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Integrated Supervised Classification of LULC in Identifying Musang King Durian Illegal Farming Location

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ABSTRACT

Musang King Durian (MKD) is in high demand due to its unique taste and aroma; hence, some opportunistic farmers grow it on a large scale. The issue arises when some MKD is planted on encroached land in remote places, making it impossible for local authorities to locate them. This study proposes to examine the changes in land use land cover (LULC) within the Benom Permanent Forest Reserved area that were reported to have land invasion activities caused by illegal MKD plantations between 2019 and 2022 using Sentinel imagery. The objectives were to investigate the location of illicit MKD farming at Mount Benom based on the interpretation of LULC changes and Normalized Different Vegetation Index (NDVI) analysis. ArcGIS and eCognition Developer software were used for data processing and analysis to identify water bodies, bare land, green areas, forests, and potential illegal MKD plantings (PIDP) areas. Between the years 2019 and 2022, it was found that there has been a significant rise in water bodies (36%), green areas (34%), and forests (19%). However, the potential illegal MKD plantation area fell by 59%, while bare land declined by 35%. These downsizing changes might occur due to illegal MKD destroyed operations executed in 2019 by the forestry department in Raub, Pahang.

1. Introduction

Durian (*Durio zibethinus*) is the king of fruits (Ei and Ismail 2022; Shamin-Shazwan et al. 2022); meanwhile, Musang King Durian (MKD) is known as the king of kings. These days, Mao Shan Wang, also referred to as Musang King (Azizi et al. 2022), is the gem in Malaysia's extensive crown of durian types. This highly regarded cultivar has an iconic legacy for its incomparable quality and flavor (Sari et al. 2021; Shamin-Shazwan et al. 2022). MKDs are prized for their seductively buttery texture, which melts on the tongue and leaves a velvety experience (Thorogood et al. 2022). MKDs, grown in the greenery orchards of Pahang and Johor, represent the ultimate achievement of Malaysian durian agriculture, pleasing palates worldwide. The unique aroma and taste of MKDs make them a highly sought-after delicacy among durian enthusiasts. The popularity of Mao Shan Wang durians has only continued to grow, with demand often exceeding supply. Despite their high price tag, these creamy and rich fruits remain a favorite among durian connoisseurs.

The district of Raub, Pahang, is known for its suitable land for the growth of MKD (Ei and Ismail 2022), which is also well known by people from other countries like China and Thailand. When the news of the illegal farmers who planted hundreds of hectares of MKD on illegal land is heard in different countries, it can significantly impact Malaysia due to MKD being one of the significant contributors to Malaysia's agro-economy. After more than 20 years of exploring illegally and making a profit of tens of millions of ringgits, it is now time for the land owned by the state government to be taken back, which can finally be shared and worked with the people more fairly and effectively as it was mentioned by State Science, Technology, Innovation, Communication and Multimedia Exco of Pahang, Datuk Mohammad Fakhruddin Mohd Ariff in 2021. The District Forestry Department of Pahang has taken a few actions whereby the trees that illegal MKD farmers planted were destroyed, involving several areas at Batu Talam Forest Reserve, Raub, and another location near Sungai Lembing Forest, Kuantan.

In previous studies, many researchers have focused on the use of the Normalized Different Vegetation Index (NDVI) to detect vegetation health (Stamford et al. 2023), tree species (Ozdarici-Ok and Ok 2023; Sheeren et al. 2016; Valderrama-Landeros et al. 2018), forest monitoring (Gallardo-Salazar et al. 2023; Pesaresi et al. 2020; Suwanto et al. 2021), agriculture (Ahmed 2016; Gandhi et al. 2015) and mangrove density (Arfan et al. 2024) but there is limited research on using NDVI to identify potential illegal activities such as illegal mining and logging. This study will contribute to filling this gap in the literature by applying NDVI analysis to identify possible illegal activities related to land use changes. Therefore, this study was conducted in Raub, a well-known durian town noted for its extensive durian cultivation, especially of the Musang King type (Ei and Ismail 2022). The application of this type of study in this field is relatively new. Therefore, the most recent topic of land invasion caused by MKD farming that is not authorized was examined. Through two main objectives, this study aims to integrate the supervised classification method of land use and land cover (LULC) changes in identifying potential illegal MKD farming: (i) using remote sensing techniques to analyze changes in LULC caused by illegal farming activities in Pahang between 2019 and 2022, and (ii) using object-based image analysis (OBIA) to identify suspected illegal MKD farming based on NDVI analysis and LULC changes in the area of interest (AOI).

More effective urban planning and natural resource management are made possible by monitoring and predicting land use and cover changes using remote sensing and GIS techniques (Butt et al. 2015; Liping et al. 2018; Muleta et al. 2017). Land use and cover changes should ideally be made to evaluate the environmental impact of human activity and inform sustainable development plans. These techniques also allow for the proactive implementation of conservation measures by identifying regions vulnerable to degradation or deforestation. It also helps identify areas vulnerable to environmental damage and act quickly to stop things from worsening. These technologies can also help assess how human activity affects ecosystems and biodiversity (Butt et al. 2015; Liping et al. 2018; Muleta et al. 2017; Rwanga and Ndambuki 2017; Singh et al. 2020).

They also support the creation of sustainable development strategies and direct conservation initiatives. Remote sensing and GIS support better decision-making and a more sustainable future by providing insightful data and valuable information. These tools are essential for tracking environmental changes and examining trends over time. GIS and remote sensing can also track natural disasters and evaluate their environmental effects. These technologies facilitate prompt response and damage mitigation measures by supplying real-time data.

A set of techniques has been devised to examine the potential location of an illegal MKD plantation in a remote and restricted land area. These processes entail identifying particular patterns connected to MKD cultivation utilizing satellite imagery and data analysis tools. Field visits may also be used for ground verification to verify the existence of illegal plantings. Field visits may also be used for ground verification to confirm the existence of illegal plantings. The extent of the problem and its possible effects on the environment can be more accurately assessed with this all-encompassing approach. Before this, an analysis of land uses and land cover changes was conducted at the selected AOI using the maximum likelihood supervised classification (MLC) algorithm technique to compare data from 2019 and 2022. This method is similar to the method applied by Butt et al. (2015), Latip et al. (2022), and Sinha et al. (2015), who compare changes in LULC. For the accuracy assessment of the classified data from LULC analysis, the result has been analyzed similarly to Huang et al. (2021), Rwanga et al. (2017), and Sinha et al. (2015) who evaluate User Accuracy (UA), Producer Accuracy (PA), Kappa Index Agreement (KIA) and Overall Accuracy (OA).

For high and extremely high-resolution data extraction, the OBIA approach could outperform the pixel-based technique (Aggarwal et al. 2016). Image classification is inextricably linked with interpreting remote sensing data for object mapping. Pixel-based and object-based are the two most popular remote sensing digital processing methods. Object-based categorization methods are currently used to classify objects on Earth's surface. OBIA has been extensively used, which entails segmenting images into homogeneous areas and identifying object characteristics utilizing spatial and contextual features (Hartoni et al. 2021). Therefore, the delineating potential MKD farm was introduced to investigate issues regarding illegal farmers that plant, grow, and gain profit from MKD that occurred on forest reserve land. This issue may seem small to some Malaysian citizens, but it could significantly impact the country. This illegal activity will negatively impact the nearby local people, environment, and economy.

