

CHAPTER 1 – INTRODUCTION

1.1. Background

Mangrove ecosystems are among the most productive and valuable coastal ecosystems, providing essential ecological, environmental, and socio-economic benefits. They protect coastlines from erosion and storm surges, provide habitats and nursery grounds for diverse terrestrial and marine species, support nutrient cycling, and help maintain coastal water quality, making them indispensable for sustaining coastal ecosystem functions and biodiversity (Suhardi et al., 2024). The ecological functions and services provided by mangroves are highly dependent on the health and condition of the ecosystem. Consequently, maintaining mangrove health has become increasingly important to ensure ecosystem resilience, biodiversity conservation, and the long-term sustainability of coastal environments (Neres et al., 2024).

The ecological functions provided by mangrove ecosystems can only be sustained when the ecosystem remains healthy condition. However, mangrove health is dynamic and may gradually decline due to various natural and anthropogenic stressors, including coastal development, land-use change, pollution, hydrological alteration, and climate-related disturbances (Suhardi et al., 2024). Before reaching irreversible damage or mortality, mangroves generally experience progressive changes in their physiological and structural conditions that reflect declining ecosystem health (Neres et al., 2024). Therefore, regular and repeated monitoring of mangrove health is essential to detect changes in ecosystem condition and support timely conservation and management actions.

The research area is located in the Segara Biru Mangrove Ecosystem, Lontar Village. Mangrove condition monitoring is currently conducted by local mangrove managers through periodic field observations. Following mangrove planting activities, monitoring requires direct visits to the planting locations to assess the condition of the planted mangroves. Based on information from local mangrove managers, the assessment generally focuses on whether mangroves are alive or dead, without providing information on intermediate health conditions or early signs of deterioration.

Consequently, gradual changes in mangrove condition that occur before visible damage, or mortality may not be identified systematically. Providing information on these changes at an earlier stage could therefore support more timely field verification and monitoring activities.

To address these limitations, a monitoring approach capable of providing consistent, objective, and spatially comprehensive information through repeated observations is required. Advances in satellite remote sensing have enabled mangrove ecosystems to be observed across large areas and over extended periods, providing consistent spatial and temporal information for monitoring vegetation and environmental changes.

The integration of multi-temporal satellite data further enables gradual changes in mangrove conditions to be examined over time, while machine learning techniques can support the classification of complex patterns derived from multidimensional satellite-based features. Therefore, the combination of remote sensing, time-series analysis, and machine learning provides a promising approach for identifying changes in mangrove conditions and supporting more timely and informed ecosystem monitoring and management (Neres et al., 2024).

Although previous studies have demonstrated the potential of satellite remote sensing and time-series analysis for monitoring mangrove conditions, challenges remain in characterizing gradual and multidimensional changes in mangrove health. Time-series satellite observations have been used to identify mangrove disturbance, decline, recovery, and regrowth, demonstrating the value of temporal information for characterizing changes in mangrove conditions over time (Yang et al., 2026).

The mangrove condition is influenced by multiple interacting environmental characteristics that may not be adequately represented by a single type of satellite-derived information. The selection and integration of complementary spectral, thermal, and synthetic aperture radar (SAR) features may provide a more comprehensive representation of vegetation condition, moisture, surface temperature, and vegetation structure. This highlights the need for a feature engineering and classification approach that can integrate complementary satellite-derived features to distinguish different mangrove condition classes and characterize their changes over time.

Building on these considerations, this study applies a machine learning-based classification approach to characterize mangrove health conditions using multi-temporal satellite data. Previous research has demonstrated the potential of time-series satellite observations for characterizing changes in mangrove conditions over time, while multi-source remote sensing data can provide complementary information on vegetation and environmental characteristics (Neres et al., 2024; Yang et al., 2024a).

The proposed approach integrates complementary spectral, thermal, and synthetic aperture radar (SAR)-derived features to represent different dimensions of mangrove conditions, including vegetation characteristics, vegetation moisture, surface water conditions, surface temperature, and vegetation structure. Machine learning is then applied to classify mangrove conditions into three classes, namely Healthy, Stressed, and Dead, based on the selected satellite derived features for each observation period. The temporal sequence of these classification results is subsequently analyzed to characterize changes in mangrove condition and degradation trajectories over time. By integrating temporal observations with complementary satellite derived features, this approach is expected to provide a more comprehensive characterization of changes in mangrove conditions than assessments based on a single observation period or individual indicators.

