

CHAPTER 2 - LITERATURE REVIEW

2.1. Mangrove Ecosystems and Mangrove Condition

Mangrove ecosystems are dynamic coastal ecosystems whose condition can change over time due to natural processes and anthropogenic pressures. Monitoring mangrove conditions is therefore important for understanding changes in vegetation and supporting appropriate management actions. However, the concept of mangrove ecosystem health is not always defined consistently in remote sensing studies, and vegetation vigor is sometimes used as a proxy for ecosystem health without sufficient consideration of other ecological conditions and field information (Neres et al., 2024).

Mangrove condition can be viewed as a continuum, ranging from relatively healthy vegetation to conditions showing stress or decline and, in severe cases, vegetation mortality. In practice, this continuum needs to be translated into operational classes that can be consistently interpreted for monitoring purposes. In this study, mangrove condition is operationally represented by three classes: Healthy, Stressed, and Dead. The Healthy class represents mangrove areas with relatively favorable conditions, the Stressed class represents areas that remain alive but show indications of reduced or altered condition, and the Dead class represents areas associated with vegetation mortality.

The three classes are defined as an operational framework for this study rather than as a universal classification of mangrove ecosystem health. The Stressed class is introduced as an intermediate condition between Healthy and Dead to provide more information than a simple alive until dead classification. This approach is consistent with the need to interpret mangrove condition using multiple indicators and supporting field information, as the assessment of mangrove health cannot always be adequately represented by a single remotely sensed indicator (Neres et al., 2024).

The three-class framework is also aligned with the practical monitoring context of the Segara Biru Mangrove ecosystem. Based on information from local mangrove managers, field monitoring generally distinguishes whether planted mangroves remain

alive or have died. The introduction of the Stressed class provides an additional intermediate condition that can be used to identify mangrove areas that are still alive but may require further attention. The satellite-based classification is therefore positioned as supporting information for field monitoring and verification rather than as a replacement for direct field assessment.

2.2. Mangrove Degradation and Temporal Changes

Mangrove degradation refers to a decline in the condition and ecological functions of mangrove ecosystems that may result from natural disturbances and anthropogenic pressures, including land-use change, coastal development, hydrological alteration, pollution, and other environmental pressures (Goldberg et al., 2020). Degradation does not always occur as an immediate transition from healthy vegetation to complete loss or mortality. Mangrove conditions may change progressively, with vegetation experiencing different levels of stress before severe deterioration or mortality occurs. Therefore, understanding mangrove degradation requires consideration of changes in ecosystem condition over time rather than relying only on a single observation period.

Mangrove ecosystems may also exhibit different temporal patterns following disturbance. A mangrove area may remain relatively stable, gradually decline in condition, or show signs of improvement following natural or assisted recovery. These changes can be observed through repeated satellite observations, allowing the temporal sequence of mangrove conditions to be examined over multiple observation periods (Bunting et al., 2022; Worthington et al., 2020). Such temporal information is important for distinguishing persistent changes from temporary variations in mangrove condition.

In the context of mangrove monitoring, temporal analysis can therefore provide additional information beyond single-date classification. By examining the sequence of classified conditions across different observation periods, changes in mangrove condition can be characterized based on their temporal patterns. In this study, the temporal sequence of Healthy, Stressed, and Dead classifications is used to characterize changes in mangrove condition during the 2020–2025 period. The analysis focuses on identifying temporal patterns of mangrove condition change within the study area,

including relatively stable conditions, recovery, progressive degradation, and fluctuating conditions, rather than determining the specific causes of these changes or forecasting future mangrove conditions.

2.3. Remote Sensing for Mangrove Monitoring

Remote sensing provides an effective approach for observing mangrove ecosystems because satellite observations can provide spatially distributed information over areas that may be difficult to monitor repeatedly through field surveys alone. Optical, thermal, and Synthetic Aperture Radar (SAR) observations can provide complementary information related to vegetation condition, surface moisture, thermal characteristics, and vegetation structure. The integration of these data sources can therefore support the assessment of mangrove conditions from multiple environmental perspectives (Maurya et al., 2021).

Optical satellite imagery is widely used for mangrove monitoring because vegetation characteristics can be represented through spectral responses in the visible, near-infrared (NIR), red-edge, and shortwave infrared (SWIR) regions. Sentinel-2 provides multispectral observations with relatively high spatial resolution and includes red-edge bands that are useful for characterizing vegetation condition and chlorophyll-related responses. Previous studies have demonstrated the applicability of Sentinel-2 imagery for mangrove monitoring and vegetation characterization (Baloloy et al., 2020).

Thermal remote sensing provides complementary information on surface thermal conditions. Landsat 8 is equipped with the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), allowing thermal observations to be used for deriving Land Surface Temperature (LST). LST can provide information about spatial variation in surface thermal conditions and can complement vegetation- and moisture-related indicators derived from multispectral imagery (Albuhaisi et al., 2024).

SAR provides another complementary source of information because microwave observations can be acquired under cloudy conditions and do not depend on reflected sunlight. Sentinel-1 C-band SAR observations can provide backscatter information related to vegetation structure and surface characteristics. The use of SAR is therefore relevant for tropical mangrove environments where cloud cover may restrict the availability of optical observations. Cross-polarized VH backscatter and the VH/VV ratio can provide additional structural information that complements optical and thermal observations (Nguyen et al., 2021).

Remote sensing therefore provides an observational foundation for mangrove condition assessment by integrating complementary optical, thermal, and SAR information. These different information sources can be transformed into satellite-derived features representing vegetation, moisture, surface-water, thermal, and structural characteristics, which can subsequently serve as inputs for feature analysis and machine learning-based classification.

2.3.1. Satellite Data Preprocessing and Harmonization

The use of multiple satellite sources requires appropriate preprocessing before the derived variables can be combined for analysis. Preprocessing aims to reduce observation-related inconsistencies and produce satellite data that are suitable for subsequent feature extraction and analysis (Skakun et al., 2022). For optical imagery, preprocessing commonly includes image selection, cloud and cloud-shadow filtering, and temporal compositing to reduce the influence of contaminated observations (Ju et al., 2025). For SAR imagery, preprocessing is required to obtain consistent radar backscatter information, while thermal imagery requires appropriate processing to derive surface temperature information. In addition to sensor-specific preprocessing, multi-source satellite analysis requires consideration of differences in spatial resolution, coordinate reference systems, acquisition characteristics, and observation dates. Spatial harmonization is required so that features from different sensors can be associated with comparable geographic locations or spatial units, while temporal harmonization is required so that observations represent comparable monitoring periods (Claverie et al., 2018; Ju et al., 2025). These procedures do not eliminate the inherent differences

between sensors; rather, they provide a consistent basis for integrating their derived variables.

For multi-temporal analysis, preprocessing should also be applied consistently across observation periods. Consistent processing helps reduce the possibility that apparent changes between years are caused by differences in image preparation rather than changes in the observed mangrove condition. Maintaining comparable preprocessing procedures across observation periods therefore supports more consistent comparison of satellite-derived variables over time (Chen et al., 2026; Claverie et al., 2018).

2.4. Multi-Source and Multi-Temporal Satellite Data

The use of multi-source satellite data allows mangrove conditions to be observed from different types of remotely sensed information. Each satellite sensor provides different characteristics that can complement one another in representing vegetation and environmental conditions. Optical data are useful for observing vegetation responses based on spectral information, while radar data provide additional information related to vegetation structure and surface characteristics. Thermal data can further provide information related to surface temperature. The integration of these data sources can therefore provide a more comprehensive representation of mangrove conditions than the use of a single satellite data source (Maurya et al., 2021).

Landsat 8 is incorporated to provide thermal information that cannot be directly obtained from Sentinel-2 multispectral observations. The thermal infrared observations from Landsat 8 can be used to derive Land Surface Temperature (LST), which provides additional information related to surface thermal conditions. In the context of this study, Landsat 8 therefore complements Sentinel-2 by providing the thermal feature used in the classification process (Manna and Sarkar, 2025; Wang et al., 2026a). The use of Landsat observations for long-term environmental monitoring also provides an important basis for analyzing changes across multiple years.

Sentinel-1 provides Synthetic Aperture Radar (SAR) observations that complement the optical and thermal information. Unlike optical sensors, SAR observations can be acquired under cloudy conditions and are therefore useful in tropical environments where cloud cover may limit the availability of optical imagery. Sentinel-1 data can also provide information related to vegetation structure and surface characteristics through radar backscatter (Zhang et al., 2022). The use of SAR data is therefore relevant for improving the representation of mangrove conditions when combined with optical and thermal observations (Zhang et al., 2022).

The integration of observations from different satellite sensors requires consideration of their differences in spatial characteristics, acquisition dates, and observation configurations. Spatial harmonization is necessary to ensure that satellite-derived variables from different sources can be associated with comparable geographic locations or spatial units, particularly when the sensors have different spatial resolutions or geometric characteristics. Studies of Landsat-8 and Sentinel-2 product have demonstrated the importance of accurate spatial co-registration when combining observations from these sensors (Rengarajan et al., 2024a). In addition, harmonized satellite datasets commonly apply procedures such as atmospheric correction, cloud and cloud-shadow masking, reflectance normalization, and common spatial gridding to improve the consistency of observations from different sensors (Ju et al., 2025). Recent work has further demonstrated that spatial and spectral harmonization can improve the consistency of multi-sensor Landsat and Sentinel-2 observations for integrated analysis (Chen et al., 2026). These harmonization considerations provide the theoretical basis for combining complementary satellite-derived variables from different sensors in a common analytical framework.

Multi-temporal satellite analysis also requires consistency across observation periods because differences in acquisition dates and sensor conditions may introduce variation that is unrelated to actual changes in mangrove condition. Applying comparable data preparation and harmonization procedures across observation periods can therefore support more consistent comparison of satellite-derived variables over time (Chen et al., 2026; Ju et al., 2025).

2.4.1. Sentinel-2 Optical Data

Sentinel-2 is an optical remote sensing mission operated by the European Space Agency (ESA) through the satellite constellation Sentinel-2A and Sentinel-2B. Dedicated to Europe's Copernicus programmed, the mission supports operational applications primarily for land services, including the monitoring of vegetation, soil and water cover, as well as the observation of inland waterways and coastal areas.

The satellite provides multispectral data with high spatial resolution (10–20 m) and broad spectral coverage for environmental and ecosystem monitoring. With the combination of the two satellites, data can be obtained with a revisit time interval of about 5 days, thus allowing the formation of a dense time-series to continuously monitor changes in vegetation conditions (Fauzi et al., 2026).

The Sentinel-2 satellites have a swath width of 290 km and together achieve a five-day revisit time. The two satellites follow the same sun-synchronous orbit with an inclination of 98.6° but are 180° out of phase. They orbit at an altitude of 786 km with a period of 101 minutes and Mean Local Solar Time at descending node: 10:30 (optimum Sun illumination for image acquisition) (Huang et al., 2025) . This capability will support monitoring of changes on the Earth's surface.

Table 2.1 presents several Sentinel-2 band combinations and spectral indices that can be applied to support different remote sensing applications. The selection of bands is determined by the characteristics of the target application, while other combinations may be considered depending on the objectives and conditions of a particular study.