The general definition and explanation of land encroachment could be described as the use or occupation of any unit of property or land by an individual who has no right of title to that property or authority to use the land in any manner. Some of the most susceptible assets have been abandoned land for agriculture or overlooked residential or business locations. In such cases, the likelihood of land invasion is substantial, mainly when the registered owners are not in the property area. With hundreds of cases waiting in courthouses, it is more necessary than ever for everyone with property to understand the legal process for land invasion. Poverty, inadequate property rights enforcement, and bad land governance are the main causes of private land encroachment.

According to Noor et al. (2020), institutional inadequacies, a lack of accountability, and ambiguity in roles and responsibilities are standard features of land administration systems. People believe there is little likelihood of being held accountable for their actions because of these vulnerabilities, which leaves the ecology open to invasion. Ismail and Ganason (2023) emphasized the necessity of regularizing land tenure and effective enforcement procedures to identify and protect private property rights. Without well-defined and upheld property rights, private landowners may find it challenging to use their properties for their intended uses. In addition, the state might forfeit potential revenue from illegal land usage. Thus, maintaining sustainable land use practices and preventing encroachment requires better land governance.

Illegal occupancy or government land encroachment is a serious environmental issue that hurts forests and wildlife. This is particularly prevalent in Pahang, Malaysia's Cameron Highlands. According to Besi et al. (2023), deforestation plays a significant role in local and global environmental change, which substantially impacts several ecosystem sectors, such as carbon cycling, the diversity of animal and plant life worldwide, and modifications to human land use patterns. The growing demand for superior agricultural products, which drives farmers to steal public lands and illegally clear forests to increase agricultural output, is a primary driver of invasions, the paper claims (Latip et al. 2022). The problem is worsened by unclear land tenure and rights, which enable encroachers to abuse public lands and a lack of law enforcement. Governmental land invasions harm the environment, make areas more susceptible to landslides and other natural disasters, causing biodiversity decrease and putting forest ecosystems at risk.

2. Materials and Methods

2.1. Study Area

The study region that has been selected is located in Raub, Pahang, and its center coordinate is 3.7935˚N, 101.8575˚E. This is because Raub has a history of delivering large MKD plantations in complex soil settings compared to other regions (Ei and Ismail 2022), and because of its ongoing problems with MKD farming that is not authorized. Raub is located in the central area of Peninsular Malaysia, which has a tropical climate and soil suitable for MKD cultivation. The typical temperatures are 25 to 30°C and there is much rainfall each year. Well-draining loamy soil with a slightly acidic pH is the type of soil found in MKD. The terrain in Raub is between 100 and 500 m above sea level, which makes it ideal for growing MKD. Rich biodiversity is another attribute of Raub that may help explain the success of MKD plants in the region. **Fig. 1** depicts the research area's location.

Fig. 1. Location of the study area.

2.2. Data Acquisition and Methodology

Multispectral images served as the primary source of spatial data for the study's acquisition. The Copernicus Open Access Hub is a web-based platform that provides unrestricted and complimentary access to an extensive compilation of Copernicus Earth Observation satellite data and products. This is where the satellite photos were obtained. Sentinel 2A and 2B satellites, which generate multispectral images (bands 2 to 4 and 8) with a 10-meter spectral resolution and a 5-day temporal resolution, are among the satellite data that are freely and publicly accessible through the Copernicus Access Hub, serving a variety of applications (Junior et al. 2023). Sentinel-2 satellite pictures were used for this investigation due to their excellent temporal and spectral resolution, which makes them perfect for mapping, area estimation, and tracking changes in LULC. Furthermore, a Certified Plan (CP) and topographic map were acquired from the Department of Survey and Mapping Malaysia (DSMM). The description of the acquired data is shown in **Table 1** and **Table 2**, involving two sets of satellite images for the years 2019 and 2022 and two sets of topographic maps covering the districts of Raub and Temerloh, while four sets of certified plans at 'Mukim Gali' (a sub-district of Raub) in **Table 3** were used to estimate the most potential MKD farming activities near Mount Benom Forest Reserve.

Table 1. Spectral band in Sentinel-2 satellite imagery data description

Sentinel-2 Bands	Spatial Resolution (m)	Acquisition Date
Band 2 (Blue)	10	
Band 3 (Green)	10	
Band 4 (Red)	10	03/01/2019
Band 5 (Vegetation Red Edge)	20	
Band 6 (Vegetation Red Edge)	20	
Band 7 (Vegetation Red Edge)	20	
Band 8 (NIR)	10	
Band 8A (Narrow NIR)	20	07/07/2022
Band 11 (SWIR)	20	
Band 12 (SWIR)	20	

Table 2. Topographic map information

Topographic Map	Series	Sheet	Edition
Raub	MY502A	AZ12	1
Kampung Genuai	MY502A	AZ21	2

Table 3. Certified plan (CP) information

PA Number	Mukim	District	Notes
PA 06-73680	Gali	Raub	The plan shows the area of the Permanent Forest Reserve of Mount Benom
PA 06-73681	Gali	Raub	
PA 06-73682	Gali	Raub	
PA 06-73683	Gali	Raub	

Different spatial data sources were selected to investigate and verify that the chosen AOI is not on private land or property by georeferencing and overlaying the data in the same projection and coordinate system. From the overlaid data, it was discovered that the end lot falls within four adjacent CPs with reference numbers PA 06-73680 until PA 06-73683. Due to the findings, the study area was set to be outside those CP areas facing the Mount Benom Permanent Forest Reserve. When confirmed, then LULC analysis could be done to extract land use and land cover features within the AOI. According to Huang and Wang (2020), in the standard supervised classification method, only shallow architectures are extracted from the images, while features are generated, selected, or described manually.

Furthermore, deep architectures and high-level features are poorly utilized in solving classification problems. Thus, the lack of deep architectures and high-level features may result in lower classification accuracy and limit the ability to capture complex patterns in the data. Therefore, the extraction of LULC changes and NDVI for vegetation discrimination were obtained by OBIA to specify the existence of illegal MKD farming activities. This is because OBIA entails segmenting images into homogeneous areas and identifying object characteristics using spatial and contextual features (Hartoni et al. 2022).

Hence, the detailed research methodology is described by a flowchart illustrated in **Fig. 2**. The whole process of the research was divided into five phases. The investigation of the study area and data acquisition fall in phases 1 and 2, respectively. Data processing is carried out in phase 3, involving the pre-processing stage of the satellite image, followed by supervised classification of LULC for 2019 and 2022, respectively. Then, both satellite images were used to analyze spectral indices using the NDVI. According to Huang et al. (2021), the primary purpose of using NDVI is to improve the analysis of information about vegetation with remotely sensed data. In line with Huang et al. (2021), the sampling of NDVI from the five existing orchards was conducted to find the average value for DMK plantations. The results derived from the NDVI analysis were then extracted using OBIA segmentation. Analysis and accuracy assessments of the classification results were conducted in phase 4. To assess the accuracy of the segmentation procedure, the NDVI value at the predicted area was compared to the average NDVI value specified for ground truthing. On the other side, the classification results were compared using the LULC and NDVI values changes in the research region from 2019 to 2022, and they were displayed as a LULC change map and graph.