This study focuses on the spatio-temporal classification of mangrove conditions and the characterization of degradation trajectories in the Segara Biru Mangrove ecosystem, Lontar Village, Banten, using multi-temporal satellite data from 2020 to 2025. The study classifies mangrove conditions into three classes, namely Healthy, Stressed, and Dead, using selected satellite-derived features from complementary spectral, thermal, and synthetic aperture radar (SAR) data. The selected features include NDVI, EVI, NDRE, NDMI, MNDWI, LST, VH, and VH/VV ratio, which represent complementary dimensions of mangrove vegetation and environmental conditions. These features are used to train and evaluate machine learning models for mangrove condition classification at each observation period. The temporal sequence of the resulting classification outputs is then analyzed to characterize changes in mangrove health conditions and health-state trajectories during the 2020–2025 period.

The trained and evaluated model also provides a basis for predicting mangrove condition classes from new monitoring observations with comparable input characteristics, while application to other locations requires additional field validation. The resulting information is intended to support systematic monitoring and provide early information that can help guide field verification of mangrove conditions in the study area.

1.2. Problem Statement

The Segara Biru Mangrove ecosystem, Lontar Village, Banten, post-planting monitoring is routinely conducted by the local community group (Kelompok Tani Hutan/KTH) through direct field observations, generally at approximately monthly intervals. During these monitoring activities, the condition of planted mangroves is assessed directly in the field, and damaged or dead plants are subsequently addressed through replanting or gap-filling activities. This monitoring practice represents an important effort by the local community to maintain the planted mangrove ecosystem. However, as the monitoring process relies primarily on direct field observations conducted at specific intervals, changes in mangrove condition that occur between monitoring periods may not be systematically documented. In particular, gradual changes in vegetation condition or environmental stress that precede visible damage or mortality may remain difficult to characterize. The current practice has not yet been complemented by a systematic satellite-based approach that can provide additional spatial and temporal information on changes in mangrove condition over time.

From a methodological perspective, the challenge is therefore not to replace existing field monitoring practices, but to complement them with an approach that can provide additional spatial and temporal information on mangrove condition. The study addresses this challenge by utilizing multi-temporal satellite observations to characterize changes in mangrove condition and classify them into three classes, namely Healthy, Stressed, and Dead. By integrating complementary spectral, thermal, and synthetic aperture radar (SAR)-derived features with time-series analysis and machine learning, the study classifies mangrove conditions into Healthy, Stressed, and Dead classes for each observation period.

The resulting temporal sequence of classifications is then used to characterize changes in mangrove health conditions and health-state trajectories in the Segara Biru Mangrove ecosystem during 2020–2025.

This approach is intended to provide complementary information that can support existing field-based monitoring and provide early information to help identify areas that may require field verification.

To provide a structured overview of the underlying research problem, the main factors contributing to the limitations of mangrove health monitoring in the study area are summarized using a fishbone diagram, as presented in Figure 1.1.