Table 2.1. Sentinel-2 Spectral Features Used for Mangrove Health Assessment

Feature Type	Feature	Sentinel-2 Bands / Formula	Relevance to Mangrove Monitoring
True Colour	RGB Composite	B4, B3, B2	Provides a natural-colour representation of the mangrove area
Vegetation	NDVI	$(B8 - B4) / (B8 + B4)$	Represents vegetation greenness and canopy condition
Vegetation	EVI	$2.5 \times (B8 - B4) / (B8 + 6B4 - 7.5B2 + 1)$	Enhances vegetation response and reduces the influence of atmospheric and soil background effects
Red-edge	NDRE	$(B8A - B5) / (B8A + B5)$	Provides information related to vegetation condition and chlorophyll response using red-edge and near-infrared bands
Moisture	NDMI	$(B8 - B11) / (B8 + B11)$	Indicates vegetation moisture condition and can help identify changes associated with vegetation stress
Water	MNDWI	$(B3 - B11) / (B3 + B11)$	Supports the identification of water-related areas and helps distinguish water surfaces from surrounding land or vegetation
SWIR	SWIR-based features	B11, B12	Provides sensitivity to surface moisture and structural characteristics, supporting the assessment of vegetation and environmental conditions

Table 2.1 summarizes the Sentinel-2 spectral features considered relevant to mangrove health monitoring. Each feature provides different information regarding vegetation condition, moisture content, water presence, and surface characteristics. The characteristics of each feature are described as follows:

1. True Colour (RGB Composite):

The true-colour composite uses the red, green, and blue bands (B4, B3, and B2, respectively) to produce an image that approximates the natural appearance of the Earth's surface. In mangrove monitoring, this representation provides a visual reference for identifying mangrove areas, surrounding water bodies, exposed soil, and other land-cover features (Bendaas et al., 2026; Perea-Ardila and Murillo-Sandoval, 2024)

2. NDVI:

The Normalized Difference Vegetation Index (NDVI) is a widely used spectral index for assessing vegetation condition. It is calculated from the near-infrared (B8) and red (B4) bands. Healthy vegetation generally reflects more near-infrared radiation and absorbs more red radiation, resulting in higher NDVI values. Therefore, NDVI can be used to characterize vegetation greenness and provide an indication of mangrove canopy condition (Aji et al., 2023; Neres et al., 2024).

3. EVI:

The Enhanced Vegetation Index (EVI) is designed to provide improved sensitivity to vegetation characteristics, particularly in areas with relatively dense vegetation. EVI uses the near-infrared (B8), red (B4), and blue (B2) bands and incorporates correction terms to reduce the influence of atmospheric conditions and soil background. This feature can complement NDVI in evaluating the condition of mangrove vegetation (Aji et al., 2023; Wei et al., 2025).

4. NDRE:

The Normalized Difference Red Edge Index (NDRE) utilizes the red-edge and near-infrared portions of the Sentinel-2 spectrum. In this study, NDRE is calculated using B5 and B8A. The red-edge region is sensitive to changes in vegetation structure and chlorophyll-related characteristics. Consequently, NDRE can provide additional information for detecting variations in mangrove vegetation condition that may not be fully captured by conventional vegetation indices (Liu and Zhu, 2024).

5. NDMI:

The Normalized Difference Moisture Index (NDMI) is used to characterize vegetation moisture conditions. The index combines the near-infrared band (B8) with the short-wave infrared band (B11), where the latter is sensitive to water content. Changes in NDMI values can therefore provide information about variations in vegetation moisture and may be useful for identifying signs of vegetation stress (Suharsono and Singgalen, 2025).

6. MNDWI:

The Modified Normalized Difference Water Index (MNDWI) uses the green band (B3) and short-wave infrared band (B11) to enhance the detection of water surfaces. In mangrove environments, MNDWI can help distinguish water bodies and water-covered areas from surrounding vegetation and other land-cover types. This information is particularly relevant because mangrove ecosystems are closely associated with tidal and coastal water environments (Yang et al., 2024a).

7. SWIR-based Features:

Short-wave infrared (SWIR) observations from Sentinel-2, particularly B11 and B12, are sensitive to surface moisture and material characteristics. Water strongly interacts with SWIR radiation, making these bands useful for characterizing moisture-related conditions. In mangrove monitoring, SWIR features can complement vegetation indices by providing additional information about moisture and surface conditions within and around the mangrove area (Miao et al., 2024; Wang et al., 2024).

The main advantage of the Sentinel-2 lies in the presence of Multi Spectral Instrument (MSI) instruments which include the Visible, Near Infrared (NIR), Shortwave Infrared (SWIR), and Red-Edge bands. The combination of these bands is very effective for detecting vegetation health, canopy structure, vegetation water content, and mangrove biomass dynamics. Therefore, Sentinel-2 is one of the main data sources used in this study for deriving optical features relevant to mangrove condition classification



Figure 2.1 Sentinel-2A Satellite Equipped with Multi Spectral Instrument (MSI)

Figure 2.1 shows the Sentinel-2A satellite carrying the MSI instrument as the main sensor for multispectral data acquisition. In this study, Sentinel-2 data was used to extract various spectral indices representing vegetation conditions, canopy moisture, and biophysical characteristics of mangrove ecosystems.

The characteristics of the Sentinel-2 band used in this study are presented in Table 2.2

Table 2.2 Spectral Characteristics of Sentinel-2 Bands and Their Relevance to Mangrove Monitoring

Band	Spectral Region	Central Wavelength (nm)	Spatial Resolution (m)	Relevance to Mangrove Monitoring
B2	Blue	490	10	Supports atmospheric effects assessment and characterization of coastal and water surfaces
B3	Green	560	10	Provides information on vegetation and water-related surface characteristics
B4	Red	665	10	Used as a key input for vegetation indices and vegetation condition assessment
B5	Red Edge 1	705	20	Sensitive to vegetation chlorophyll-related properties
B6	Red Edge 2	740	20	Supports assessment of vegetation condition and physiological changes
B7	Red Edge 3	783	20	Provides information related to vegetation biomass and canopy characteristics
B8	NIR	842	10	Sensitive to vegetation structure, biomass, and canopy vigor
B8A	Narrow NIR	865	20	Provides additional spectral information for detailed vegetation analysis
B11	SWIR 1	1610	20	Sensitive to vegetation and soil moisture conditions
B12	SWIR 2	2190	20	Provides information related to vegetation moisture and environmental stress

* Adapted from (Drusch et al., 2012) and ESA (2024).

As presented in Table 2.2, the spectral regions most relevant to this study include the red band (B4), red-edge bands (B5–B7), near-infrared bands (B8 and B8A), and short-wave infrared bands (B11 and B12). These bands provide complementary information on vegetation characteristics, canopy condition, and moisture-related properties of the mangrove environment.

Their spectral responses can be further transformed into vegetation, moisture, and water-related indices, including NDVI, EVI, NDRE, NDMI, and MNDWI, which provide additional representations of mangrove and surrounding environmental conditions. The inclusion of red-edge observations is particularly useful for vegetation assessment because these wavelengths provide additional sensitivity to variations in vegetation properties beyond the conventional visible and near-infrared bands. Consequently, the combination of these spectral regions provides a more comprehensive basis for characterizing spatial and temporal variations in mangrove health.

2.4.2. Landsat 8 Thermal Data

Landsat 8 is an Earth observation satellite operated by the United States Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA). The satellite is equipped with Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) instruments that allow simultaneous recording of spectral and thermal information on the earth's surface (Paul and Mahmood, 2025).

Landsat 8 Satellite Orbit Facts:

- a. The Landsat 8 satellites have a swath width of 185 km
- b. Orbits the Earth in a sun-synchronous, near-polar orbit (98.2 degrees inclination)
- c. Achieved an altitude of 705 km (438 mi)
- d. Completes one Earth orbit every 99 minutes
- e. Has a 16-day cycle with an equatorial crossing time of 10:12 a.m. +/- 5 minutes

In figure 2.2, Landsat 8 provides multi-temporal data that is widely used in monitoring environmental and ecosystem changes.

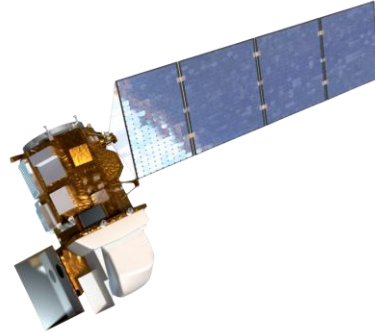


Figure 2.2 Landsat 8 Satellite Equipped with OLI and TIRS Sensors

Figure 2.2 shows the Landsat 8 satellite carrying the OLI and TIRS sensors. In this study, Landsat 8 data were used mainly to derive Land Surface Temperature (LST) as the thermal feature representing the thermal condition of the land surface.

Table 2.3 Landsat 8 OLI/TIRS Band Specifications and Ecological Applications

Band	Wavelength (μm)	Description
1 – Coastal/Aerosol	0.43 – 0.45	Aerosol and coastal zone analysis
2 – Blue	0.45 – 0.51	Bathymetric mapping; distinguishes soil from vegetation
3 – Green	0.53 – 0.59	Enhances vegetation peak reflectance
4 – Red	0.64 – 0.67	Differentiates vegetation types and condition
5 – Near Infrared (NIR)	0.85 – 0.88	Biomass content and shoreline mapping
6 – SWIR 1	1.57 – 1.65	Soil and vegetation moisture; penetrates thin clouds
7 – SWIR 2	2.11 – 2.29	Moisture content and cloud penetration
8 – Panchromatic	0.50 – 0.68	15 m resolution; image sharpening
9 – Cirrus	1.36 – 1.38	Detection of cirrus clouds
10 – TIRS 1	10.60 – 11.19	Land surface temperature and soil moisture
11 – TIRS 2	11.50 – 12.51	Improved temperature mapping and soil moisture estimation

**Source: Adapted from Roy et al. (2014) and USGS (2024).*

According to the spectral information presented in Table 2.3, this study primarily utilizes Band 5 (NIR), Band 6 (SWIR 1), Band 7 (SWIR 2), and Band 10 (TIRS 1). These bands offer complementary information related to vegetation characteristics, surface moisture conditions, and land surface temperature, which are important for deriving ecological indicators from remote sensing data. Among these bands, Band 10 is particularly important because its thermal information enables the estimation of Land Surface Temperature (LST).

The resulting LST information is incorporated as a thermal ecological indicator to support the assessment of mangrove ecosystem conditions and their temporal change trajectories (Rahmila et al., 2026).

To provide a clearer overview of the satellite datasets considered in this study, Table 2.4 presents a comparative assessment of Landsat 8, Sentinel-2, and Sentinel-1 SAR based on their orbital and sensor characteristics. The comparison also highlights the specific contribution of each satellite mission to the research framework.



Table 2.4 Comparative Characteristics of Sentinel-2, Landsat 8, and Sentinel-1

Characteristic	Landsat 8	Sentinel-2 (A & B)	Sentinel-1 SAR (A & B)
Swath Width	185 km	290 km	Approximately 250 km
Orbital Altitude	705 km	786 km	Approximately 693 km
Orbit Duration	99 minutes	101 minutes	Approximately 98.6 minutes
Revisit Cycle	16 days (8 days when combined with Landsat 9)	5 days (combined operation of Sentinel-2A and Sentinel-2B)	6 days (combined operation of Sentinel-1A and Sentinel-1B)
Equator Crossing Time	10:12 AM local time	10:30 AM local time	N/A
Sensor Advantage	Thermal Infrared Sensor (TIRS) Provides 10 m spatial resolution and enables the estimation of land surface temperature.	Provides 10 m spatial resolution and multispectral imagery.	C-band Synthetic Aperture Radar (SAR) enables observations under cloudy conditions and during both daytime and nighttime.
Primary Advantage for This Study	Provides thermal observations for deriving Land Surface Temperature (LST).	Offers high spatial resolution and multiple spectral bands for vegetation and moisture-related indices.	Provides cloud-independent radar observations for characterizing vegetation structure, surface moisture, and mangrove conditions.
Role in This Study	Used mainly to derive LST as an additional environmental feature.	Serves as the primary source of multispectral data and spectral indices for mangrove condition classification.	Used to derive radar-based features, including VH, VV, and the VH/VV ratio, to complement optical satellite data.

