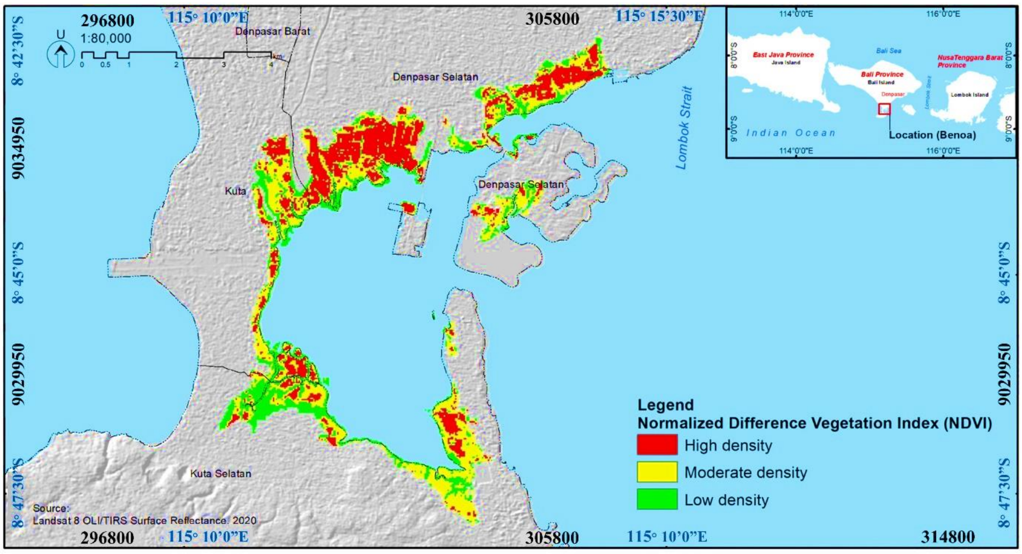

Figure 5. Map of the Mangrove Vegetation Density Class.

Bali is among the Indonesian provinces that have abundant natural coastal resource potential, including mangrove forests. The changes in canopy density are not only responsible for their ecological quality but also have further potential to serve as disaster barriers and promote ecotourism. Bali Island, well-known as the Island of the Gods, has potential as a mangrove area, which is largely distributed around Benoa Bay, and administratively located in Denpasar City and Badung Regency. Mangrove distribution and density are not only important for future mangrove planning and enhancing this potential but also provide a basis for replanting and preserving mangrove forests.

Table 2. Vegetation Density Class of Mangrove Vegetation.

Density Class	Area (ha)	%
High (dense)	413.15	32.67
Moderate	510.85	40.39
Low (sparse)	340.51	26.92

3.2. Management and Conservation of Mangrove Ecosystems using Remote Sensing Data

The geographical location of the mangrove ecosystem, which is located at the transition between sea and land, provides unique characteristics when compared to other vegetation objects. These characteristics can be analysed using remote sensing images based on the spectral characteristics of the mangrove ecosystem.

Given the various benefits of the mangrove ecosystem, it requires proper management so that its existence can be protected and sustainable use can be achieved. To support the management of mangroves, spatial data and information are needed regarding their distribution and density based on remote sensing technology and Geographic Information Systems.

Mangrove ecosystem management begins with the interpretation of remote sensing imagery. Mangrove and non-mangrove ecosystems can be distinguised by visually interpreting images using composite images. The preparation of this color composite image aims to enhance the identification of the objects in the image to obtain a clearer visual image. Mangrove density can be classified using bands on satellite imagery ; namely, red and near infrared bands. Using these two types of band makes it possible to produce a vegetation index value, which can establish the green level and amount of vegetation.

Next, it is also necessary to monitor changes in land area and analyze the distribution of mangroves. Data that can be used to analyze mangrove ecosystem management are multitemporal satellite images such as Landsat and Sentinel. The use of multitemporal data is intended to make it easier to monitor changes in land use within the mangrove ecosystem over time. Mangrove monitoring for management and conservation purposes can be carried out, including monitoring any changes in the mangrove area and its density as well as analysis based on the visual interpretation of multitemporal remote sensing data. The purpose of managing and conserving mangroves using remote sensing imagery is to simplify the analysis process and save costs while at the same time gathering accurate results.

4. Conclusion

The supervised classification of the 564-composite Landsat 8 OLI image can identify mangroves from a distinct range of 73–75 pixel values. Visually, mangroves appear in a dark hue, with a moderately coarse texture, shaped into clusters, and site-associated with the land-sea interface or intertidal zone. This classification has also shown that mangroves in Badung Regency and Denpasar City grow on the deepest or most curved coastline of the Benoa Bay area, and that the distribution pattern follows the downstream river network. From 2016 through 2020, the mangrove area has increased from 1,245.96 ha to 1,269.20 ha, or by 1.83%. The relationship between mangrove distribution and vegetation density shows ideal growth and, in general, the mangrove area observed has a moderate vegetation density with a total area of 510,85 ha (40%), followed by high density (413,15 ha/ 33%) and low density (340,51 ha/ 27%). The mangrove ecosystem can be managed and conserved by conducting remote sensing data analysis to monitor changes and determine the distribution and density of mangroves. Mangrove management and conservation using remote sensing data can also monitor changes in the mangrove area and its density from time to time using multitemporal remote sensing data.

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