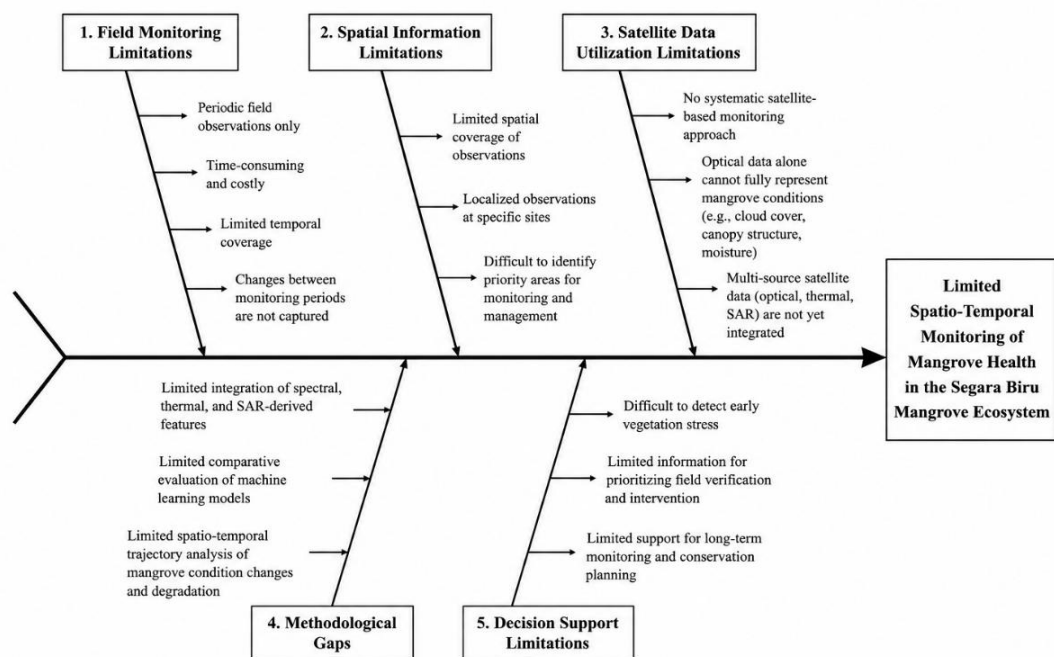


Figure 1.1 Fishbone Diagram of the Research Problems

1.3. Research Objectives

The main objective of this study is to develop and evaluate a machine learning-based approach for classifying mangrove health in the Segara Biru Mangrove Area of Interest (AOI), Lontar Village, Serang District, Banten, using multi-source satellite data from 2020 to 2025.

To achieve this main objective, the specific objectives of this study are:

1. To evaluate the relevance and configuration of satellite-derived features for distinguishing mangrove health classes of Healthy, Stressed, and Dead.
2. To compare the classification performance of Random Forest, Support Vector Machine, and XGBoost, including feature configuration, hyperparameter optimization, and class-imbalance handling, for mangrove health classification.
3. To apply the final classification model to annual satellite-derived data from 2020 to 2025 and characterize the resulting mangrove health classifications, health-state trajectories, and transitions within the study area.

1.4. Research Questions

Based on the research problem and objectives, this study addresses the following research questions:

1. Research Question 1 (RQ1): How do satellite-derived feature selection and feature configuration using Gini Index, Information Gain, Gain Ratio, Chi-Square, and redundancy analysis affect the classification performance of Healthy, Stressed, and Dead mangrove conditions in the Segara Biru Mangrove area during 2020–2025?
2. Research Question 2 (RQ2): How do Random Forest, Support Vector Machine, and XGBoost differ in classifying Healthy, Stressed, and Dead mangrove conditions using the evaluated feature configurations, and how does class-imbalance handling affect their classification performance under Stratified 5-Fold Cross Validation?

3. Research Question 3 (RQ3): Which satellite-derived features contribute most to the classification of mangrove health conditions in the Segara Biru Mangrove area, and what do their relative contributions indicate about vegetation, moisture, thermal, and radar characteristics associated with Healthy, Stressed, and Dead conditions?

1.5. Hypothesis

Based on the research questions, the hypotheses of this study are formulated as follows:

1. Hypothesis RQ1: Satellite-derived feature selection and configuration based on Gini Index, Information Gain, Gain Ratio, Chi-Square, and redundancy analysis affect mangrove health classification performance, with a selected and more concise feature set that is more suitable for the characteristics of the study area and is expected to provide better classification performance for the Healthy, Stressed, and Dead classes.
2. Hypothesis RQ2: Random Forest, Support Vector Machine, and XGBoost exhibit different classification performance for Healthy, Stressed, and Dead mangrove conditions, and class-imbalance handling through balanced training is expected to improve classification accuracy under Stratified 5-Fold Cross Validation.
3. Hypothesis RQ3: Satellite-derived features contribute unequally to mangrove health classification, with vegetation-, moisture-, thermal-, and radar-related variables showing different levels of predictive importance as indicated by SHAP and permutation importance analysis.

1.6. Scope and Limitations of Studys

This study defines the scope of the research in terms of the study area, mangrove health classification, satellite-derived predictors, machine learning models, and the period of observation. The scope is established to ensure that the analysis remains focused on machine learning-based mangrove health classification, while the limitations define the factors that should be considered when interpreting and applying the results.