Overall, the three satellite missions provide complementary information for mangrove ecosystem assessment. Landsat 8 contributes thermal observations, Sentinel-2 provides detailed multispectral information for vegetation and moisture analysis, while Sentinel-1 adds radar-based observations that can strengthen the characterization of mangrove structure and surface conditions. Their combined characteristics therefore support a more comprehensive assessment of mangrove ecosystem dynamics.

2.5. Satellite-Derived Features for Mangrove Condition Assessment

Satellite-derived features provide quantitative information that can be used to characterize different aspects of mangrove conditions. Because mangrove ecosystems are influenced by multiple vegetation, hydrological, thermal, and structural characteristics, a single satellite-derived indicator may not adequately represent the condition of the ecosystem.

Features derived from optical, thermal, and Synthetic Aperture Radar (SAR) observations can therefore be combined to provide complementary information on vegetation characteristics, moisture conditions, surface-water conditions, thermal variation, and vegetation structure. Previous mangrove remote sensing studies have demonstrated the value of combining multiple satellite-derived variables rather than relying on a single indicator (Maurya et al., 2021; C. Nguyen et al., 2021).

In this study, the initial candidate feature set consists of eight satellite-derived variables: NDVI, EVI, NDRE, NDMI, MNDWI, LST_Celsius, VH, and VH/VV Ratio. These variables were selected as initial candidate predictors because they represent different dimensions of mangrove and environmental conditions that are potentially relevant to distinguishing the three operational mangrove condition classes, namely Healthy, Stressed, and Dead.

The selected features are not considered direct measurements of mangrove health. Instead, they are treated as satellite-derived proxies representing different characteristics of vegetation and environmental conditions. Their actual relevance to the classification task is subsequently evaluated empirically through feature relevance analysis, redundancy assessment, feature-scenario comparison, and model-based feature interpretation. The main characteristics and intended roles of the initial candidate features are summarized in Table 2.5. The table clarifies the relationship between each feature, its spectral or technical definition, the information represented, the satellite source, and its intended role in this study.



Table 2.5 Summary of Initial Candidate Satellite-Derived Features for Mangrove Condition Assessment

Spectral / Feature Variable	Technical Description	Spectral Formula / Derivation	Main Information Represented	Data Source	Role in This Study	Reference
NDVI	Normalized Difference Vegetation Index; a general indicator of vegetation greenness and canopy condition based on the contrast between Red and NIR reflectance.	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$	General vegetation greenness and vigor	Sentinel-2	Represents general vegetation condition	(Liu et al., 2022; Setiawan et al., 2025)
EVI	Enhanced Vegetation Index; provides complementary vegetation information and is designed to reduce some effects of background and atmospheric influences.	$2.5 \times (\text{NIR} - \text{Red}) / (\text{NIR} + 6 \times \text{Red} - 7.5 \times \text{Blue} + 1)$	Vegetation vigor and canopy response	Sentinel-2	Complements NDVI in representing vegetation condition	(Nagler et al., 2005; Pahlevan et al., 2021)
NDRE	Normalized Difference Red Edge Index; uses red-edge and near-infrared information to capture additional variation in vegetation condition.	$(\text{Narrow NIR} - \text{Red Edge}) / (\text{Narrow NIR} + \text{Red Edge})$	Red-edge response related to vegetation condition and chlorophyll	Sentinel-2	Provides additional sensitivity to vegetation condition and potential stress	(Zhu et al., 2023)
NDMI	Normalized Difference Moisture Index; uses NIR and SWIR information to represent vegetation moisture condition.	$(\text{NIR} - \text{SWIR1}) / (\text{NIR} + \text{SWIR1})$	Vegetation moisture condition	Sentinel-2	Represents moisture-related variation in vegetation	(Alongi, 2020)

Spectral / Feature Variable	Technical Description	Spectral Formula / Derivation	Main Information Represented	Data Source	Role in This Study	Reference
MNDWI	Modified Normalized Difference Water Index; uses Green and SWIR information to enhance surface-water-related responses.	$(\text{Green} - \text{SWIR1}) / (\text{Green} + \text{SWIR1})$	Surface-water-related conditions	Sentinel-2	Provides complementary information on surface-water conditions	(Chen et al., 2025; Wang et al., 2020)
LST_Celsius	Land Surface Temperature derived from Landsat 8 thermal observations.	Derived from Landsat 8 surface-temperature product	Land-surface thermal condition	Landsat 8	Represents the thermal dimension of the observed environment	(Albuhaisi et al., 2024)
VH	Cross-polarized Sentinel-1 SAR backscatter measured with vertical transmission and horizontal reception.	SAR backscatter coefficient	Radar scattering and vegetation structural characteristics	Sentinel-1	Provides complementary structural information	(C. Nguyen et al., 2021)
VH/VV Ratio	Relative relationship between VH and VV radar backscatter.	VH / VV	Relative radar scattering characteristics	Sentinel-1	Provides additional information on relative radar response	(Audebert et al., 2018; Fu et al., 2025a)

The eight features represent complementary information from three satellite sources. Sentinel-2 provides the main optical features, Landsat 8 contributes the thermal variable, and Sentinel-1 provides radar information. The detailed characteristics of each feature are described in the following subsections.

2.5.1. NDVI

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used spectral vegetation indices for satellite-based vegetation monitoring. It is derived from the contrast between red and near-infrared reflectance and is commonly used to characterize vegetation greenness, canopy density, and general vegetation vigor. Because green vegetation strongly absorbs red radiation while reflecting a relatively high proportion of near-infrared radiation, differences between these spectral responses can be used to indicate variations in vegetation condition. (Raza et al., 2024; Razali et al., 2019)

In mangrove ecosystems, NDVI has been widely applied to characterize vegetation condition and spatial or temporal variation in canopy characteristics. Higher NDVI values generally indicate denser and greener vegetation, whereas lower values may be associated with reduced vegetation cover, sparse canopy conditions, or vegetation stress. However, NDVI should not be interpreted as a direct measurement of mangrove health because its response can also be affected by canopy structure, background conditions, atmospheric effects, and vegetation density. Its interpretation is therefore more appropriate when considered together with complementary indicators representing other environmental and structural characteristics

NDVI is mathematically expressed as the normalized difference between near-infrared and red reflectance using Equation (2.1).

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (2.1)$$

where:

- **NIR** represents the Near Infrared band (Band 8);
- **Red** represents the Red band (Band 4).

The resulting NDVI values were retained as one of the optical predictor variables in the analytical dataset.

2.5.2. EVI

The Enhanced Vegetation Index (EVI) is a vegetation index developed to provide complementary information on vegetation characteristics while reducing some of the limitations associated with conventional vegetation indices. EVI incorporates the blue, red, and near-infrared spectral responses and is designed to reduce the influence of atmospheric conditions and background reflectance. It can also provide improved sensitivity to vegetation variation in areas with relatively dense canopy cover (Wei et al., 2025).

In mangrove ecosystems, EVI can provide information related to vegetation vigor and canopy response. Its formulation allows vegetation characteristics to be represented from a spectral combination that differs from NDVI, making it a useful complementary indicator when vegetation conditions vary across dense and heterogeneous canopies. However, EVI should not be interpreted as a direct measure of mangrove health because its response may also be influenced by canopy structure, atmospheric conditions, and background characteristics.

EVI is mathematically from Sentinel-2 MSI Band 8 (NIR), Band 4 (Red), and Band 2 (Blue) using Equation (2.2):

$$EVI = Gx \frac{NIR - Red}{NIR + C_1 x Red - C_2 x Blue + L} \quad (2.2)$$

where:

- **NIR** represents near-infrared reflectance (Band 8);
- **Red** represents red reflectance (Band 4);
- **Blue** represents blue reflectance (Band 2);
- **G** is the gain factor (2.5);
- **L** is the canopy background adjustment factor (1.0);
- **C₁** and **C₂** are aerosol resistance coefficients with values of 6.0 and 7.5, respectively.

The resulting EVI values were retained as an optical predictor variable.

2.5.3. NDRE

The Normalized Difference Red Edge Index (NDRE) uses red-edge and near-infrared spectral information to provide additional sensitivity to vegetation characteristics. The red-edge region is particularly responsive to changes in vegetation reflectance and can provide information associated with chlorophyll content and physiological variation that may not be fully captured by conventional red–NIR vegetation indices (Liu and Zhu, 2024).

In mangrove ecosystems, red-edge information can be useful for identifying subtle variations in vegetation condition and canopy characteristics. NDRE has also been used to examine variation in mangrove vegetation responses, including characteristics associated with canopy productivity and physiological condition (Zhang et al., 2024). However, as with other vegetation indices, NDRE should be interpreted as a spectral proxy rather than as a direct measurement of mangrove health.

NDRE is expressed using Sentinel-2 MSI Band 8 (NIR) and Band 5 (Red Edge) according to Equation (2.3):

$$NDRE = \frac{NIR - RedEdge}{NIR + RedEdge} \quad (2.3)$$

where:

- **NIR** represents the narrow near-infrared reflectance (Band 8); and
- **RedEdge** represents red-edge reflectance (Band 5).

The resulting NDRE values were retained as an optical predictor variable.

2.5.4. NDMI

The Normalized Difference Moisture Index (NDMI) is a spectral index used to characterize vegetation moisture conditions from the contrast between near-infrared and shortwave-infrared reflectance. Shortwave-infrared wavelengths are sensitive to water absorption, allowing NDMI to provide information related to the moisture status of vegetation and canopy conditions.

Moisture is particularly relevant in mangrove ecosystems because vegetation condition is closely associated with hydrological and coastal environmental characteristics. Changes in vegetation moisture may therefore provide additional information on vegetation stress or environmental variation that is not captured by greenness-oriented indices alone. NDMI can consequently complement indices such as NDVI, EVI, and NDRE by introducing information related to vegetation moisture (Suharsono and Singgalen, 2025).

NDMI is expressed using Sentinel-2 MSI Band 8 (NIR) and Band 11 (SWIR) according to Equation (2.4):

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \quad (2.4)$$

where:

- **NIR** represents near-infrared reflectance (Band 8); and
- **SWIR** represents shortwave-infrared reflectance (Band 11).

NDMI should not be interpreted as a direct measurement of mangrove health, because moisture responses can also be influenced by hydrological conditions and other environmental factors.

2.5.5. MNDWI

The Modified Normalized Difference Water Index (MNDWI) is a water-related spectral index designed to enhance surface-water responses by using green and shortwave-infrared reflectance. Compared with conventional water indices that use near-infrared information, the use of SWIR can improve the separation of water-related responses from some non-water surfaces.

MNDWI is particularly relevant to coastal and mangrove environments because surface-water conditions are closely associated with mangrove ecosystems and their hydrological context. It can provide complementary information on water-related conditions surrounding or within vegetated coastal areas (Yang et al., 2024b).

MNDWI is expressed using Sentinel-2 MSI Band 3 (Green) and Band 11 (SWIR) according to Equation (2.5):

$$MNDWI = \frac{Green - SWIR}{Green + SWIR} \quad (2.5)$$

where:

- **Green** represents green reflectance (Band 3); and
- **SWIR** represents shortwave-infrared reflectance (Band 11).

MNDWI primarily provides information about surface-water-related conditions and should therefore be interpreted as an environmental feature rather than as a direct indicator of mangrove health.

