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Vegetation cover change detection (2000–2020) in Raub District, Malaysia using supervised and unsupervised classification techniques

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Abstract: This study evaluates and compares four algorithms: maximum likelihood classification (MLC), minimum distance classifier (MDC), parallelepiped classifier (PPC), and *k*-means clustering, on their performance in detecting change of vegetation cover from multi-temporal Landsat images in Raub District, Malaysia in 2000–2020. The accuracy assessment is based on 150 stratified random points using overall accuracy (*OA*), user's accuracy (*UA*), producer's accuracy (*PA*), and kappa coefficient (*KC*). MLC resulted as the most accurate for all the years with *OA* ranging from 86.8 to 92.7% and kappa values between 0.79 and 0.86; besides it was found to be better for distinguishing some spectrally similar land covers such as oil palm (*UA* = 90%; *PA* = 90–100%) and rubber plantation (*UA* = 70–90%; *PA* = 100%). The *k*-means result has moderate accuracy with *KC* values ranging from 72.0 to 85.3% but this method mostly confused open grassy area with sparse forest area. MDC and PPC did not perform well; *OA* got as low as 47.6%. Moreover, high omission error was found in PPC when certain classes were absolutely omitted in a particular year. Dense forest decline was more than 27% (115,000–118,200 ha in 2000 to 83,500–86,100 ha by 2020), accompanied by about an 88% increase in areas under oil palm plantations. Open grassy areas doubled. The overall classification performances ranged best to poorest as: MLC > *k*-mean > MDC > PPC. These findings validate that MLC is the most dependable method for instituting policy-relevant monitoring over highly heterogeneous tropical landscapes while *k*-means delivers a rapid prelude and MDC/PPC are options with limited data or computational constraints.

Keywords: accuracy assessment, *k*-mean, maximum likelihood classification (MLC), minimum distance classifier (MDC), parallelepiped classifier (PPC), tropical deforestation

INTRODUCTION

Malaysia's land cover dynamics are undergoing profound transformations. Agricultural expansion largely comprises oil palm and rubber plantations, coupled with urbanisation and infrastructural development taking place in the country. Such changes have great implications on biodiversity loss, climate regulation, and hydrological stability of highly biodiverse areas like regions as Pahang. Remote sensing studies show a huge forest cover drop in Malaysia over the last two decades where more dense forests are continuously replaced by monoculture plantations and degraded open areas (Othman *et al*., 2019). Monoculture plantations further enhance habitat fragmentation while reducing carbon sequestration capacity besides increasing erosion and sedimentation in the river basins (Shrestha, 2011). Even after several policy commitments effective monitoring of these types of landcover changes is still missing due to accessibility to data, classification accuracy, and integration of temporal change analysis into decision-making processes. To bridge these gaps demands classification robustness in perceiving subtle spectral differences within the heterogeneous tropical landscapes, where classes of vegetation most often demonstrate high intra-class variability and then overlap between spectrums.

It is within this context that the choice of appropriate remote sensing classification techniques in such a way as to enhance reliable land cover mapping and change detection proves very critical. Among these, maximum likelihood classification (MLC), minimum distance classifier (MDC), parallelepiped classifier (PPC), and *k*-means clustering provide methodological strengths and weaknesses from some perspectives when applied in Malaysia's actual rather complex tropical environments. MLC builds on a more comprehensive variance–covariance-based description of class spectral distributions, thus enabling discrimination among spectrally similar classes, for example, oil palm and rubber plantations, often found in Malaysian landscapes (Hu and Tan, 2025). MDC does not include variance–covariance because this method is less time-consuming; hence, situations always found around heterogeneous areas with large spectral overlaps prove less dependable (Sharma Banjade, Rai and Subedi, 2023). PPC is reliable where well-defined class boundaries exist but return high omission errors wherein the variability within classes. Method *k*-means being an unsupervised algorithm performs well where data is not available or for a preliminary assessment, but since the method is based only on spectral similarity, it mostly misclassifies sparse forest with open grassy areas. Such methodological nuances are critical in deciding what classification strategy would be appropriate to meet accuracy and efficiency requirements as well as the availability of data in tropical vegetation monitoring.

