CHAPTER I

INTRODUCTION

1.1 Background

Land use around the world is currently increasing massively as human needs for housing, agriculture, and industry grow (Gaur et al., 2020). This phenomenon trigerred significant changes in land use and land cover (LULC), which have significant impacts on ecosystems and natural resources (Dale et al., 1998). These changes not only indicate infrastructure development but also indicate changes in broader environmental dynamics (Mendoza et al., 2011).

Thus, LULC monitoring is essential because it allows us to identify and understand changes in environmental conditions over time (Tassi et al., 2021). This is important for managing the environmental impacts of human activities, regulating resource use efficiently, and ensuring sustainable development. Through LULC monitoring, it is feasible to evaluate the effectiveness of land management plans and respond proactively to enviromental issues or climate change (Olorunfemi et al., 2020). It also provides critical data for emergency planning to improve the accuracy and speed of response in crises (Fekete, 2023).

The availability of visual data from satellites and airborne sources has grown significantly in recent decades, as remote sensing technology has advanced and the number of satellites in operation has increased (Rogan & Chen, 2004). GIS (Geographic Information System) and remote sensing, as part of geospatial methods, have proven effective in assessing LULC changes at various spatial scale levels (Aboelnour et al., 2018). Remote sensing is an important technology in LULC monitoring, enabling extensive and continuous data collection without direct interaction with the monitored area (Selvaraj et al., 2023). Remote sensing provides real-time and detailed images of the Earth's surface, which is very useful for observing changes in land use and vegetation conditions over time. With its ability to capture data on a large scale and in isolated places, remote sensing is a great instrument for monitoring LULC effectively and efficiently (Aboelnour et al., 2018).

The integration of machine learning with remote sensing has revolutionized the way LULC is monitored. With its advanced data analysis capabilities, machine learning enables automated interpretation of big data generated by remote sensing. Machine learning algorithms can quickly classify, recognize patterns, and predict LULC changes with high accuracy based on imagery acquired from satellites or aerial sensors (Maxwell et al., 2018). This approach speeds up the data analysis process and improves the ability to identify long-term trends and sudden land-use changes. This information enables policy makers to take appropriate steps in optimizing environmental planning (F. Li et al., 2023).

Pixel-based analysis of remote sensing data is a common method used to classify LULC in the past. This procedure checks the spectral characteristics of each pixel or image element in the region of interest (Riggan Jr et al., 2009). In pixel-based classification, each pixel point representing a different element on the earth's surface is analyzed using spectral data stored in digital value format. Pixel-based approaches are unable to determine the minimum mapping unit, so overclassification of individual pixels often occurs (Balha et al., 2021). Initially, this method was designed for low-resolution imagery, but many studies have shown problems when applied to high-resolution imagery. Classification accuracy decreases due to the presence of noise resembling 'salt and pepper' when pixel-based methods are applied to high-resolution images (Gao & Mas, 2008).

As a solution to this problem, the object-based LULC classification approach can be used as an alternative to the single pixel-based classification method (Blaschke, 2010). Object-based classification uses image segmentation and forms a hierarchical network of homogeneous objects according to feature boundaries. This approach considers spatial characteristics such as size, shape, texture, color, pattern, and relationships between objects, then divides the image into similar objects (Riggan Jr et al., 2009). This method creates a more natural and detailed segmentation, by combining richer contextual and spatial information, similar to how humans interpret images. Over the past decade, this modern approach has become increasingly popular in remote sensing (Blaschke et al., 2014).

The use of pixel-based classification methods is common in research to obtain LULC data. In recent years, machine learning algoritgms such as Support Vector

Machine (SVM) and Random Forest (RF) have become dominant methods in LULC classification studies because they show excellent performance in terms of accuracy and computational efficiency (Aryal et al., 2023; Basheer et al., 2022; Deilmai et al., 2014; Lemenkova, 2024; Phan et al., 2020; Savitha & Reshma, 2024). Meanwhile, object-based classification has been developed as another approach in LULC classification techniques. Object-based analysis requires an additional pre-processing step of image segmentation before classification can be performed. Advanced image segmentation techniques such as SNIC (Simple Non-Iterative Clustering) has been widely used in the context of object-based LULC classification due to their capability to efficiently generate high-quality superpixels while maintaining boundary compliance (Karakuş, 2024; Naderi, 2023; Shafizadeh-Moghadam et al., 2021; Tassi & Vizzari, 2020), while G-Means segmentation has also been shown to perform well in automatically determining the optimal number of segments based on data distribution (Varma et al., 2023; Wang et al., 2022).

According to the explanation above, this study compares the effectiveness of pixel-based and object-based LULC classification by using several algorithms in a particular area. The comparison of the two methods aims to analyze how each approach has different characteristics when interpreting LULC. The findings of this study are expected to be able to provide a contribution in the form of in the form of a more optimal and efficient method for monitoring LULC changes.

1.2 Problem Identification

According to the background above, the problems that can be identified in this study are as follows:

1. Uncertainty in the Effectiveness and Accuracy of Machine Learning Models.

   Although several algorithms have been widely applied in pixel-based or object-based LULC classification, there is still uncertainty about how well and accurately machine learning models perform with these algorithms for different geographic and environmental conditions.

2. Difficulty in Selecting Features.

    In pixel-based and object-based LULC classification, proper feature selection is required to improve classification accuracy. Moreover, object-based classification requires the identification of discrete objects in images, which often have significant variability in texture, index, or spectral characteristics.

3. Difficulty in Selecting Algorithm Parameters.

    The effectiveness of pixel-based and object-based LULC classification is dependent on the algorithm parameters. Incorrect parameter settings can affect the accuracy of the final classification results.

1.3 Research Scope

To overcome the problems that have been found previously, this study needs to be limited in scope so that the research can be carried out in more depth and specifically. The limitations of this study are as follows.

1. This study will focus on monitoring land cover changes in the Chonburi Province, Thailand.
2. This study will only use Sentinel-2 L2A satellite imagery for a period of 3 years (2021 – 2023).
3. This study will classify 5 classes, namely bare soil, built-up, forest, agriculture, and water.
4. This study will compare 2 image segmentation algorithms, namely the Simple Non-Iterative Clustering and G-Means.
5. This study will use 2 supervised classification algorithms, namely Random Forest and Support Vector Machine.
6. This study will use a confusion matrix to evaluate the model.
7. The process of data collection, modeling, and analysis uses the Google Earth Engine platform.
8. Determination of the parameters used in the classification algorithm will be done by hyperparameter tuning.
9. The cloud masking process will use band QA60, where pixels indicated by clouds will not be taken into account.

1.4 Research Questions

Based on the background that has been described, the following problem can be formulated.

1. How is the modeling process in pixel-based and object-based LULC classification?
2. How does the performance of pixel-based and object-based LULC classification models compare?

1.5 Research Objectives

Based on the research questions that have been described, the following are objectives to be achieved from this study.

1. To create pixel-based and object-based LULC classification models.
2. To compare the performance of pixel-based and object-based LULC classification models, so a more optimal method for LULC classification in a particular area can be determined.

1.6 Research Significance

Based on the objectives that have been described, this study is expected to obtain the following benefits.

1. Theoretical Significance

   The author hopes that the results of this study can contribute to the development of science in this field. In addition, this study is also expected to be a reference for students or other researchers who want to conduct further research.
2. Practical Significance

   The author hopes this study can improve spatial planning, natural resource management, environmental monitoring, agricultural optimization, disaster mitigation, infrastructure improvement, and biodiversity conservation in the research area, thereby supporting more effective decision-making in various sectors.