2.5.6. Land Surface Temperature as Thermal Ecological Indicator

Land Surface Temperature (LST) represents the temperature of the Earth's land surface as observed through thermal remote sensing. Surface temperature is influenced by factors such as vegetation cover, surface moisture, land-surface characteristics, and atmospheric conditions. LST therefore provides a thermal dimension that is different from the spectral information derived from optical vegetation and moisture indices (Rendana et al., 2023).

In mangrove ecosystems, thermal information can provide complementary environmental context because differences in surface temperature may be associated with vegetation cover, moisture availability, and surface characteristics. LST can therefore be considered alongside vegetation and moisture indicators to provide a more multidimensional representation of mangrove conditions.

However, LST should not be interpreted as a direct measurement of mangrove health. Surface temperature can be affected by multiple environmental processes, meaning that its interpretation should consider other vegetation and environmental indicators.

LST is derived from thermal infrared observations. The general relationship between the thermal signal and land-surface temperature depends on the thermal remote sensing product and its associated processing procedure.

The Landsat 8 Collection 2 Level-2 surface temperature product was used, with the ST_B10 band selected as the thermal input. Images were filtered using the CLOUD_COVER metadata, and cloud and cloud-shadow pixels were masked using the QA_PIXEL band. The ST_B10 values were then converted to degrees Celsius using the scale factor and additive offset provided for the dataset:

$$LST_{Celsius} = (ST_B10 \times 0.00341802) + 149.0 - 273.15 \quad (2.6)$$

where *ST_B10* represents the Landsat 8 surface-temperature band. The resulting LST values were retained as the thermal predictor variable, *LST_Celsius*, for subsequent analytical dataset construction.

2.5.7. VH

VH represents the cross-polarized backscatter channel of Synthetic Aperture Radar (SAR) observations, in which the radar signal is transmitted vertically and received horizontally. Radar backscatter is influenced by the interaction between microwave energy and vegetation structure, surface characteristics, and moisture conditions (Fu et al., 2025b).

In mangrove environments, SAR provides information that complements optical observations because radar signals can interact with vegetation structure and remain useful under conditions where optical observations may be affected by cloud cover. VH can therefore provide structural and scattering information that is not directly represented by optical vegetation indices (H. Nguyen et al., 2021).

The interpretation of VH depends on vegetation structure, surface conditions, moisture, and radar acquisition characteristics. Consequently, VH should be considered a complementary structural feature rather than a direct measurement of mangrove health.

2.5.8. VH/VV Ratio

The VH/VV Ratio represents the relative relationship between cross-polarized VH and co-polarized VV radar backscatter. Rather than considering the magnitude of an individual polarization response, the ratio provides information on the relative scattering behaviour of the two polarization channels.

In vegetation and mangrove environments, the relative response between VH and VV may provide complementary information on vegetation structure and radar scattering characteristics. The ratio can therefore be considered together with individual backscatter measures when evaluating whether additional structural information can be obtained from SAR observations (Audebert et al., 2018; Fu et al., 2025a).

At the same time, VH/VV Ratio may contain information that overlaps with the individual VH and VV responses. This makes redundancy assessment relevant when multiple SAR-derived variables are considered together. As with the other satellite-derived features, the ratio should be interpreted as a radar-based proxy rather than a direct measure of mangrove health.

The VH/VV Ratio is expressed from the preprocessed VH and VV backscatter coefficients using Equation (2.7):

$$VH/VV \text{ Ratio} = \frac{VH}{VV} \quad (2.7)$$

where:

- **VH** denotes the cross-polarized radar backscatter coefficient; and
- **VV** denotes the co-polarized radar backscatter coefficient.

The resulting VH/VV Ratio was retained as a radar predictor variable for subsequent analytical dataset construction.

2.5.9. Complementary Information from Multiple Features

Mangrove condition is a multidimensional phenomenon involving vegetation characteristics, moisture availability, surface-water conditions, thermal conditions, and vegetation structure. Consequently, a single satellite-derived feature may not adequately represent all characteristics relevant to mangrove condition assessment. Combining complementary information from optical, thermal, and Synthetic Aperture Radar (SAR) observations can therefore provide a broader representation of mangrove environments.

Vegetation indices such as NDVI, EVI, and NDRE primarily represent spectral characteristics of vegetation, including greenness, canopy response, and red-edge-related vegetation variation. NDMI provides complementary information related to vegetation moisture, while MNDWI represents surface-water-related characteristics. LST contributes information on surface thermal conditions, whereas VH and VV Ratio provide radar-based information related to scattering and vegetation structural characteristics. These feature groups therefore represent different dimensions of the mangrove environment that cannot be fully captured by a single spectral response.

The combination of different feature types can provide complementary information for mangrove condition assessment, but the presence of multiple predictors does not necessarily mean that all variables contribute equally. Features representing similar characteristics may contain overlapping information, while some variables may provide relatively distinct information. Consequently, the suitability of a multi-feature predictor set depends not only on the diversity of information represented but also on the degree of redundancy among the variables.

This consideration is particularly relevant when multiple indices can be derived from the same satellite source. For example, several vegetation indices may describe related aspects of vegetation response, while different water- or moisture-related indices may represent overlapping environmental characteristics. Similarly, multiple SAR-derived variables may contain related information because they are derived from the same radar observations.

Therefore, the use of multiple features should be guided by the complementarity of the information they provide rather than simply by increasing the number of predictors.

A multi-feature approach can therefore provide a more comprehensive candidate predictor space for mangrove condition assessment, while feature relevance and redundancy should be evaluated to determine whether the resulting variables provide distinct and useful information. This principle provides the theoretical basis for subsequent feature-selection and feature-configuration analysis in this study.

2.5.10. Comparative Considerations for Satellite-Derived Feature Selection

Satellite remote sensing provides a broad range of spectral bands and derived indices that can be used to characterize vegetation, moisture, water, thermal conditions, and surface properties. The availability of multiple candidate features, however, does not imply that all variables are equally appropriate for a particular classification objective. Feature selection should consider the environmental characteristic represented by each variable, its complementarity with other predictors, and the possibility of overlapping information among features.

For vegetation characterization, NDVI provides a general representation of vegetation greenness, while EVI provides a complementary vegetation response that incorporates blue, red, and near-infrared spectral information and can provide greater sensitivity to canopy variation under dense vegetation conditions. NDRE provides information from the red-edge spectral region and can provide additional sensitivity to variation in vegetation characteristics. SAVI, in comparison, incorporates a soil-adjustment factor and is therefore particularly relevant when soil background influences vegetation spectral responses. Recent comparative applications of vegetation indices have demonstrated that different vegetation indices can exhibit different responses depending on vegetation characteristics and surface conditions (Zahir et al., 2024).

Water and moisture-related indices provide another group of potentially relevant predictors. NDWI is widely used to represent surface-water conditions, whereas MNDWI modifies the conventional NDWI formulation by replacing the near-infrared component with SWIR and may provide improved discrimination of water-related

responses under complex backgrounds. Comparative studies have shown that the performance of water indices can vary according to surface-water characteristics and background conditions (Günen and Atasever, 2024). Tasseled Cap Wetness provides an integrated wetness-related transformation that represents moisture-related characteristics of soil and vegetation and remains applicable to multispectral remote-sensing analysis (Wang et al., 2026b).

Thermal and SAR observations provide additional information dimensions that are not directly represented by optical vegetation indices. LST provides information on land-surface thermal conditions, whereas VH and VH/VV Ratio provide radar-based information associated with scattering and vegetation structure. The combination of optical and radar observations can therefore provide complementary information on vegetation and structural characteristics that are not represented by either data type alone. Recent remote-sensing applications have demonstrated the value of combining spectral and radar information for vegetation and ecosystem characterisation. Accordingly, the selection of satellite-derived features should be guided by the characteristics represented by each variable, their relevance to the classification objective, and the degree of complementarity and redundancy within the candidate predictor set. The objective is therefore not to maximise the number of available indices, but to establish a scientifically justified candidate feature space that can subsequently be evaluated through empirical feature-selection and feature-configuration procedures.

Table 2.6 Comparative Considerations for Satellite-Derived Features

Feature / Feature Group	Main Information	General Consideration
NDVI	Vegetation greenness	General vegetation indicator
EVI	Vegetation vigor and canopy response	Complementary vegetation representation
NDRE	Red-edge vegetation response	Additional sensitivity to vegetation characteristics

Feature / Feature Group	Main Information	General Consideration
SAVI	Vegetation with soil adjustment	Relevant where soil-background effects are important
NDWI	Surface-water response	General water-related indicator
MNDWI	Surface-water response	Uses SWIR to enhance water-related discrimination under complex backgrounds
NDMI	Vegetation moisture	Moisture-related vegetation information
LSWI	Vegetation or surface wetness	Alternative moisture-related representation
NBR	Vegetation disturbance and burn response	Primarily associated with fire and disturbance assessment
BSI	Bare-surface response	More directly associated with exposed soil or bare surfaces
Tasseled Cap Wetness	Integrated wetness response	Represents broader moisture-related characteristics
LST	Thermal condition	Adds thermal information to optical and SAR predictors
VH	Radar backscatter	Provides SAR-based structural and scattering information
VH/VV Ratio	Relative radar response	Provides complementary relative polarisation information

2.6. Feature Engineering and Feature Selection

2.6.1. Feature Engineering

Feature engineering refers to the process of deriving, transforming, and organizing input variables so that relevant characteristics of an observed phenomenon can be represented in a form suitable for machine learning. In remote sensing applications, feature engineering is particularly important because individual spectral, thermal, or radar observations may capture different aspects of vegetation and environmental conditions. Combining complementary information from multiple sources can therefore provide a more comprehensive representation of the characteristics being classified (Li et al., 2024; H. Nguyen et al., 2021).

In remote sensing-based environmental classification, feature engineering may involve the derivation of spectral indices, thermal indicators, and radar-based variables from satellite observations. Spectral indices can represent vegetation characteristics and moisture conditions, thermal variables can provide information related to surface temperature, while synthetic aperture radar (SAR) variables can provide information related to vegetation structure and surface characteristics. The integration of these variables allows different characteristics of an observed environment to be represented within a common feature space.

The feature set is derived from three satellite data sources, Sentinel-2 provides the optical observations used to derive NDVI, EVI, NDRE, NDMI, and MNDWI. Landsat 8 provides the thermal information represented by LST_Celsius, while Sentinel-1 provides SAR-based variables represented by VH and VH/VV Ratio. These variables represent complementary characteristics of mangrove conditions from optical, thermal, and radar observations. The use of complementary optical, thermal, and SAR information is consistent with previous remote sensing studies that combine multiple satellite sources to obtain a broader representation of mangrove and environmental conditions (Li et al., 2024; Nguyen et al., 2021).

The integration of multisource variables allows different dimensions of mangrove condition to be represented within a common feature space. The resulting features describe vegetation characteristics, vegetation moisture, surface-water-related conditions, thermal characteristics, and radar backscatter information. Such integration is relevant because different variables may provide complementary information, while some variables may also contain overlapping or redundant information. Previous studies have demonstrated the value of combining multiple feature types when characterizing complex environmental conditions from remote sensing observations (Li et al., 2024; Nguyen et al., 2021).

In this study, eight satellite-derived variables are used as the input feature set: NDVI, EVI, NDRE, NDMI, MNDWI, LST_Celsius, VH, and VH/VV Ratio. These variables provide the input representation for distinguishing the three mangrove condition classes defined in this study: Healthy, Stressed, and Dead. Their relevance and contribution are subsequently evaluated through feature selection and feature-importance analyses.