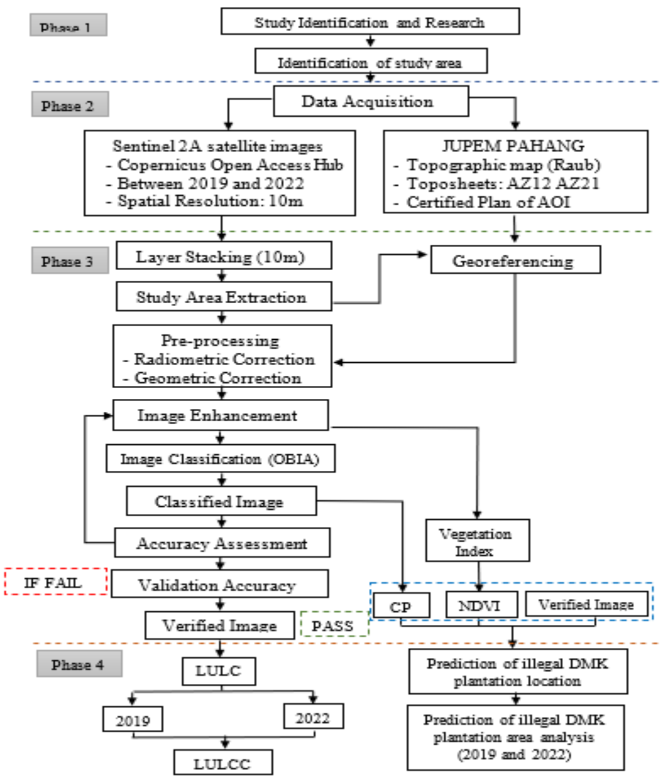


Fig. 2. Flowchart of research methodology.

2.1 Data Processing

After being first downloaded, the Sentinel-2A satellite images underwent pre-processing, including georeferencing, radiometric, and geometric corrections. This ensured that the images were aligned correctly and calibrated for additional processing. Specifically, geometric correction is a crucial method for lining up the geometry of the image with geographic coordinate systems and map projections. This guarantees that the picture faithfully captures real-world elements and enables users to retrieve specific geographic data. Users can use the data in various ways, such as aligning the image with the appropriate map projection, measuring space precisely, performing mapping operations, and combining the image with additional geographic data. According to Gandhi et al. (2015), geometric rectification improves the image's usefulness by facilitating more effective analysis and decision-making in various applications.

The georeferencing data were then continued with mosaicking and sub-setting of the AOI to move forward with the LULC procedure. Following the analysis of both satellite image data, per-pixel signatures were assigned, and the forest was divided into five groups according to the precise Digital Number (DN) value of different landscape characteristics. According to **Table 4**, the classifications were bare land, PIDP, woodland, green space, and water bodies.

Table 4. Classes delineated based on supervised classification

Class Name	Description
Bare land	Land areas of exposed soil and barren regions influenced by human intervention
PIDP	Plantation similar to MKD NDVI value
Forest	Woodland, deep forest
Green Area	Shrub, Crop fields, and fallow lands
Water bodies	River, lake, pond

Note: modified from Butt et al. (2015).

To proceed with further processing, the Area of Interest (AOI) in these studies had been determined by sub-setting the area with a high possibility of illegal MKD farming activity. Typically, applications such as tracking crop health, evaluating changes in land cover, and researching ecosystems make use of the Normalized Difference Vegetation Index (NDVI) because it is an effective instrument for agricultural and environmental monitoring since it offers insightful data on the quantity and quality of vegetation in a particular region. Identification and mapping of tree species using the NDVI method has been utilized in Arekhi et al. (2017), Bergmüller et al. (2022), Gallardo et al. (2023), Madonsela et al. (2018), Mustafa et al. (2015), Pesaresi et al. (2020), Sheeren et al. (2016), Suwanto et al. (2021), and Valderrama et al. (2018).

The use of the NDVI method in this study entails computing the NDVI values for the subset area, which is necessary for acquiring insights into the vegetation health and vitality of the durian plantation in that region. Equation 1 illustrates the general method used to calculate the NDVI value (Huang et al. 2020; NDVI 2018; Stamford et al. 2023) of a plant inside a particular study area:

$$NDVI = (NIR - RED) / (NIR + RED) \quad (1)$$

where RED is the red reflectance (corresponding to band 6), and NIR is the near-infrared reflectance (corresponding to band 8). Mathematically, $NDVI$ also could be expressed as follows (Huang et al. 2020) (Equation 2):

$$N_{DVI} = (N_{IR}NIR - R_{ed}Red) / (N_{IR}NIR + R_{ed}Red) \quad (2)$$

where N_{DVI} is the normalized difference vegetation index. R_{ed} and N_{IR} are spectral radiance (or reflectance) measurements recorded with sensors in red (visible) and *NIR* regions, respectively. Reflectance is a unitless measure of the ratio of radiation reflected by an object relative to the radiation incident upon the object. The NDVI values typically range from -1 to 1, where negative values represent non-vegetated surfaces (like water, barren land, rocks, sands, or concrete surfaces) and are favorable for vegetation, including crops, shrubs, grasses, and forests. Healthy and dense vegetation generally yields higher positive NDVI values (Gandhi et al. 2015).

2.4 Determination of MKD NDVI Value for Ground Truthing

The NDVI-based vegetation index is frequently used and has proven effective in describing vegetation density and condition. An image differencing technique was applied, in which NDVI values from two images were subtracted to get NDVI changes. This was then transformed into an NDVI (indicating vegetation density) change map. Vegetation values typically vary from 0.1 to 0.7, but index values might be -1.0 to 1.0. NDVI values above zero indicate the presence of vegetation classes, while moderate and high values indicate stressed and healthy vegetation, respectively. Near zero and negative values indicate non-vegetation classes like water, snow, built-up areas, and barren land. Active vegetation has a positive NDVI, often ranging from 0.1 to 0.6, indicating increased photosynthetic activity and canopy density (Ahmed 2016).

Conversely, Huang et al. (2021) found that the forest's NDVI value, ascertained using Sentinel imagery, yields values ranging from 0.7 to 0.8. Thus, a systematic technique was developed to identify the suitable NDVI values for MKD plants by analyzing the various NDVI values of durian orchards in the Raub district. Subsequently, standard durian orchards were selected based on size and planting density. Thus, finding specific areas of interest within each orchard created a new subset in the chosen imagery. Then, NDVI values were generated to obtain ground truth information based on the actual locations of MKD orchards.

These observations were used to validate NDVI estimates acquired from remote sensing. The geographical distribution of NDVI was analyzed by collecting NDVI values based on subset imagery for each orchard and comparing results. The lowest and greatest NDVI values were identified within each orchard, signifying the minimum and maximum NDVI expressions in the durian trees. Furthermore, the average NDVI value for each orchard was determined, showing the range of NDVI values gives insight into variability (**Fig. 3**). Because the reference data for this study was limited, this type of data was essential, which is why this particular approach was chosen to locate the durian crop at the chosen AOI.