This study carries out an extensive comparative assessment between MLC, MDC, PPC, and *k*-means classification algorithms in terms of their ability to detect vegetation cover changes over the Raub District of Pahang State, Malaysia for a series as long as twenty years, specifically from 2000 to 2020, taking into account these environmental and methodological premises. A specific objective includes quantification of temporal change among the five major classes of vegetation: dense forest, sparse forest, oil palm plantation, rubber plantation, and open grassy area, from multi-temporal Landsat imagery and an assessment plus comparison in terms of standard measures on the accuracy of supervised against unsupervised results (kappa), followed by a critical discussion on how larger methodical weaknesses hinder application potential in the typically heterogenous tropical landscape patterns found across Malaysia. Hence, this research shall be developed with integration between accuracy appraisal and change detection analysis that improves methodological choices for empirically validated land cover monitoring towards sustainable land management in biodiversity-sensitive region policies.

Land use/land cover (LULC) change represents one of the most important global environmental issues with changes initiated by agricultural development, deforestation, infrastructure development, and urbanisation. In recent decades, large-scale conversions from natural vegetation to monoculture plantations, croplands, and built-up areas have significantly altered ecosystem structure and function across tropical, temperate, and boreal zones (Othman *et al.*, 2019; Tiko *et al.*, 2025). These changes have profound impacts on biodiversity, carbon storage, and hydrological regulation, which in turn cascade into broader socio-economic consequences. Monitoring such dynamics at policy-relevant spatial and temporal scales requires robust, accurate, and repeatable analytical techniques. Remote sensing provides this potential since multi-temporal satellite data can regularly observe LULC transitions and make them available for analysis (Chen *et al.*, 2025). The reliability of these assessments depends largely on the classification method applied and the rigor of the classification performance evaluation.

Supervised classification is the basic approach in remote sensing whereby the analyst selects representative training samples for each class of land cover. The classifier then uses these labelled data to model the spectral characteristics of each class throughout the entire image (Richards and Jia, 2006). The method utilises a priori knowledge about study areas and allows statistical decision rules that maximise the separability between classes, hence reducing misclassification rates (Chowdhury, 2024). In modern applications, supervised methods always find huge relevance even with increasing popularity for object-based and machine learning approaches due to interpretability issues, less computational intensity, and multi-temporal datasets' compatibility (Chen *et al.*, 2025). Maximum likelihood classification (MLC) has been very popular and statistically valid in heterogeneous landscapes. It assumes that the spectral distribution of classes falls under a multivariate normal distribution and calculates for every pixel its probability to belong to any particular class, assigning it finally to the class with the highest posterior probability (Foody, 2002; Hu and Tan, 2025). This hence allows MLC to take into consideration not only the mean vector but also variance-covariance structure information within training data where spectral signatures from different classes seem to be overlapping. In agricultural-forest mosaics or some types of mixed vegetation, this is rather common. Recent studies prove that MLC is still better than simpler supervised methods regarding total accuracy and Kappa coefficients when intra-class variability is high (Varga *et al.*, 2022; Chen *et al.*, 2025).

The minimum distance (MDC) algorithm computes the distance between the mean spectral value of each class and that of the pixel. It does not consider variance or covariance information, thus essentially assuming spherical class boundaries. Therefore, it runs faster but introduces more errors whenever classes are elliptically or anisotropically distributed in the spectral space (Varga *et al.*, 2022). The decision boundary of a parallelepiped classifier is aligned with axes and is determined by minimum to maximum values (standard deviations) for each band. It can be calculated very quickly but has two very important weaknesses: (1) any pixel that falls outside all parallelepipeds will be unclassified, thus reducing completeness, and (2) if a pixel falls inside more than one parallelepiped, this becomes an assignment problem where there is ambiguity (NV5 Geospatial Software, 2024). This becomes a real problem in intricate landscapes as spectral overlaps among classes become frequent. In view of these methodological considerations, MLC can be said to have ensured the best possible statistical rigor, accuracy, and robustness in multi-temporal land cover analyses. The method incorporates class variance–covariance thereby ensuring more reliable discrimination among spectrally similar classes leading to reduced omission as well as commission errors and outputting classification results that are even much more suitable for change detection as well as environmental monitoring that has direct relevance to policies being formulated (Chen *et al.*, 2025; Hu and Tan, 2025).