2.6.2. Feature Selection

Feature selection refers to the process of identifying informative input variables while reducing variables that provide limited, irrelevant, or redundant information. The purpose of feature selection is not simply to reduce the number of variables, but to identify an input feature set that provides useful information for the classification task. Feature selection can simplify the feature space, reduce redundancy, and improve the efficiency and interpretability of machine learning models. This consideration is particularly relevant in remote sensing because spectral and environmental variables may contain correlated or overlapping information (Salii et al., 2026).

Feature selection methods are commonly categorized into filter, wrapper, and embedded approaches. Filter methods evaluate the characteristics or statistical relationships of features independently of a particular machine learning model. Wrapper methods evaluate different feature subsets according to the predictive performance of a selected model, whereas embedded methods perform feature selection as part of the model-training process. These approaches provide different mechanisms

for evaluating feature relevance and selecting an appropriate feature set according to the characteristics of the dataset and the modelling objective.

In remote sensing classification, feature selection is particularly relevant because multiple spectral, thermal, and environmental variables may contain correlated or overlapping information. Variables derived from related spectral bands may describe similar vegetation characteristics, while variables obtained from different sensors may provide either complementary or partially redundant information. Therefore, evaluating feature relevance and redundancy can help determine whether the available variables provide useful information for distinguishing the target classes.

Among filter-based approaches, statistical and impurity-based measures can be used to rank candidate features according to their relationship with the target classes. In this study, the theoretical principles of the Gini Index, Information Gain, Gain Ratio, and Chi-Square Test are relevant because these measures are subsequently applied to evaluate the satellite-derived features.

a. Gini Index

The Gini Index is an impurity-based measure commonly associated with decision-tree classification. It measures the degree of class impurity within a node based on the distribution of observations among the target classes. For a node containing observations from K classes, Gini impurity can be expressed as:

$$Gini = 1 - \sum_{k=1}^k pk^2 \quad (2.8)$$

where pk represents the proportion of observations belonging to class k . A lower Gini impurity indicates a more homogeneous node. In tree-based feature evaluation, variables that contribute to greater reductions in impurity can be considered more informative for separating the target classes (Breiman, 2001).

b. Information Gain and Gain Ratio

Information Gain measures the reduction in uncertainty about the target class resulting from the use of a feature. It is based on the concept of entropy, which represents the uncertainty associated with the class distribution. The entropy of a dataset can be expressed as:

$$H(s) = - \sum_{k=1}^K pk \log_2(pk) \quad (2.9)$$

where pk represents the proportion of observations belonging to class k . Information Gain is defined as the difference between the original entropy and the weighted entropy after partitioning the data according to a feature.

The limitation of Information Gain is that it can favor variables with a large number of distinct values. **Gain Ratio** addresses this limitation by normalizing Information Gain according to the intrinsic information of the feature. Consequently, Gain Ratio provides an adjusted measure for comparing the information contribution of features with different numbers of possible values.

c. Chi-Square Test

The Chi-Square Test evaluates the statistical association between a predictor variable and a categorical target variable. It compares the observed frequencies of combinations between feature categories and target classes with the frequencies expected under the assumption that the two variables are independent. The Chi-Square statistic can be expressed as:

$$\chi^2 = \sum_i \sum_j \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \quad (2.10)$$

Where O_{ij} represents the observed frequency and E_{ij} represents the expected frequency for the corresponding combination of feature category i and target class j . A larger Chi-Square statistic indicates a greater departure from the assumption of independence and therefore a stronger statistical association between the feature and the target variable.

The four approaches provide complementary perspectives for evaluating feature relevance. The Gini Index evaluates impurity reduction, Information Gain evaluates the reduction in class uncertainty, Gain Ratio adjusts Information Gain according to intrinsic information, and the Chi-Square Test evaluates statistical association between features and target classes. The use of multiple criteria can therefore provide a broader assessment of feature relevance than relying on a single evaluation measure.

Feature selection may subsequently be used to construct different feature subsets or configurations. These configurations can be evaluated according to predictive performance to determine whether a reduced or systematically selected set of variables retains sufficient information for the classification task. This is particularly relevant when candidate variables contain redundant information, because increasing the number of input variables does not necessarily guarantee improved predictive performance.

In this study, feature selection is used to evaluate the relevance and suitability of the eight satellite-derived variables for mangrove condition classification. The application of the feature-selection methods, the construction of feature configurations, and the experimental procedures are described in **Chapter 3**, while the resulting feature rankings and performance comparisons are presented and discussed in **Chapter 4**.

2.6.3. Feature Importance and Model Interpretation

Feature importance analysis provides an additional means of evaluating how input variables contribute to predictions generated by a trained machine learning model. Feature importance differs from feature selection in its purpose. Feature selection focuses on determining which variables are suitable for inclusion in the feature space, whereas feature importance evaluates the relative contribution of variables to predictions after a model has been trained.

For tree-based models, model-based feature importance can be derived from the contribution of individual variables to the construction of decision trees. In Random Forest, for example, feature importance can be estimated from the contribution of

variables to impurity reduction across the ensemble of decision trees (Breiman, 2001). Such measures provide an internal estimate of feature relevance within the trained model. However, model-based importance is dependent on the characteristics of the model and may not fully describe how predictive performance changes when information from a feature is disrupted.

Permutation Importance provides a model-agnostic approach for evaluating feature contribution. The method measures the change in model performance after the values of a feature are randomly permuted while the remaining variables are kept unchanged. A larger decrease in predictive performance after permutation indicates greater reliance of the model on the information provided by that feature. Permutation-based analysis can therefore provide an additional perspective on feature contribution beyond model-specific importance measures.

SHAP (SHapley Additive exPlanations) provides another approach for interpreting machine learning predictions based on Shapley-value concepts. SHAP assigns contribution values to individual features for model predictions and can be aggregated across observations to obtain a global representation of feature importance. Individual SHAP values can also be examined to understand how specific features contribute to particular predictions, providing both global and local perspectives for model interpretation (Lee et al., 2021).

Feature importance and model interpretation are particularly useful in remote sensing classification because predictive performance alone does not indicate which satellite-derived variables contribute most strongly to the classification results. Evaluating feature contributions can provide additional insight into the relative contribution of optical, thermal, and SAR-derived information and can help determine whether different feature types provide complementary information.

In this study, feature importance and model interpretation complement the feature-selection analysis by providing additional evidence regarding the contribution of the eight satellite-derived variables. Permutation Importance and SHAP are used to

evaluate and interpret feature contributions in the trained classification model. The resulting feature-importance rankings and explainability outputs are presented and interpreted in Chapter 4, rather than being treated as predetermined assumptions in Chapter 2.

2.7. Machine Learning Algorithms

Machine learning provides a data-driven approach for classification by learning relationships between input variables and predefined target classes from labelled observations. In remote sensing applications, machine learning is useful when the relationship between satellite-derived variables and ecological conditions is complex and cannot be adequately represented using a single threshold or linear rule. The integration of spectral, thermal, and SAR-derived features can provide multiple complementary predictors for distinguishing mangrove condition classes (Yadav and Maxwell, 2023).

Machine learning in this study is used to classify mangrove conditions into three operational classes: Healthy, Stressed, and Dead. Three supervised learning algorithms are evaluated, namely Support Vector Machine (SVM), Random Forest (RF), and eXtreme Gradient Boosting (XGBoost). These algorithms were selected because they represent different learning mechanisms and have been widely applied to classification problems involving remote sensing and environmental data. Their comparative evaluation provides a basis for determining how different learning strategies respond to the satellite-derived feature space used in this study.

The three algorithms differ in their underlying principles. SVM constructs decision boundaries by maximizing the separation between classes, RF combines predictions from multiple decision trees, while XGBoost builds trees sequentially to reduce prediction errors. These differences may lead to different classification behaviour when the input variables contain nonlinear relationships, correlated information, or overlapping class characteristics.

2.7.1. Support Vector Machine (SVM)

Support Vector Machine is a supervised learning algorithm that identifies a decision boundary that maximizes the margin between observations from different classes (Ibrahim et al., 2026). The observations that contribute directly to defining this boundary are referred to as support vectors. For linearly separable data, the decision function can be expressed as:

$$f(x) = \sum_{i=1}^n \alpha_i y_i k(x, x_i) + b \quad (2.11)$$

where α_i represents the weight associated with the i -th the support vector, y_i denotes the corresponding class labels, $k(x, x_i)$ is the kernel function mapping inputs into a higher-dimensional space, and b represents the bias term. Kernel functions allow SVM to represent nonlinear relationships by implicitly mapping the input observations into a higher-dimensional feature space.

The Radial Basis Function (RBF) kernel is commonly used when nonlinear decision boundaries are expected. In remote sensing classification, this characteristic can be useful when different land-cover or vegetation conditions have overlapping spectral characteristics. SVM can also perform effectively with relatively limited training samples and high-dimensional feature spaces. However, its performance can be sensitive to the selection of hyperparameters, particularly the regularization parameter and kernel parameters.

SVM provides in this study a margin-based classification approach that is complementary to the tree-based algorithms. Its inclusion allows the classification performance of a kernel-based method to be compared with ensemble tree methods under the same feature and evaluation framework.

2.7.2. Random Forest (RF)

Random Forest is an ensemble learning algorithm that constructs multiple decision trees using randomized subsets of observations and predictor variables (Breiman, 2001; Cherian and K, 2024). For classification, the final prediction is generally determined through majority voting across the individual trees. The ensemble prediction can be represented conceptually as:

$$RF_{(x)} = mode \{f_1(x), f_2(x), \dots, f_N(x)\} \quad (2.12)$$

where N represents the number of trees and $f_i(x)$ represents the prediction generated by the i -th tree.

The use of multiple trees and randomized sampling can reduce the dependence of the model on any single decision tree and can improve its robustness to variation in the training data. RF can also model nonlinear relationships and interactions among predictors without requiring a predefined parametric relationship. These characteristics make it suitable for remote sensing applications in which spectral, environmental, and structural variables may interact in complex ways.

Another advantage of RF is its ability to provide model-based measures of feature importance. These measures can be used to examine the relative contribution of predictor variables to the classification process. However, RF still requires appropriate preprocessing and parameter selection, and its feature importance measures should be interpreted together with complementary methods when detailed model interpretation is required. In this study, RF represents an ensemble tree-based classification approach and is evaluated alongside SVM and XGBoost using the same input feature framework and model evaluation procedures.

2.7.3. eXtreme Gradient Boosting (XGBoost)

eXtreme Gradient Boosting (XGBoost) is a gradient boosting algorithm based on an ensemble of decision trees (Chen et al., 2025; Pahlevan et al., 2021). Unlike RF, in which trees are constructed as an ensemble with randomized sampling, XGBoost builds trees sequentially so that subsequent trees focus on reducing the errors produced by the existing ensemble (Tjen and Zuhri, 2026). The prediction can be expressed as the additive contribution of the individual trees:

$$\hat{y}_i = \sum_{k=1}^k f_k(x_i) \quad (2.13)$$

where $\hat{y}_i$ is the result of the prediction for the first observation, K is the number of decision trees built, and $f_k(x_i)$ is prediction function of the K -th Decision Tree.

XGBoost optimizes a regularized objective function that combines prediction loss with a penalty for model complexity. This regularization is intended to control tree complexity and reduce overfitting. The general objective function can be expressed as:

$$Obj = \sum_j L(y_j, \hat{y}_j) + \sum_k \Omega(f_k) \quad (2.14)$$

with L represents the loss function and $\Omega(f_k)$ represents the regularization term associated with the k -th tree. The combination of sequential boosting and regularization enables XGBoost to model complex nonlinear relationships and interactions among predictor variables.