2.5 Image Classification Using OBIA

The OBIA technique was utilized in this study's image classification to distinguish MKD orchards from other classes, which included bare ground, lake bodies, forests, and other green spaces. Apostol et al. (2020), Hossain and Chen (2019), Kotaridis and Lazaridou (2021), Ozdarici and Ok (2023), and Rizvi et al. (2019) all successfully used OBIA to categorize tree crowns using object segmentation from remote sensing data. Kotaridis and Lazaridou (2021) claim that OBIA combines expertise from a wide range of fields in creating and applying geographic information. Traditionally, OBIA includes two principal steps: image segmentation and object classification.

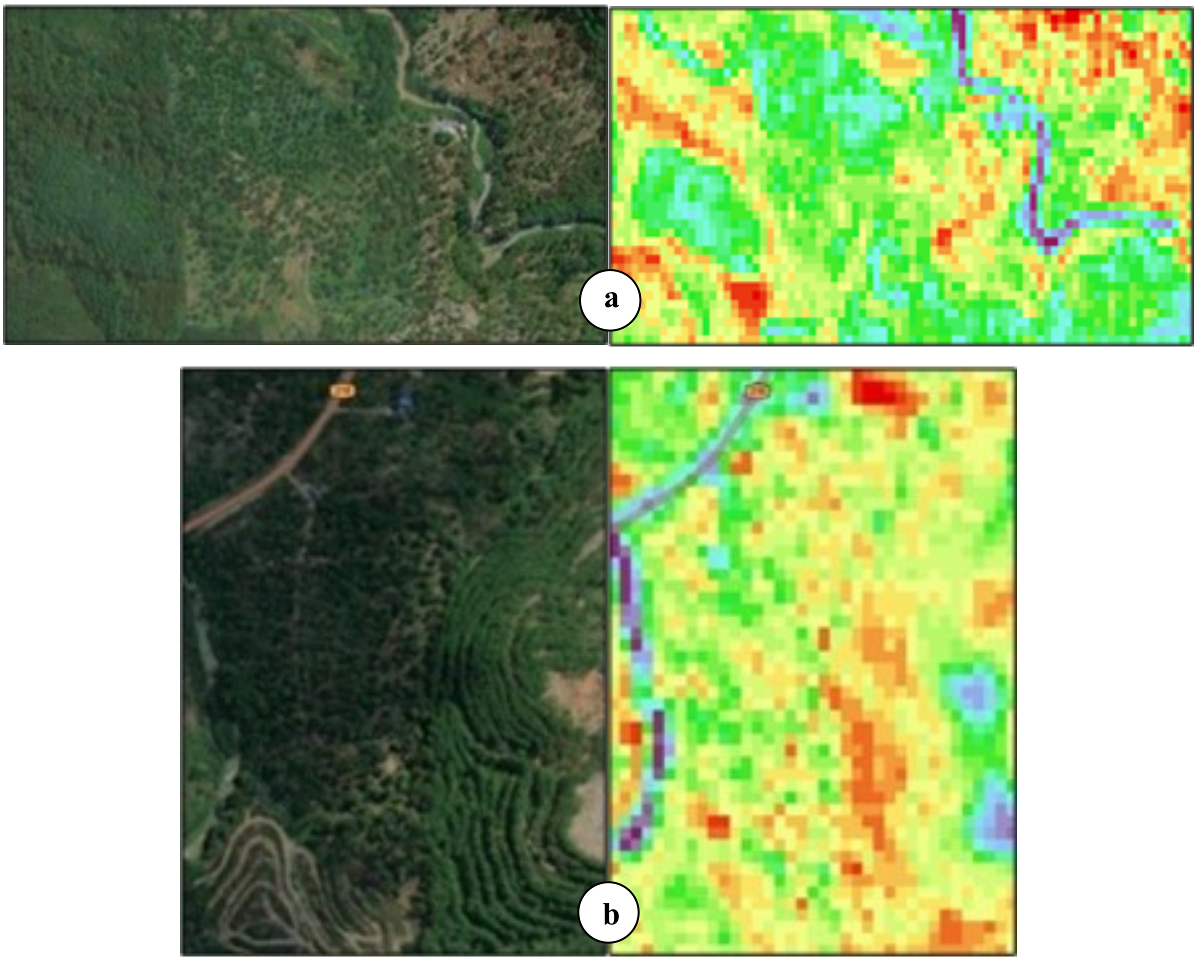


Fig. 3. Examples of selected location of MKD orchard (left image) and NDVI result (right image) (a) Durian Orchard Newleaf Plantation (3°44'52.91"N, 101°49'46.50" E) (b) Durian MK (or Dusun Taman Ria) (3°45'41.55" N, 101°49'56.71" E).

OBIA divides the chosen image into segments or objects based on spectral, spatial, or textural homogeneity criteria. This step helps to create meaningful and manageable units for analysis. Once the image is segmented, various features (attributes) are extracted from each object. These features include spectral information, texture, shape, size, and contextual relationships with neighboring objects. The extracted features are then used for classification purposes. Machine learning algorithms or rule-based systems can classify objects into different classes or land cover types. After the classification process, post-processing steps could be applied to refine the results. This tendency would involve merging or splitting objects, eliminating small or spurious objects, and improving the overall accuracy of the classification (GISGeography 2023).

In this study, the random samples of each class were classified to refer to the polygon based on the segmentation, and the same goes for the other images that need to undergo the same steps. The research produced more accurate and thorough classification findings using OBIA, which considered the spatial patterns and the context of land cover variables. The method provides an advanced comprehension of the location and dynamics of different land cover types in the Mount Benom region. It also could facilitate education conservation and management decisions, notably in detecting MKD plantings and potential illegal plantation activities inside the research region.

2.6 Accuracy Assessment

This work used the OBIA approach for image classification to classify different land cover classes, including Bare Land, Water Bodies, MKD, Forest, and Green Areas. The OBIA methodology extends beyond conventional pixel-based techniques by classifying pixels into meaningful objects based on spectral and spatial properties. Polygons were constructed using image segmentation, and random samples were selected for each land cover class. Based on the segmented objects' spectral, textural, and contextual characteristics, the OBIA classifier classified the land cover. The same process was applied to additional pictures to ensure uniformity and cross-dataset comparison.