Unsupervised classification in remote sensing is defined as the method of clustering image pixels by their spectral similarities with no prior information or ground truths for training data (Lillesand, Kiefer and Chipman, 2015). In most cases, this will be followed up by labelling where the analyst determines what each cluster represents and assigns that cluster to a land cover class using extra information such as high-resolution imagery or observations from the field. The labelling is normally done after running the k-means algorithm which happened to be the most popular among them all. Basically, it partitions the dataset into k clusters by an internal iterative process minimising within-cluster variance (Han and Lee, 2023). The major strength of unsupervised classification is that it does not depend on reference data, thus quite handy in data-poor situations, for preliminary mapping exercises, or to explore some analytical work where pattern detection is the objective without any pre-established class definitions (Hu and Tan, 2025). Method k-means is easily computed and feasible for large datasets, which makes it applicable to perform rapid assessments over a wide area when that area happens to be remote or poorly accessible. Some recent innovations have made their way into the method by paralleling it and improving initialisation to move toward tackling sensitivity regarding initial cluster centers as well as issues related to local minima (Han and Lee, 2023).

The unsupervised classification bears intrinsic weakness. Since no a priori knowledge is used in its development, thus unable to model class-specific spectral variance or covariance, there would be much more misclassification in heterogeneous landscapes with overlap among spectral signatures (Hu and Tan, 2025). The output of this algorithm can also vary from run to run due to the phenomenon known as "label switching" because the same cluster index from different images might refer to different land cover types. This complicates multi-temporal analysis when change detection is concerned. In addition, spectrally similar vegetation types aggregate into one cluster most of the time reducing thematic detail and accuracy. Method k-means can be very useful in the absence of ancillary data or as another approach within hybrid methods that also implement supervised classifications. Where thematic accuracy is a concern, especially in policy-oriented land cover monitoring and change detection, unsupervised results are best used only as a baseline or background mapping to be improved on later by more specific, supervised mappings (Chen *et al.*, 2025; Hu and Tan, 2025).

MATERIALS AND METHODOLOGY

STUDY AREA

The study area is located in Raub District, on the western side of Pahang State, Peninsular Malaysia (Fig. 1). Raub extends over predominantly rural and forest land; its neighbouring districts are Bentong to the south and Lipis to the north, with Kuala Lipis and Jerantut on its eastern front. The district is situated between approximately 3°40'N to 3°55'N and 101°35'E to 101°55'E, covering about 2,271 km^2. Rich in biodiversity within thick tropical rainforests, fertile land suitable for agriculture development defines it as an ecological draw card for Raub itself. Traditionally known as a gold mining area together with rubber estates within the district boundaries, recent decades have increasingly shifted land use towards oil palm plantations besides mixed agriculture activities. This observed change has effects on land cover patterns that include forest fragmentation and plantation agriculture expanding plus newly found open grassy patches. The study area gets a wet tropical climate with lots of rain and small changes in seasons helping plants grow all year. Yet, the current land making works in Raub have brought about spatial and ecological difference, setting it up as a great spot for looking at

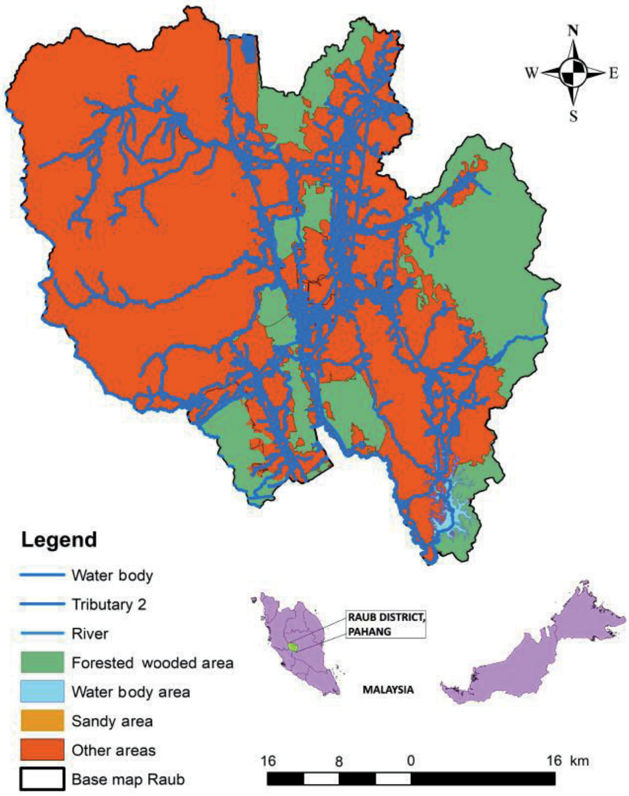


Fig. 1. The study area of Raub Districts, Pahang; source: own elaboration

land use change and comparing different ways of classifying things seen from far away. The study place was marked out using shapefiles of admin limits and shown in UTM Zone 47 North (WGS 84) for keeping space the same all through the check.