XGBoost is therefore included in this study as a boosting-based tree ensemble that provides a different learning strategy from both RF and SVM. Its performance is evaluated empirically rather than assumed to be superior to the other algorithms.

2.7.4. Comparative Characteristics of RF, SVM, and XGBoost

The three algorithms provide different approaches to supervised classification. SVM is based on margin maximization and kernel functions, RF uses an ensemble of independently constructed decision trees, and XGBoost uses sequential boosting to iteratively improve the ensemble. These differences provide a theoretical basis for comparing their behaviour using the same satellite-derived feature set, in table 2.7 is a comparison of the algorithms used, as follows:

Table 2.7 Comparison of Machine Learning Algorithms

Algorithm	Learning principle	Main characteristics	Relevance to this study	Recent Reference
Support Vector Machine (SVM)	Margin-based classification with kernel functions	Effective for nonlinear boundaries and relatively small/high-dimensional datasets; sensitive to hyperparameter selection	Provides a kernel-based approach for distinguishing overlapping mangrove condition classes	(Qin and Liu, 2022; Rondon et al., 2023)
Random Forest (RF)	Bagged ensemble of decision trees	Models nonlinear relationships, handles interactions among predictors, and provides model-based feature importance	Provides an ensemble tree-based approach for integrating complementary spectral, thermal, and SAR-derived features	(Shen et al., 2025)
Extreme Gradient Boosting (XGBoost)	Sequential gradient boosting of decision trees	Captures nonlinear relationships and interactions through iterative error reduction and regularization	Provides a boosting-based approach for comparison with RF and SVM	(Rondon et al., 2023)

The three algorithms provide different approaches to learning the relationship between satellite-derived features and mangrove condition classes. RF uses an ensemble of independently developed decision trees, SVM focuses on finding an optimal class boundary, and XGBoost sequentially improves a series of decision trees. Therefore, no single algorithm is assumed in advance to be the best model for the study.

The performance of RF, SVM, and XGBoost was evaluated using the same training and validation framework. The comparison will consider appropriate classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix results. Where necessary, class imbalance will also be considered during the modelling and evaluation process. The model that provided the highest classification performance was subsequently selected as the final trained model.

The comparative approach is also relevant to the feature engineering process described in Section 2.6. The models will not only be evaluated using the complete set of eight selected features but may also be compared across different feature combinations. This allows the study to examine the relationship between feature configuration and model performance rather than assuming that adding more features will always improve classification results.

2.8. Classification Evaluation, Validation, and Class Imbalance

2.8.1. Classification Performance Metrics

The performance of a classification model needs to be evaluated to determine how well it distinguishes between the Healthy, Stressed, and Dead mangrove condition classes. In classification problems, a confusion matrix provides information on correctly and incorrectly classified observations for each class and serves as a basis for calculating several performance metrics.

- a. Accuracy represents the proportion of correctly classified observations relative to the total number of observations. Although accuracy provides a general measure of classification performance, it may be misleading when the class distribution is imbalanced because the majority class contributes more strongly to the overall score.
- b. Precision measures the proportion of correctly predicted observations among all observations assigned to a particular class. It therefore indicates the reliability of the model's positive predictions for a given class.
- c. Recall, also referred to as sensitivity, measures the proportion of correctly identified observations relative to all actual observations belonging to a particular class. Recall is particularly important when failing to identify observations from a specific class has practical consequences.
- d. The F1-score represents the harmonic mean of precision and recall. It provides a balanced measure when both false-positive and false-negative errors need to be considered. The F1-score is expressed as:

The performance of a classification model needs to be evaluated to determine how well it can distinguish between the Healthy, Stressed, and Dead mangrove condition classes. In classification problems, the confusion matrix provides information on correctly and incorrectly classified samples for each class and can be used as a basis for calculating evaluation metrics. In this study, accuracy, precision, recall, and F1-score are considered to evaluate the classification performance from both overall and class-level perspectives.

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2.15)$$

For multiclass classification, F1-score can be summarized using different averaging approaches. **Macro F1-score** calculates the F1-score independently for each class and then assigns equal weight to all classes. This makes Macro F1 particularly useful for imbalanced classification because minority classes receive the same importance as the majority class. In contrast, weighted averages assign greater influence to classes with larger numbers of observations.

A confusion matrix provides additional information beyond summary metrics by showing the distribution of correct and incorrect predictions across the target classes. It can therefore be used to identify which classes are most frequently confused and to support a more detailed interpretation of classification performance.

2.8.2. Validation

Model validation is necessary to assess whether the predictive performance of a machine learning model is consistent beyond the data used for model training. A model may achieve high performance on training observations while performing less effectively on unseen observations. Therefore, validation procedures are used to obtain a more reliable estimate of model generalization.

- a. K-Fold Cross Validation is a commonly used validation approach in which the available observations are divided into K subsets or folds. During each iteration, one fold is used for validation while the remaining folds are used for training. The procedure is repeated until every fold has been used as the validation set, and the resulting performance measures can then be summarized across the iterations.
- b. Stratified K-Fold Cross Validation extends this approach by maintaining approximately the same proportion of observations from each target class in every fold. This is particularly useful for classification datasets with unequal class distributions because it helps ensure that each validation fold contains observations representing the target classes.

The use of stratified validation can therefore provide a more consistent basis for comparing classification models when the target classes are imbalanced. Performance can also be reported across individual folds, allowing the stability and variability of model performance to be examined rather than relying only on a single performance estimate.

Field observations and other reference information can additionally provide supporting evidence for assessing satellite-based classification results. Such reference information is particularly relevant in environmentally remote sensing because satellite-derived classifications represent indirect observations of ecosystem conditions and may require comparison with observations of actual conditions.

2.8.3. Class Imbalance

Class imbalance occurs when the number of observations differs substantially among the classes in a classification dataset. An imbalanced distribution can cause a machine learning model to become more influenced by the majority class, potentially reducing its ability to correctly identify minority classes. This issue is particularly important when minority classes represent conditions that are environmentally or practically important.

Remote sensing classification in class imbalance may arise because different land-cover or environmental conditions are not equally represented in the available reference observations. A model trained on such data may achieve relatively high overall accuracy by correctly classifying the majority class while providing lower performance for minority classes. Therefore, evaluating class-specific metrics such as precision, recall, and F1-score is important when assessing classification performance under imbalanced conditions.

Several approaches can be used to address class imbalance, including oversampling, undersampling, and synthetic sampling. Oversampling increases the representation of minority classes, whereas undersampling reduces the number of observations from the majority class. Synthetic sampling methods generate additional observations based on

existing minority-class observations. The suitability of a particular balancing strategy depends on the characteristics and distribution of the dataset, and different approaches may produce different effects on classification performance (Taskiran et al., 2025; Vaithianathan et al., 2024). Because class imbalance can affect both overall and class-specific performance, model evaluation should consider multiple complementary metrics rather than relying solely on accuracy. Macro F1-score provides a useful summary when equal consideration of all target classes is required. The evaluation of class-specific performance can further reveal whether a model provides adequate recognition of minority conditions.

Class-imbalance handling can be implemented through several resampling strategies. In this study, the original dataset without resampling is treated as the Baseline condition, while Random OverSampler (ROS) increases the number of minority-class observations by duplicating existing samples and Random UnderSampler (RUS) reduces the majority-class observations by removing selected samples. SMOTE generates synthetic minority-class observations by interpolating between existing minority samples and their nearest neighbours, whereas Borderline-SMOTE concentrates synthetic sample generation on minority observations located near class boundaries (Elreedy et al., 2024). ADASYN further adapts the amount of synthetic data generation according to the difficulty of learning individual minority samples, giving greater emphasis to samples located in more difficult regions of the feature space (Carvalho et al., 2025).

Hybrid resampling methods combine synthetic oversampling with data-cleaning or undersampling procedures. SMOTEENN combines SMOTE with Edited Nearest Neighbours to remove potentially noisy or ambiguous observations after oversampling, while SMOTETomek combines SMOTE with Tomek Links to reduce overlapping or ambiguous samples near class boundaries (Carvalho et al., 2025). These methods provide alternative strategies for improving class representation and reducing problematic observations in imbalanced datasets. The effectiveness of these approaches can vary according to the characteristics of the dataset, and no single resampling method

is expected to perform consistently best across all classification problems (Leng et al., 2024).

2.9. Temporal Analysis of Mangrove Condition Changes and Degradation

Trajectories

Mangrove conditions may change over time as a result of environmental stress, disturbance, recovery, or other processes affecting vegetation and ecosystem conditions. Therefore, observations from a single period may not be sufficient to describe the direction and pattern of mangrove condition changes. Multi-temporal satellite observations provide an opportunity to examine these changes by comparing mangrove conditions across different observation periods (Bunting et al., 2022; Goldberg et al., 2020).

Temporal analysis is performed following the mangrove condition classification process. The classification results from each observation period between 2020 and 2025 are organized as temporal sequences associated with each spatial location. These sequences of Healthy, Stressed, and Dead classes are analyzed to identify patterns of mangrove condition changes over time. A transition from Healthy to Stressed and subsequently to Dead may represent a degradation trajectory, whereas a transition from Stressed to Healthy may indicate a recovery process. Meanwhile, consistent classification results across multiple observation periods may reflect relatively stable mangrove conditions.

The temporal sequence is used to describe the direction and patterns of mangrove condition changes rather than to predict future conditions. This approach enables the identification of temporal health-state trajectories derived from multi-temporal satellite-based classification results. The resulting trajectories provide insights into the historical development of mangrove conditions during the 2020–2025 period and contribute to a more comprehensive understanding of mangrove ecosystem dynamics within the study area (Bunting et al., 2022; Worthington et al., 2020).

This approach also supports the broader objective of the study, in which satellite-derived features are used to classify mangrove conditions at each observation period and the resulting classifications are subsequently examined as a temporal sequence. Thus, the features described in this section form the basis for the feature engineering and machine learning processes discussed in the following sections and ultimately support the characterization of spatial and temporal changes in mangrove conditions.

2.9.1. Potential Application of the Trained Classification Model

The machine learning models developed in this study are trained using satellite-derived features extracted from multi-source satellite data and reference observations collected within the study area. After the training process, the resulting classification model may be applied to classify new observations with comparable input characteristics, provided that the same data preprocessing procedures, feature extraction methods, and feature definitions are consistently applied.

The primary objective of this study is not to evaluate the operational application of the trained model for future monitoring. Instead, the research focuses on developing and evaluating a machine learning classification framework for classifying mangrove health conditions into Healthy, Stressed, and Dead classes and characterizing their temporal trajectories during the 2020–2025 observation period. Consequently, applying the trained model to observations collected under different environmental conditions, in different study areas, or during future monitoring campaigns would require additional validation and is therefore beyond the scope of this research.

Despite this limitation, the trained classification model provides a practical basis for supporting future monitoring activities. When new observations have comparable input characteristics and are processed using the same methodology, the model may provide preliminary classification results that assist in identifying areas requiring further field verification. These results are intended to complement, rather than replace, direct field observations, which remain essential for mangrove monitoring and management.

2.10. Critical Review of Previous Studies

2.10.1. Critical Review of Previous Studies

Previous studies have shown that remote sensing has become one of the most widely used approaches for monitoring mangrove ecosystems. The availability of satellite imagery with different spatial, spectral, and temporal characteristics enables researchers to map mangrove distribution, detect land cover changes, estimate vegetation conditions, and support coastal ecosystem management (Maurya et al., 2021). Recent developments have also demonstrated that machine learning methods can improve the classification performance compared with conventional image classification techniques, particularly when multiple satellite-derived features are incorporated (Sheykhmousa et al., 2020).