1.6.1. Scope of the Study

The scope of this study includes:

1. The study is conducted within the Area of Interest (AOI) of Segara Biru Mangrove, Lontar Village, Serang District, Banten.
2. The study focuses on the classification of mangrove health into three classes: Healthy, Stressed, and Dead, using GPS-referenced ground observations as the response labels.
3. The study integrates satellite data from Sentinel-2, Sentinel-1, and Landsat 8 to represent complementary optical, radar, and thermal information related to mangrove condition.
4. Eight satellite-derived features are evaluated as predictor variables, consisting of NDVI, EVI, NDRE, NDMI, MNDWI, LST_Celsius, VH, and VH/VV Ratio.
5. Feature relevance and feature configuration are evaluated using Gini Index, Information Gain, Gain Ratio, Chi-Square, redundancy analysis, and comparative feature-scenario evaluation. The contribution of features in the final model is further examined using SHAP and permutation importance.
6. The study compares Random Forest, Support Vector Machine, and XGBoost for the classification of Healthy, Stressed, and Dead mangrove conditions.
7. Hyperparameter optimisation and Stratified 5-Fold Cross Validation are used to evaluate and compare model performance using classification metrics including Accuracy, Precision, Recall, and F1-score.
8. Class imbalance is explicitly evaluated by comparing the original ground-reference distribution with balanced training conditions using the resampling strategies implemented in the experiments.

9. Satellite observations from 2020–2025 are used to produce annual mangrove health classifications and to compare the distribution of Healthy, Stressed, and Dead classes across the observation period.
10. The resulting annual classifications are used to characterise observed health-state transitions and mangrove trajectories during 2020–2025, including stable, recovery, degradation, and fluctuating patterns where supported by the classification results.
11. The resulting classification information is intended to support local mangrove monitoring and field verification, particularly by providing preliminary information on areas that may require further field checking.

1.6.2. Limitations of the Study

The limitations of this study include:

1. The study is limited to the Segara Biru Mangrove AOI, and the generalisability of the trained model to other mangrove ecosystems is not established without additional local ground-reference data and validation.
2. The ground-reference dataset consists of 321 field observations collected on 19 and 21 July 2026. The number, spatial distribution, and observation period of these samples may not represent all possible mangrove conditions within the AOI or in other locations.
3. The Healthy, Stressed, and Dead labels are based on in-situ visual assessment. The KTH members accompanying the survey generally distinguished healthy and dead conditions based on local ecological knowledge, while the researcher operationalised the observations into three classes by introducing the intermediate Stressed category. Consequently, the labelling process retains an element of observer-based interpretation.
4. The three satellite sources have different spatial resolutions, acquisition frequencies, and observation characteristics. Although preprocessing, temporal compositing, spatial extraction, and feature integration were applied to harmonise the datasets, these differences cannot be completely eliminated.
5. The study does not investigate spatial and temporal effects as independent explanatory variables. The 2020–2025 period is used to generate and compare

annual classification results, while the spatial maps are used to represent the distribution of the classified mangrove conditions within the AOI.

6. Other environmental factors that may influence mangrove health are not explicitly included as predictor variables, including tidal conditions, salinity, topography, and meteorological variables. Their independent effects on mangrove health are therefore not quantified.
7. The classification results depend on the quality and representativeness of the available ground-reference data and satellite-derived predictors. Model performance may therefore differ under environmental conditions that are not adequately represented in the training data.
8. The trained model is not considered directly ready for routine operational implementation by KTH. Practical implementation would require appropriate training, technical guidance, data preparation procedures, and continued field verification before routine use.
9. The transferability of the model to other locations is outside the direct validation scope of this study. Application to different mangrove ecosystems would require additional ground-reference observations and local validation.
10. The study does not directly measure mangrove carbon stocks, CO₂ emissions, CH₄ emissions, greenhouse-gas fluxes, or carbon-credit potential. Satellite-derived variables are used as predictors for mangrove health classification and are not interpreted as direct measurements of these processes.
11. The study does not include socioeconomic analysis, direct monetary valuation, or quantitative assessment of monitoring cost savings.
12. The study does not forecast future mangrove health conditions beyond the 2020–2025 observation period. The analysis is limited to describing the classification results and observed health-state transitions within the available period.

1.7. Significance of Study

This study is expected to provide academic, methodological, and practical contributions to mangrove health assessment and monitoring. The contributions are particularly relevant to the use of satellite-derived information and machine learning to support condition-based mangrove monitoring in the Segara Biru Mangrove area.