A stratified random technique was utilized to illustrate the different land cover classes in the region and assess the accuracy of land cover maps created using satellite photographs. Visual interpretation and ground truth data were used to determine accuracy. Error matrices were used to compare the classification results with the reference data statistically. Furthermore, because the nonparametric Kappa test considers all elements in the confusion matrix, not just the diagonal ones, it was utilized to evaluate classification accuracy (Huang et al. 2020). The agreement between user-assigned ratings and predefined producer ratings is measured by kappa. Anand (2017) states that every evaluation measure, such as producer accuracy, user accuracy, overall accuracy, and the Kappa coefficient, was meticulously calculated using the pertinent formulae specified for each measurement throughout the accuracy assessment. The formula is as shown in Equations 3, 4, 5, and 6:

$$\text{Accuracy (Producer's accuracy)} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels of that category derived}} \quad (3)$$

$$\text{Reliability (User's accuracy)} = \frac{\text{Total number of correct pixels in a category}}{\begin{array}{c}\text{Total number of pixels of that category derived}\\ \text{from the reference data (column total)}\end{array}} \quad (4)$$

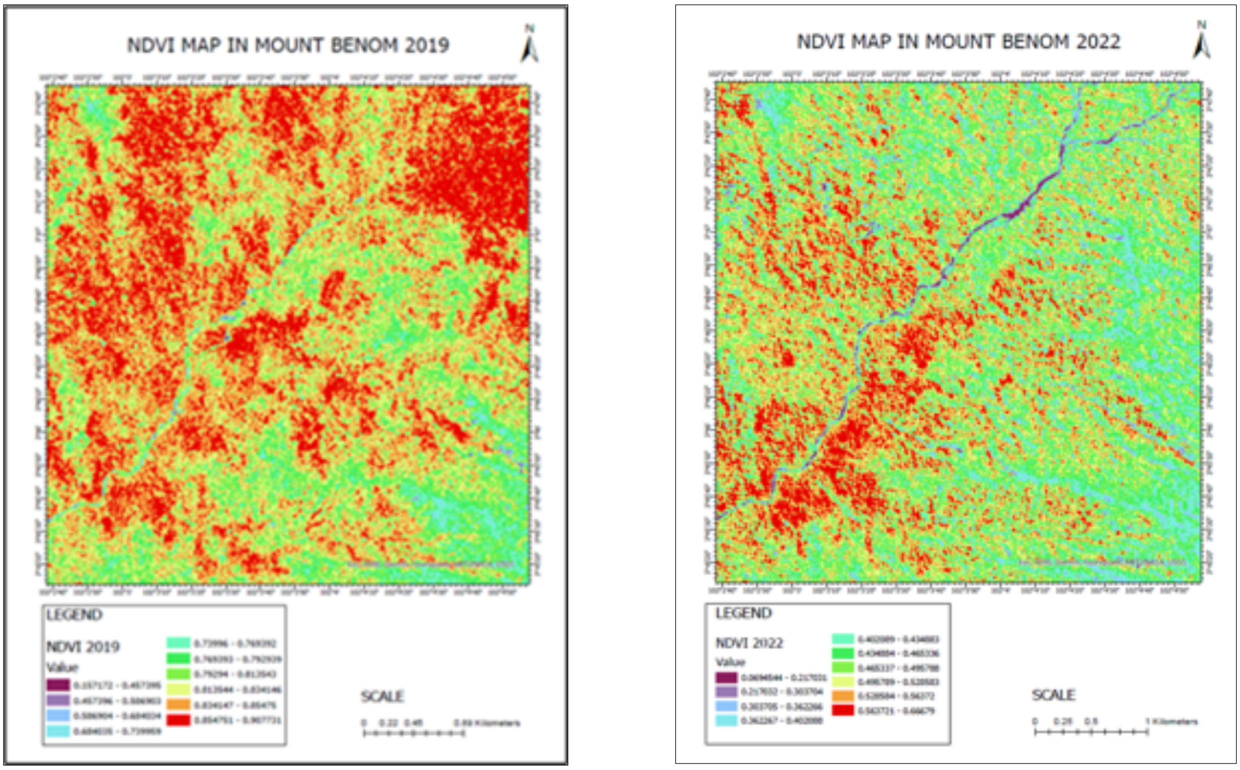
$$\text{Overall Accuracy} = \frac{\text{The sum of the diagonal elements}}{\text{Total number of accuracy sites (pixels)}} \quad (5)$$

$$K_{hat} = (Obs - exp) / (1 - Exp) \quad (6)$$

where *Obs* is observing correct (OA), and *Exp* is expected correctly.

3. Results and Discussion

From the analysis, Mount Benom's NDVI map 2019 was successfully produced, resulting in various NDVI values, with the most outstanding value reaching 0.907731 and the lowest at 0.157172. Meanwhile, the 2022 NDVI map of Mount Benom provides significant information on the vegetation health within AOI whereby the maximum NDVI value of 0.666 has been attained alongside the lowest NDVI value of 0.0694544 reveals information on the variety of vegetation conditions, as shown in **Fig. 4**. According to the findings, the NDVI value in 2019 indicates that there is still a significant amount of woodland around Mount Benom, but the value has decreased by 2022.



(a) (b)

Fig. 4. Result of NDVI mapping for the years (a) 2019 and (b) 2022.

The decline in NDVI maximum value between 2019 and 2022 was similar to the finding discovered by Ahmed (2016), who studied different NDVI over two years. On the other hand, the decrease in NDVI value was due to the primary reason: the depletion of vegetation in natural forests, mainly due to high deforestation. A similar finding of the study was the implication of land use and land cover change for mountain resource degradation, which shows a reasonable shift in vegetation due to the expansion of agricultural land. Thus, complete information about the quantification of vegetation change and the possible reasons for the problem should be addressed.

3.1 Comparison of NDVI Value from Reference MKD Plantation

Table 5 and **Table 6** below show the NDVI value of MKD Planation in 2019 and 2022 from six different registered MKD orchards. This method was developed to support finding the closest MKD plantation NDVI value that a spectral radiometer instrument could not obtain. Even though the location of each orchard is different, they are still in the vicinity of the Raub district. In 2019 and 2022, the lowest NDVI value was 0.43, recorded at Durian MK orchard, while the highest was 0.56 at Durian Orchard Newleaf Plantation. From all six sampling sites, the average low and high NDVI for the MKD orchard in Raub was obtained as 0.47 and 0.53, respectively. From two different years of study, this analysis reveals that the NDVI value for the MKD orchard is below the range of NDVI for deep forest, which was discovered to be above 0.7 by Huang et al. (2021).

Table 5. NDVI value of reference MKD plantation in 2019

Name	Coordinate	NDVI Value	
		Lowest	**Highest**
Durian Orchard Newleaf Plantation	3°44'52.91" N, 101°49'46.50" E	0.51	0.56
Durian MK	3°45'41.55" N, 101°49'56.71" E	0.43	0.53
Ah Fai Durian Orchard	3°45'47.53" N, 101°51'02.04" E	0.48	0.54
Fern Eco Farm	3°45'34.67" N, 101°49'49.73" E	0.44	0.47
MKD Leisure Farm	3°46'28.84" N, 101°57'25.13" E	0.48	0.54
Leman's Durian Orchard	3°42'21.10" N, 101°49'18.38" E	0.47	0.53
Range NDVI Value of MKD Tree		0.47	0.53

Table 6. NDVI value of reference MKD plantation in 2022

Name	Coordinate	NDVI Value	
		Lowest	**Highest**
Durian Orchard Newleaf Plantation	3°44'52.91" N, 101°49'46.50" E	0.51	0.56
Durian MK	3°45'41.55" N, 101°49'56.71" E	0.43	0.53
Ah Fai Durian Orchard	3°45'47.53" N, 101°51'02.04" E	0.48	0.54
Fern Eco Farm	3°45'34.67" N, 101°49'49.73" E	0.44	0.47
MKD Leisure Farm	3°46'28.84" N, 101°57'25.13" E	0.48	0.54
Leman's Durian Orchard	3°42'21.10" N, 101°49'18.38" E	0.47	0.53
Range NDVI Value of MKD Tree		0.47	0.53