Several studies have focused on improving mangrove mapping by integrating different satellite datasets and feature types. (Y. Zhang et al., 2021) demonstrated that Sentinel-2 imagery combined with Random Forest and object-oriented analysis produced accurate mangrove mapping results. Similarly, (Zhang et al., 2023) proposed a multi-feature ensemble classification approach that integrated spectral, textural, and geometric information extracted from Sentinel-2 imagery. These studies indicate that combining complementary features can improve classification performance. However, their primary objective remained the spatial delineation of mangrove forests rather than the assessment of mangrove health conditions.

Other studies have emphasized the importance of satellite-derived features for improving mangrove monitoring. (Baloloy et al., 2020) introduced the Mangrove Vegetation Index (MVI) to improve mangrove extraction using Sentinel-2 data, while (Wang et al., 2024) demonstrated that integrating multiple feature groups could better represent mangrove characteristics than relying on a single feature type. Although these studies successfully improved mangrove mapping performance, feature engineering and feature selection were generally applied to optimize mapping accuracy rather than to distinguish different mangrove health conditions.

Machine learning has also been increasingly applied in mangrove studies. (Cherian and K, 2024) compared Random Forest and Support Vector Machine for mangrove mapping in Indonesia, whereas the Sarawak study (2026) demonstrated the potential of combining Sentinel-1, Sentinel-2, and XGBoost for estimating mangrove extent and above-ground biomass. These studies confirmed that different machine learning algorithms produce different classification performances depending on the characteristics of the input features. Nevertheless, most previous studies evaluated model performance for mapping or biomass estimation, while fewer studies investigated machine learning for classifying mangrove health conditions using complementary satellite-derived features.

Overall, previous studies have provided valuable contributions to mangrove mapping, remote sensing, and machine learning applications. However, most studies addressed these components separately. Limited studies have integrated multi-source satellite data, complementary satellite-derived features, comparative machine learning models, and temporal analysis into a unified framework for monitoring changes in mangrove health conditions. This limitation provides the basis for the proposed approach in the present study.

To facilitate a systematic comparison of previous studies, Table 2.8 summarizes the main characteristics of the selected literature based on the research focus, satellite data, machine learning methods, temporal analysis, validation approach, and the main strengths and limitations of each study. The comparison provides an overview of the current state of research and serves as the basis for identifying the research gap addressed in this study.

Table 2.8 Literature Matrix of Previous Studies Related to Mangrove Monitoring and Classification

No.	Author(s) and Year	Research Focus	Satellite Data / Data Source	Machine Learning / Method	Main Strength	Main Limitation
1	(Hai et al., 2022)	Assessment of mangrove health by integrating spatial metrics and multi-temporal remote sensing data in Mui Ca Mau, Vietnam.	SPOT-4 (1995) and SPOT-5 (2004 and 2015) multi-temporal satellite imagery, supported by field survey data	Random Forest (RF), Pearson Correlation Analysis, Analytic Hierarchy Process (AHP), and landscape spatial metrics (CONTIG, PLADJ, PD, SHEI).	Combines image classification and landscape spatial metrics to evaluate mangrove health and generate a comprehensive mangrove health map.	The study focuses on health mapping at selected observation years and does not analyse annual health trajectories or long-term spatio-temporal transition patterns.
2	(Baloloy et al., 2020)	Development of Mangrove Vegetation Index (MVI) for mangrove mapping	Sentinel-2	Mangrove Vegetation Index (MVI)	Proposed a spectral index specifically designed to improve mangrove extraction.	Focused on mangrove mapping rather than mangrove health classification.
3	(Sheykhmousa et al., 2020)	Review of machine learning algorithms for remote sensing image classification	Multiple remote sensing datasets	Random Forest, SVM, ANN, Decision Tree, etc.	Comprehensive comparison of machine learning algorithms for remote sensing applications.	General remote sensing review and not specifically focused on mangrove health.
4	(M. Zhang et al., 2021)	Mangrove mapping using object-oriented analysis	Sentinel-2 and Gaofen-2	Random Forest	Demonstrated high classification accuracy using object-oriented analysis	Focused on spatial mapping without temporal health assessment

No.	Author(s) and Year	Research Focus	Satellite Data / Data Source	Machine Learning / Method	Main Strength	Main Limitation
5	(Maurya et al., 2021)	Review of remote sensing techniques for mangrove monitoring	Multi-source remote sensing	Various image classification techniques	Comprehensive review of remote sensing applications in mangrove ecosystems	Did not specifically discuss feature engineering or comparative machine learning models
6	(Zhang et al., 2023)	Multi-feature ensemble classification for mangrove mapping	Sentinel-2	Nearest Neighbor Classification	Integrated spectral, textural, and geometric features	Focused on mangrove mapping instead of health condition classification
7	(Ambarwari and Husni, 2023)	Machine learning applications for mangrove mapping	Moderate-resolution multispectral imagery	Machine Learning Review	Summarized recent machine learning applications for mangrove monitoring in Indonesia	Review study without experimental comparison
8	(Wang et al., 2024)	Multi-feature parameter integration for mangrove mapping	Multi-source remote sensing	Multi-feature classification	Demonstrated the benefit of integrating multiple feature groups	Did not evaluate temporal changes in mangrove condition
9	(Hartoni et al., 2022)	Comparison of Random Forest and Support Vector Machine for mangrove mapping	Satellite imagery	Random Forest and Support Vector Machine	Compared classification performance in the Indonesian context	Focused on mangrove mapping rather than health condition classification

No.	Author(s) and Year	Research Focus	Satellite Data / Data Source	Machine Learning / Method	Main Strength	Main Limitation
10	(Alidin et al., 2026)	Mangrove extent and above-ground biomass mapping	Sentinel-1 and Sentinel-2	XGBoost	Combined optical and SAR data with field validation	Focused on biomass estimation rather than mangrove health classification
11	(Hudjimartsu et al., 2026)	Mangrove Health Index assessment	Sentinel-2	Machine Learning	Proposed a machine learning-based mangrove health assessment approach	Did not analyze temporal changes or degradation trajectories

As shown in Table 2.8, previous studies have demonstrated significant progress in applying remote sensing and machine learning for mangrove monitoring. Most studies focused on improving mangrove mapping accuracy using satellite imagery, spectral indices, or machine learning algorithms. Several studies also incorporated multiple feature types or compared different classification models to improve mapping performance. The literature indicates that relatively few studies have integrated complementary satellite-derived features, comparative machine learning models, and temporal analysis within a single framework for monitoring mangrove health conditions. This observation suggests that opportunities remain to develop a more comprehensive framework capable of supporting both spatial and temporal monitoring of mangrove conditions.



2.10.2. Comparative Research Gap Analysis

Previous studies have demonstrated significant progress in remote sensing applications for mangrove monitoring; several research gaps remain. Most studies have focused on improving mangrove mapping accuracy, land cover classification, biomass estimation, or vegetation extraction using individual satellite datasets or specific feature groups. While these studies have successfully demonstrated the capability of satellite remote sensing for mangrove applications, relatively few have integrated multiple complementary satellite-derived features, comparative machine learning models, and temporal analysis within a single monitoring framework.

Another limitation observed in previous studies is that machine learning has generally been applied to optimize mapping performance rather than to classify mangrove health conditions. Most studies evaluated the performance of a single machine learning algorithm or compared only a limited number of classification approaches. Furthermore, feature engineering and feature selection were commonly employed to improve classification accuracy, but their contribution to distinguishing different mangrove health conditions was rarely discussed explicitly.

Temporal information has also received increasing attention in recent years. However, many studies analyzed changes between observation periods primarily for land-cover change detection or mangrove extent mapping. Fewer studies characterized the temporal progression of mangrove health conditions or interpreted these changes as degradation trajectories. Consequently, opportunities remain to integrate multi-source satellite observations, complementary satellite-derived features, comparative machine learning models, and temporal analysis into a unified framework for mangrove health classification. Based on these observations, this study proposes an integrated framework that combines multi-source satellite data, complementary satellite-derived features, feature engineering, comparative machine learning classification, temporal analysis, and model evaluation to classify mangrove health into Healthy, Stressed, and Dead classes. The temporal sequence of classification results is then analyzed to characterize mangrove degradation trajectories during the observation period (Hudjimartsu et al., 2026). In addition, the trained model is designed to predict

mangrove health classes for new monitoring observations with comparable input characteristics, providing preliminary information that can support field verification rather than replacing direct field monitoring.

The research gaps identified from the previous studies are summarized in Table 2.9. The comparison highlights the main methodological components implemented by previous studies and contrasts them with the proposed approach adopted in this research.

Table 2.9 Literature Matrix of Previous Studies Related to Mangrove Monitoring and Classification

Research Component	Previous Studies	Proposed Study
Multi-source satellite data	Partially implemented	Sentinel-2, Landsat 8, and Sentinel-1
Multi-temporal observations	Limited to change detection or mapping	Multi-temporal observations (2020–2025)
Complementary satellite-derived features	Mostly limited feature combinations	Eight complementary features (NDVI, EVI, NDRE, NDMI, MNDWI, LST, VH, VH/VV Ratio)
Feature engineering	Limited discussion	Feature engineering and feature selection before model development
Comparative machine learning models	Single model or limited comparison	Random Forest, Support Vector Machine, and XGBoost
Hyperparameter optimization	Rarely discussed	Hyperparameter tuning for model optimization
Feature importance analysis	Rarely reported	Feature importance analysis to evaluate feature contribution
Class imbalance handling	Limited	Evaluation of imbalance handling methods where appropriate
Temporal trajectory analysis	Mostly change detection	Characterization of mangrove condition trajectories
Prediction on new monitoring observations	Rarely discussed	Prediction using trained model on comparable input characteristics
Practical application	Mapping and monitoring	Supporting field monitoring and verification

As summarized in Table 2.9, the proposed study integrates several methodological components that are generally addressed separately in previous studies. The proposed framework combines complementary satellite-derived features, comparative machine learning models, and temporal analysis to classify mangrove health conditions and characterize their temporal trajectories. Furthermore, the trained classification model provides the capability to classify new monitoring observations with comparable input characteristics, enabling its application to subsequent monitoring activities within similar mangrove environments. These components form the methodological foundation of the proposed study and are described further in the following subsection.

2.10.3. Building Blocks of the Proposed Study

The review and comparative analysis of previous studies indicate that existing research has not yet integrated all methodological components required for a comprehensive mangrove health classification framework. Previous studies have generally emphasized specific aspects of the workflow, including satellite data utilization, feature extraction, machine learning classification, or temporal analysis, while limited attention has been given to combining these components within a unified framework.