1.7.1. Academic Contribution

This study contributes to the academic development of machine learning-based mangrove health classification by examining the classification of mangrove conditions into three classes: Healthy, Stressed, and Dead. The study provides empirical evidence on the use of satellite-derived vegetation, moisture-related, thermal, and radar information for distinguishing different mangrove health conditions.

The study also contributes through the systematic evaluation of satellite-derived features using Gini Index, Information Gain, Gain Ratio, Chi-Square, redundancy analysis, and comparative feature-configuration evaluation. The comparative evaluation of Random Forest, Support Vector Machine, and XGBoost, together with hyperparameter optimization, class-imbalance handling, and Stratified 5-Fold Cross Validation, provides empirical evidence for evaluating alternative machine learning configurations for mangrove health classification.

Furthermore, the use of Permutation Importance and SHAP provides model-based evidence regarding the relative contribution of individual satellite-derived features within the final classification model. The annual classification results and subsequent health-state trajectory and transition analyses also provide additional information for interpreting changes in the classified mangrove health conditions during the 2020–2025 observation period.

1.7.2. Practical Contribution

Practically, this study is expected to provide supporting satellite-based information for the mangrove monitoring activities of the Kelompok Tani Hutan (KTH) Segara Biru. The classification outputs can provide an initial indication of areas classified as Healthy, Stressed, or Dead, which may then be prioritised for field verification and further observation.

The information can complement the existing field-based monitoring activities by providing an initial overview of mangrove conditions before monitoring teams conduct direct observations. In this context, the satellite-based results are intended to support rather than replace field monitoring and verification.

For practical adoption by KTH, appropriate capacity building and user guidance would be required to support the interpretation and use of the classification results. The satellite-based results should therefore be treated as supporting evidence for monitoring and management decisions rather than as the sole basis for intervention.

1.8. Thesis Structure

To provide a comprehensive overview, this thesis is arranged with the following writing systematics:

- a. **Chapter 1: Introduction.** This chapter presents the background and problem statement of the study, followed by the research objectives, research questions, hypotheses, significance of the study, scope and limitations, and thesis structure. The chapter establishes the research context and defines the focus of the machine learning-based mangrove health classification in the Segara Biru Mangrove AOI.
- b. **Chapter 2: Literature Review.** This chapter discusses the theoretical foundations and previous studies relevant to mangrove health assessment, mangrove condition and degradation, remote sensing, satellite-derived features, multi-source satellite data, and machine learning classification. It also reviews feature selection, model evaluation, class imbalance, and relevant mangrove remote sensing studies to establish the research gap and methodological basis of the study.
- c. **Chapter 3: Research Methodology.** This chapter describes the study area, ground-reference data collection and labelling, satellite datasets, data preprocessing and harmonisation, satellite-derived feature extraction, feature relevance and selection procedures, feature-scenario evaluation, machine learning models, hyperparameter optimisation, class-imbalance handling, and model validation using Stratified 5-Fold Cross Validation. The chapter also describes the procedures used to generate annual mangrove health classifications and to derive transition and trajectory information from the classification results.
- d. **Chapter 4: Results and Discussion.** This chapter presents and discusses the results of the study, including the characteristics of the ground-reference dataset, satellite-derived feature relevance and selection using Gini Index, Information Gain, Gain Ratio, and Chi-Square, feature-scenario evaluation, and the comparison of Random Forest, Support Vector Machine, and XGBoost. The chapter also presents hyperparameter optimisation results, class-imbalance and balanced-training evaluation, confusion matrix and error analysis, final model

performance, and feature interpretation using SHAP and permutation importance. The annual mangrove health classification results for 2020–2025 are subsequently presented together with area statistics, health-state transitions, and spatio-temporal trajectory classifications. The findings are discussed in relation to the research questions, hypotheses, relevant literature, and implications for local mangrove monitoring.

- e. **Chapter 5: Conclusion and Recommendations.** This chapter summarises the main findings of the study and presents conclusions corresponding to the research objectives, research questions, and hypotheses. It also discusses the practical implications of the findings for supporting local mangrove monitoring, acknowledges the limitations of the study, and provides recommendations for future research, including additional field validation, model improvement, and potential application to other mangrove areas.