3.2 Result for NDVI Segmentation Using OBIA for MKD Area Determination

The OBIA approach was used to classify the following classes: barren terrain, water bodies, prospective illegal DMK plantings (PIDP), forests, and green regions. Random samples from each class are classified, and a polygon is based on segmentation. The same is done with the other image, which must go through the same stages. Multiresolution segmentations were used in the Land Use/Land Cover (LULC) classification to identify impermeable surfaces from vegetation. Visual interpretation of several segmentations was used to determine the ideal scale parameters of each land cover class. The segmentation of "green" (vegetation) as well as "grey" (impervious) areas has been enhanced by giving more weight to the influence of the infrared band. The vegetation classes had been extracted by setting the Scale parameter to 20, Shape (0.3), and Compactness (0.7). Post-processing was performed on all categorized land cover classes exported for use in an ArcGIS geodatabase. Likewise, by Moskal et al. (2011), in the year 2009, a complete and precise LULC map for the study region was produced using this classification technique, which effectively distinguished impervious surfaces from vegetation.

However, this research had one more multiresolution segmentation with a different value in the segmentation parameter. This step involves trial and error to find the most suitable segmentation value to classify forest areas. The second segmentation was also generated to find suitable segmentation for the study area, which focused on the forestry area, by adopting a similar approach (Czarnecki 2012). **Table 7** and **Fig. 5** show the segmentation process results. The study achieved more accurate and thorough classification results by utilizing OBIA, which considered spatial patterns and the context of land cover factors (GISGeography 2023). The strategy improves understanding of the position and dynamics of various land cover types in the Mount Benom region. It supports informative conservation and management decisions, particularly in detecting DMK plantings and possibly illegal plantation activities inside the research area.

Table 7. Segmentation's parameter

	Parameter		
	Scale	**Shape**	**Compactness**
1st Segmentation	20	0.3	0.7
2nd Segmentation	30	0.2	0.5

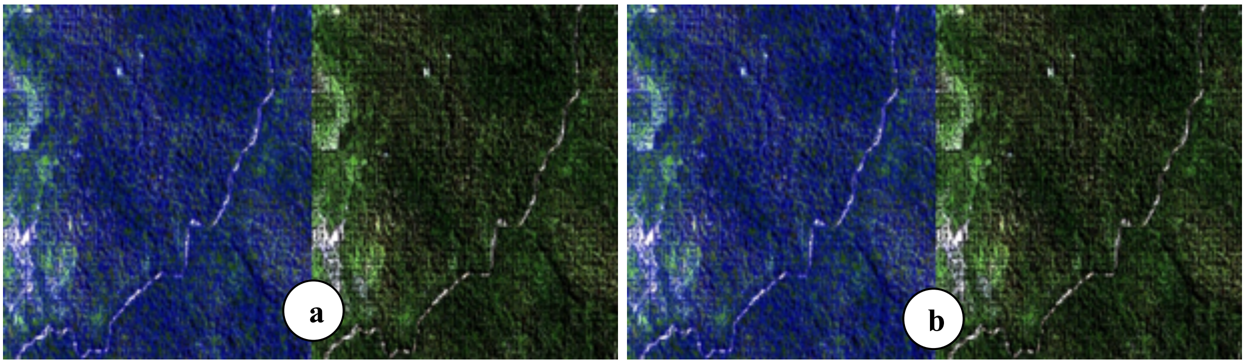


Fig. 5. Result of image segmentation (a) first and (b) second segmentation.

3.3 *Result of LULC in Years 2019 and 2022*

The Mount Benom's Land Use Land Cover (LULC) map for 2019 and 2022 (**Fig. 6** and **7**) gives essential information about the landscape's composition and interactions between humans and the environment. The map is divided into five unique classes: bare land, PIDP, forest, green area, and water bodies, as well as a legend boundary line for the "*Hutan Simpan Kekal Gunung Benom*". This map is crucial to study the land use trends in the area of interest.

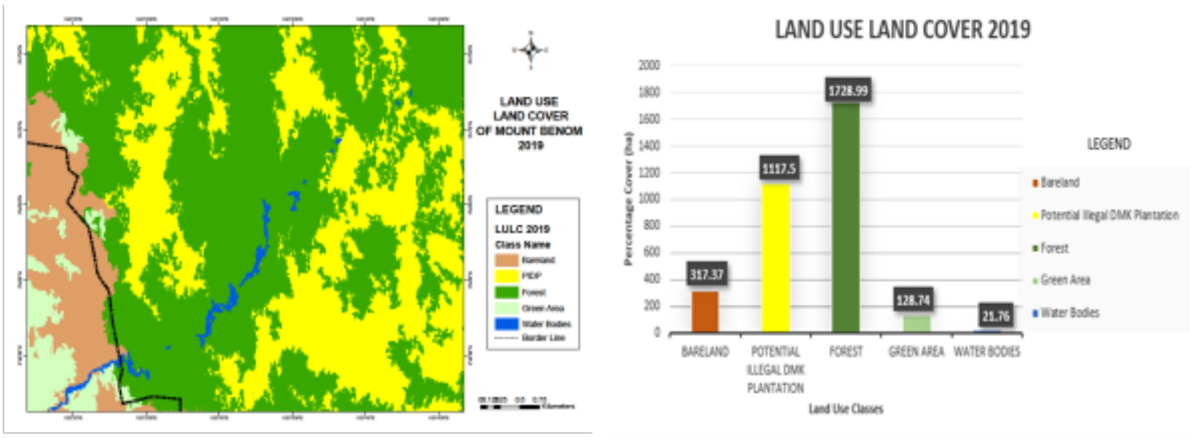


Fig. 6. Result of LULC of Mount Benom in 2019 and its description.

The existence of a significant forest class emphasizes Mount Benom's conservation relevance since forested regions provide crucial habitats for species and sustain essential ecosystem functions. The Green Area class includes information on different types of covering of vegetation that may not be thick wood. Bare land is defined as expanses of land with little or no vegetative cover, such as rock surfaces, or an area that contains no vegetation or there is vegetation area; however, it is limited. These places can form naturally or due to human activity, such as deforestation, land clearance, and others. Meanwhile, the PIDP region denotes the area that may be covered in MKD planting throughout the AOI. Using the availability of existing data or secondary data, this research focuses on identifying and mapping the growth of PIDP within the AOI.