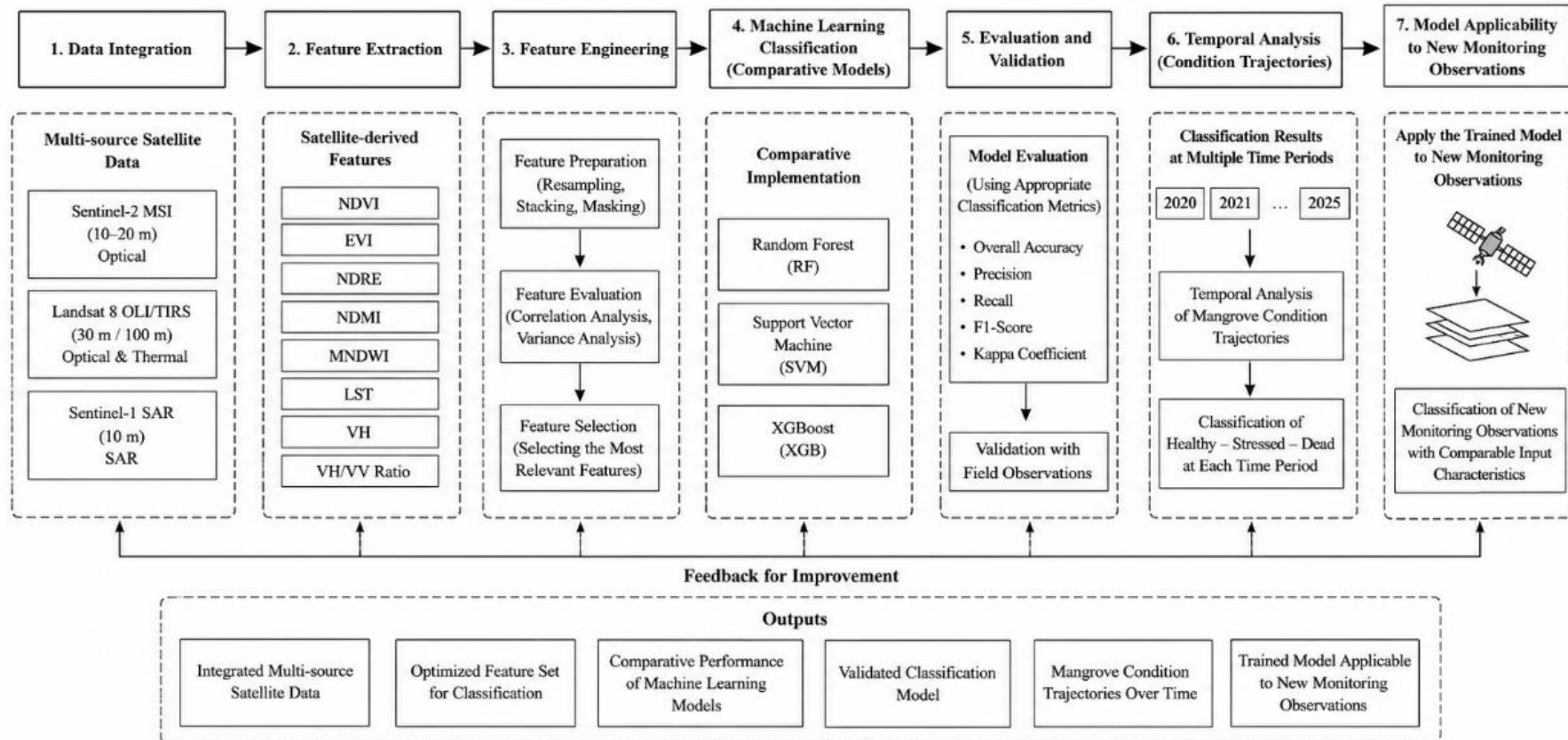
To address these limitations, the proposed framework integrates several complementary methodological components. Multi-source satellite observations from Sentinel-2, Landsat 8, and Sentinel-1 are combined to capture complementary information related to vegetation characteristics, land surface temperature, moisture conditions, and vegetation structure. The framework further incorporates multiple satellite-derived features, including NDVI, EVI, NDRE, NDMI, MNDWI, LST, VH, and the VH/VV ratio, to represent the diverse environmental conditions associated with mangrove health.

Feature engineering constitutes the next stage of the framework through feature extraction, feature evaluation, and feature selection prior to model development. This process aims to identify the most informative feature combinations for distinguishing Healthy, Stressed, and Dead mangrove conditions. The selected features are subsequently used as input for three machine learning algorithms, namely Random

Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). Each model is trained and evaluated using the same dataset to enable an objective comparison of their classification performance.

Model performance is assessed using standard classification evaluation metrics and validated with available field observations to ensure the reliability of the classification results. The classified outputs are then analyzed temporally by examining the sequence of mangrove condition classes throughout the observation period. Rather than predicting future conditions, this analysis characterizes degradation and recovery trajectories based on historical changes in mangrove health. Once trained and validated, the resulting classification model can be applied to future monitoring data with comparable input characteristics, thereby supporting continuous mangrove health monitoring in similar coastal environments.

These methodological components are designed as an integrated framework in which each stage supports the subsequent analysis. The relationships among the proposed components are illustrated in Figure 2.3, which serves as the conceptual foundation for the research framework presented in the following section.



Note: The building blocks are sequential, and the output of each block becomes the input for the next block.

Figure 2.3 Building Blocks of the Proposed Study

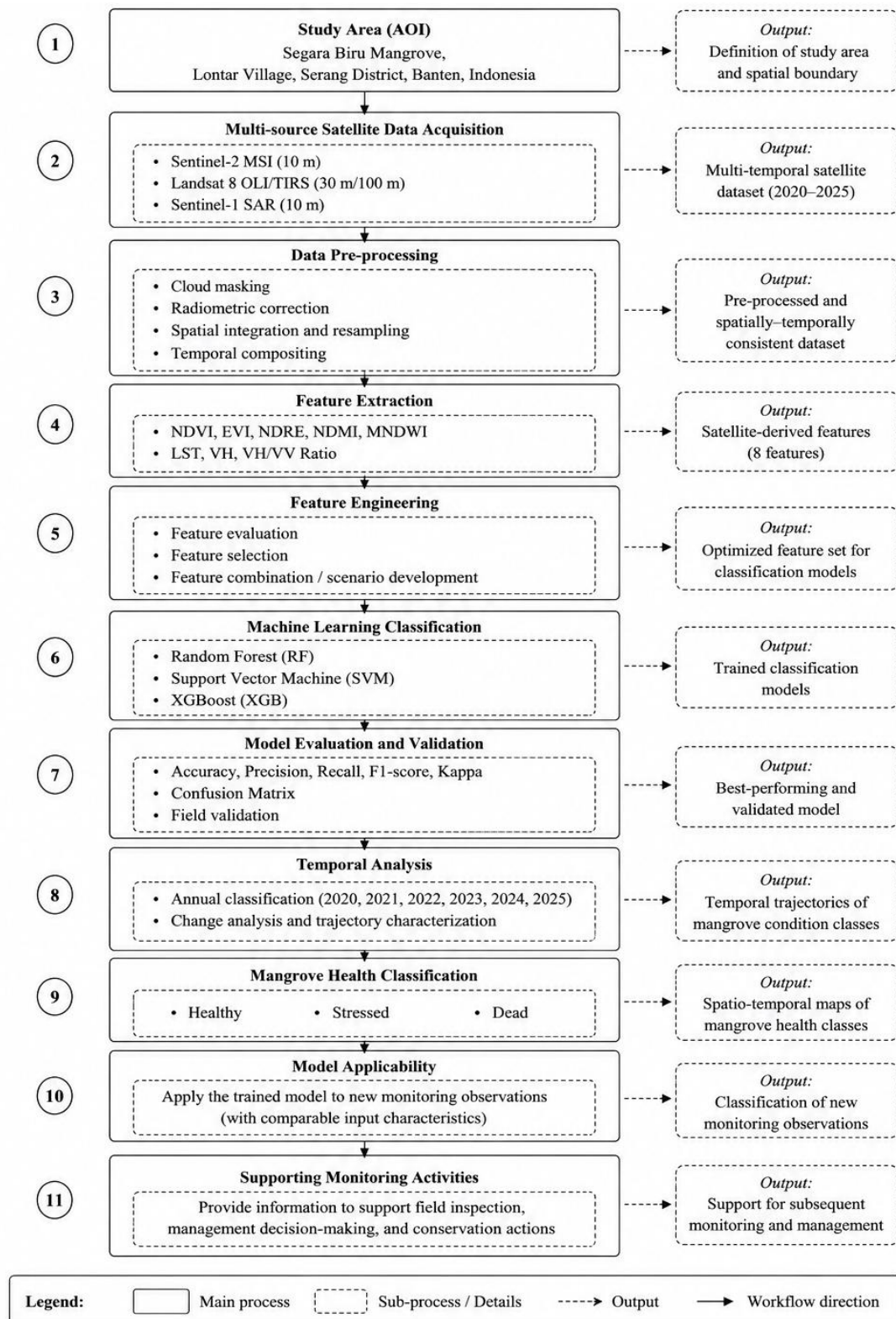
2.11. Research Framework

2.11.1. Introduction to the Research Framework

The conceptual research framework summarizes the overall methodology adopted in this study and illustrates the relationships among the methodological components presented in the previous sections. It provides a systematic overview of how these components are logically integrated into a unified workflow, beginning with the acquisition and preparation of multi-source satellite data and ending with the characterization of temporal trajectories of mangrove condition classes through machine learning classification and temporal analysis.

Unlike the methodological building blocks presented in the previous section, which describe the principal methodological components of the study, the research framework emphasizes the logical sequence of research activities and the relationships among each stage of the proposed methodology. The framework illustrates the overall research process, including satellite data preparation, feature extraction, feature engineering, machine learning classification, model evaluation, annual mangrove health classification, and temporal trajectory analysis.

The overall conceptual research framework adopted in this study is illustrated in Figure 2.4 and provides the methodological basis for the research procedures described in Chapter 3.



Note: The numbers indicate the sequence of research activities from data preparation to the utilization of results for monitoring purposes.

Figure 2.4 Research Framework

2.11.2. Explanation of the Research Framework

The research framework begins with the acquisition of multi-source satellite data covering the study period from 2020 to 2025. Sentinel-2 imagery provides multispectral information for vegetation and moisture-related features, Landsat 8 contributes thermal information through Land Surface Temperature (LST), and Sentinel-1 supplies radar backscatter information that complements optical observations. These datasets are prepared through appropriate preprocessing procedures to produce representative annual datasets for subsequent analysis.

The preprocessed satellite data are then used to derive the satellite-derived features employed in this study. Eight features, namely NDVI, EVI, NDRE, NDMI, MNDWI, LST, VH, and the VH/VV Ratio, are extracted to represent different characteristics of mangrove conditions. The extracted features are subsequently integrated with reference observations to establish the classification dataset used for machine learning model development.

Before model development, the extracted features undergo a feature engineering process. This stage includes descriptive statistical analysis, feature evaluation, feature selection, and the development and evaluation of feature combination scenarios. These analyses are intended to evaluate feature relevance, identify potential redundancy, and compare different feature configurations prior to model training.

Class-imbalance handling is subsequently evaluated using alternative resampling strategies, and the selected balancing approach is incorporated into the model-training workflow. The Random Forest, Support Vector Machine, and XGBoost models are then evaluated using hyperparameter optimization and Stratified 5-Fold Cross Validation to compare their classification performance.

The classification models are then developed using Random Forest, Support Vector Machine, and XGBoost. Their performances are compared using the same training and evaluation procedures, followed by hyperparameter tuning to obtain the most suitable model for mangrove health classification. The selected model is further interpreted through feature importance analysis to improve the understanding of each feature's contribution to the classification results.

The best-performing model is subsequently applied to classify the annual satellite composites, producing annual mangrove health maps consisting of Healthy, Stressed, and Dead classes. The classified maps are then used to calculate the spatial distribution and area proportion of each class for every observation year.

The classification results from all observation periods are analyzed sequentially to characterize the temporal trajectories of mangrove condition classes during 2020-2025. The overall framework provides a systematic workflow that integrates multi-source satellite data, feature engineering, machine learning classification, and temporal analysis into a coherent methodology for assessing mangrove health conditions within the study area. This framework serves as the methodological foundation for the implementation of the research procedures described in Chapter 3.