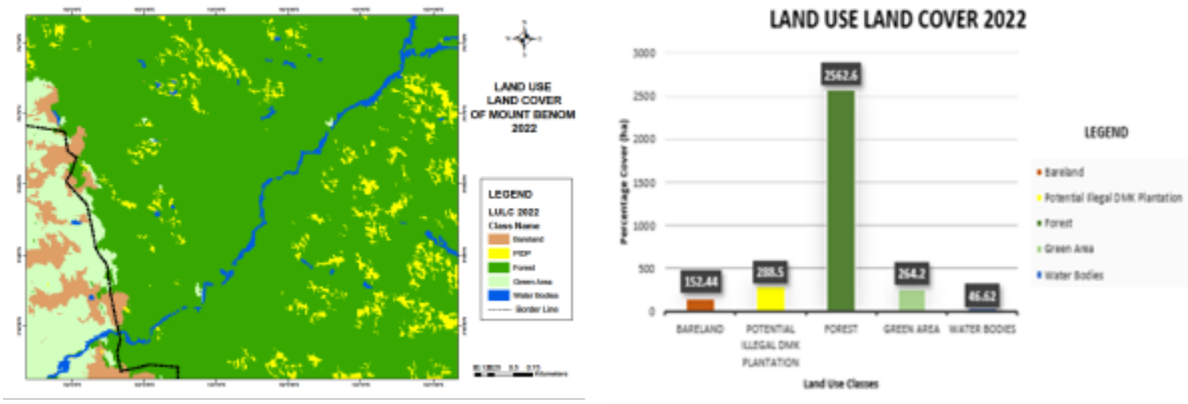


Fig. 7. Result of LULC of Mount Benom in 2022 and its description.

Researchers thoroughly understand the landscape's structure, human-environment relationships, and ecological relevance by evaluating the LULC map. This helpful information may assist decision-making processes connected to the AOI. This study aims to assess the LULC changes caused by unlawful MKD cultivation in Pahang. Studying changes in land cover over time using consecutive LULC maps will allow for continuing environmental evaluation and adaptive management measures to preserve the survival and sustainability of Mount Benom's ecosystems. An accuracy assessment was performed to confirm the validity of the LULC map, correlating the map's results against ground-truth information or images of high resolution to pinpoint areas for improvement and increase the classification's dependability. This research also refers to the NDVI value range of MKD plantation to verify the position of the PIDP itself. It might be due to the existing open-source data not being sufficient to use satellite images from other platforms, such as Google Earth Pro.

3.4 Result of Accuracy Assessment of LULC of Mount Benom in Years 2019 and 2022

The accuracy assessment of Mount Benom's LULC map in 2019 has produced positive findings, showing an overall accuracy (OA) of 90% as well as a Kappa Index of Agreement (KIA) of 88% (**Table 8**). These accuracy ratings assure the dependability of the land cover classification. The majority of the Forest class, which covers around 1,728.99 hectares (ha), is one significant finding from the bar chart. The PIDP class is one of the most substantial land cover classes, accounting for 1,117.5 ha. The massive size of PIDP shows the region's financial worth of durian production. However, because Mount Benom is a forest reserve area, such a vast PIDP creates issues regarding potential consequences on the natural ecology and the necessity for sustainable land use practices.

Table 9 shows that the result of OA of 89% indicates that 89% of the map's pixels are correctly categorized. In comparison, a KIA or Kappa Coefficient (KC) of 86% indicates significant consistency between the classified data and the ground truth data. The accuracy evaluation of Mount Benom's LULC map for 2022 produced promising findings, indicating a substantial consistency between the classified data and the ground truth data. These findings are similar to those of Liping et al. (2018), who successfully classified LULC using an error matrix.

Table 8. Accuracy error matrix of LULC 2019

Classes	Bare Land	PIDP	Forest	Green Areas	Water Bodies	Total (User)
Bare Land	14	0	0	1	0	15
PIDP	0	14	1	0	0	15
Forest	0	2	13	0	0	15
Green Areas	2	0	0	13	0	15
Water Bodies	0	0	1	0	14	15
Total (Producer)	16	16	15	14	14	75
OA			0.90			
KIA			0.88			

Table 9. Accuracy error matrix of LULC 2022

Classes	Bare Land	PIDP	Forest	Green Areas	Water Bodies	Total (User)
Bare Land	13	0	0	1	1	15
PIDP	0	14	1	0	0	15
Forest	0	1	13	0	1	15
Green Areas	1	0	0	14	0	15
Water Bodies	0	0	2	0	13	15
Total (Producer)	14	15	16	15	15	75
OA			0.89			
KIA			0.86			

The Forest will be the primary land cover type in 2022, spanning around 2,562.6 ha. The PIDP class covers 288.5 ha and illustrates the region's increase in durian farming. The development of MKD, an economically valued crop, may contribute to the region's economic growth. However, the place to plant the potential MKD plantation is illegal because Mount Benom is a permanent forest reserve land.

3.5 Result of Land Use Land Cover Changes (LULCC)

The Mount Benom LULC changes map from 2019 and 2022 in **Fig. 8** gives critical insights into the changing landscape and land use trends throughout this period. The map includes several land cover types, such as forest, green area, MKD or PIDP, and water bodies, as well as a drawn border line defining the forest reserve land boundary (**Fig. 9**). The existence of illegal MKD plantations inside the forest reserve area, on the other hand, illustrates a severe issue of land management and conservation efforts. The display of LULC changes on the map from one class to the next, or even between the same class, enables the determination of places of transition and prospective changes to land use activities. Conversion from PIDP to the forest, for example, may indicate either effective attempts at reforestation or the abandonment of MKD plantings.

On the other hand, there is reason for concern regarding the presence of illicit MKD crops inside forest reserve territory. The natural environment is in danger due to the expansion of PIDP production into the protected area. This pattern emphasizes how crucial it is to step up enforcement and monitoring to safeguard the forest reserve's integrity and stop illegal land usage. Moreover, transitions from barren land to verdant places are pretty common and could be connected to farming activities. While certain agricultural operations might be allowed outside forest reserves, it is important to ensure they do not intrude into protected areas or degrade the state of the forest ecosystem. The borderline on the map is essential for differentiating between changes occurring within the forest reserve territory and potential changes occurring in adjacent areas. This propensity makes it easier to gauge the amount of human activity and how it might affect the forest reserve's ecological well-being.

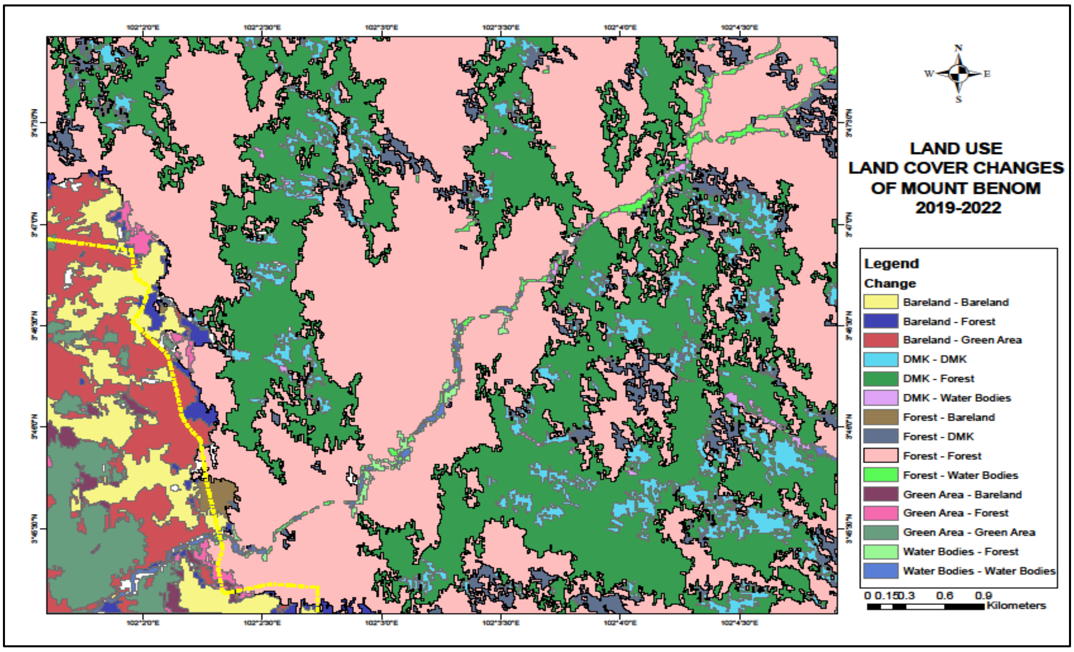


Fig. 8. Mount Benom LULC changes map between 2019 and 2022.

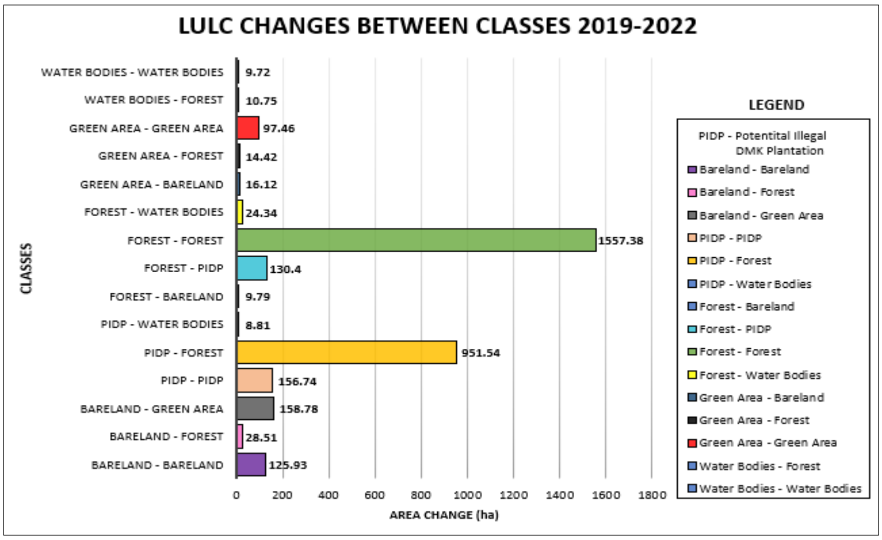
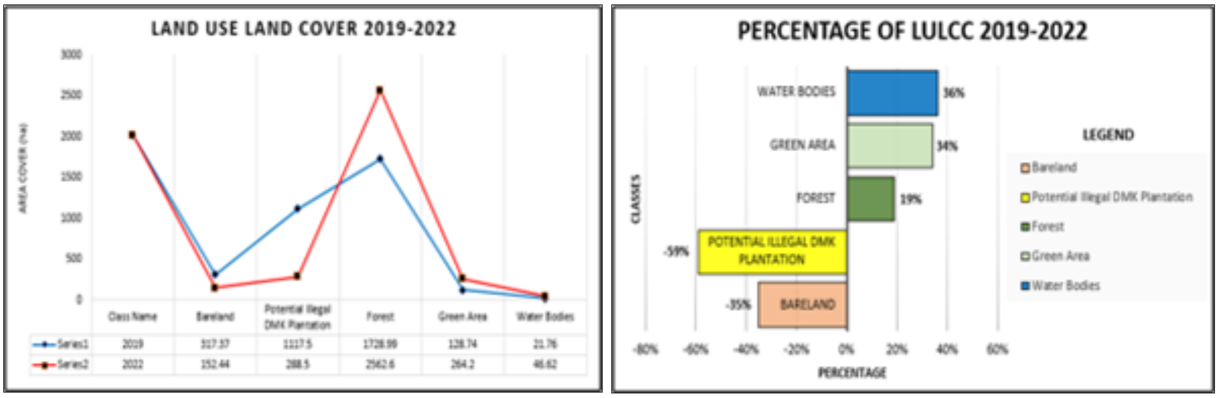


Fig. 9. Overall changes of LULC between classes in 2019 and 2022 at Mount Benom, Raub, Pahang.

Conversion from PIDP to forest, for example, may indicate either effective attempts at reforestation or the abandonment of MKD plantings. The presence of illicit MKD plants within forest reserve boundaries, on the other hand, is cause for concern. The growth of PIDP planting areas in the protected region threatens natural biodiversity. The graphic (**Fig. 10**) highlights a significant transition from forest to forest, which amounts to 1,557.38 ha. This result is similar to Liping et al. (2018), who produced diagrams showing each land use's increase and decrease. This result implies a significant stability in forest cover over three years, indicating the maintenance of the ecological balance. On the other hand, the shift of 130.4 ha from forest to PIDP implies considerable encroachment within the forest reserve area for durian production.



(a) (b)

Fig. 10. Comparison of (a) LULC and (b) percentage of LULCC for 2019 and 2022.

The decline of bare land, from 317.37 ha in 2019 to 152.44 ha in 2022, is one notable trend in the line chart. PIDP decreased from 1,117.5 ha in 2019 to 288.5 ha in 2022. The line chart also shows a significant rise in forest cover, about 1,728.99 ha in 2019, reaching 2,562.6 ha in 2022. The graph bar shows considerable increases in water bodies and green areas, with 36% and 34% increases, respectively. The PIDP class, in particular, exhibits a significant reduction of -59%, indicating possible illegal cultivation or other causes influencing PIDP around Mount Benom. Moreover, it was found that this notable shift was caused by the number of illegal logging cases that the Pahang Forest Department recorded and intercepted in 2019 and the lack of any cases in 2022. These problems must be resolved to support forest conservation efforts and maintain land use management in the area.

4. Conclusions

The study's findings have significant ramifications for related organizations in charge of law enforcement, environmental preservation, and land management in the Mount Benom area. If illegal MKD crops are found inside the authorized forest reserve, notification and action must be immediately taken. Identifying illicit activities in the study highlights the necessity of enhanced law enforcement, monitoring, and control to prevent further encroachment and deterioration of forested regions. Moreover, this study can promote cooperation between government agencies and parties involved in land management and environmental conservation. The reliable geographic data and analysis provided could help with well-informed discussions and evidence-based decision-making. To effectively tackle unlawful operations, for example, cooperation between multiple government agencies, including the Forestry Department, the Royal Malaysian Police, and the Customs Department, is essential. Ultimately, the conclusions affect individuals tasked with overseeing and managing the Mount Benom area. Using geospatial data to determine the number of possible unlawful MKD plantings, authorities may address the problems caused by unauthorized land use and create proactive plans to preserve the diversity and ecosystem health of the forest reserve. Effective enforcement, conservation, and sustainable development in the region will necessitate cooperation among numerous authorities.

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