SATELLITE DATA ACQUISITION, IMAGE PREPROCESSING AND VEGETATION CLASSIFICATION SCHEME

To capture vegetation patterns and changes over time, Landsat satellite images were used for the years 2000, 2010, and 2020. They were downloaded from Earth Explorer (Tab. 1). The imagery for both the year 2000 and 2010 come from the Landsat 5 Thematic Mapper (TM) sensor while data for the year 2020 is available in Landsat 8 Operational Land Imager (OLI). All images selected have less than a ten percent cloud cover as well as being acquired during a dry season to minimise atmospheric interference and maximise spectral separability.

Table 1. Landsat satellite imagery used for vegetation analysis in Raub District (2000–2020)

Date	Sensor	Bands used	Spatial resolution (m)	Cloud cover (%)
24 Aug 2000	Landsat 5 TM	Bands 1–5, 7	30	<10
01 Jun 2010	Landsat 5 TM	Bands 1–5, 7	30	<10
09 Apr 2020	Landsat 8 OLI	Bands 1–7	30	<10

Source: https://www.usgs.gov/landsat-missions/landsat-satellite-missions.

Preprocessing of all the images was done in ENVI, QGIS, and Python so as to make them consistent and comparable. The dark object subtraction (DOS) method has been used here for haze reduction towards getting good surface reflectance values. These have then been geometrically corrected and reprojected into the UTM Zone 47N coordinate system. Subsetting took place with the help of a boundary shapefile that had already been defined for the study area. After that spectral bands were stacked to form composite layers ready for classification. The classification scheme was intended to reflect the major vegetation types identified within the study area (Tab. 2). It has been applied equally in all methods of classification and years used to undertake a comparison.

Table 2. Classification categories and descriptions of dominant vegetation types in Raub District

Category	Description
Dense forest	highly compact and closed-canopy forest areas with rich biomass
Sparse forest	forested areas with lower canopy density or more fragmented tree cover
Oil palm plantation	commercial plantations cultivated for oil palm production
Rubber plantation	areas planted with rubber trees, typically in linear patterns
Open grassy area	open fields dominated by grasses or herbaceous vegetation

Source: own elaboration.

SUPERVISED AND UNSUPERVISED CLASSIFICATION TECHNIQUES APPROACH

In remote sensing, classification techniques can be broadly categorised as supervised and unsupervised. The two categories differ in their data requirements, operational principles, and resultant accuracies. In this study, the two categories were implemented through *k*-means clustering, maximum likelihood classification (MLC), minimum distance classifier (MDC), and parallelepiped classifier (PPC). Method *k*-means, being an unsupervised algorithm, was run on annual composite images with five initial cluster centers where pixels were grouped only by spectral similarity without using any training data. Clusters were then relabelled to pre-defined vegetation classes manually with the help of Google Earth imagery and Landsat composites. The other three methods: MLC, MDC, and PPC; are supervised and needed 70–100 manually digitised samples per class from high-resolution imagery and verified vegetation patches for training. MLC assigns a pixel to the class that has the highest posterior probability assuming a multivariate normal distribution of spectral signatures; MDC classifies a pixel by the shortest Euclidean distance to class means; PPC assigns all pixels whose spectral values fall within minimum-maximum thresholds for each class. Hence, probability-based, distance-based, range-based, and unsupervised methods could strictly rigorously comparatively evaluate which one would accurately detect vegetation change in such heterogeneous landscapes found in the tropics.

The MLC method is generally more statistically based among the above three methods and works in a probability domain assuming for each class a multivariate normal distribution. It assigns a pixel vector, *x,* to that class, *i,* for which the following discriminant function $(g_i)X$ is maximum (Eq. 1):

$$g_i(X) = -\frac{1}{2}\mathrm{In}|\Sigma_i| - \frac{1}{2}(X - m_i)^T \sum\nolimits_i^{-1} (X - m_i) + \mathrm{In}\ P(w_i) \quad (1)$$

where: m_i = vector, Σ_i = covariance matric, $|\Sigma_i|$ = determinant, $P(w_i)$ = prior probability of class i, X = vector of input features (Li *et al*., 2012).

Through the use of both variance and covariance, MLC is highly responsive to high spectral overlap, therefore making it capable of separating spectrally similar classes like oil palm and rubber plantations that occur within heterogeneous tropical landscapes (Shiraishi *et al*., 2014). MDC is also a simple supervised technique by which pixels are allocated to that class whose mean spectral vector has the minimum Euclidean distance (Eq. 2).

$$d_i(X) = \sqrt{\sum_{b=1}^{n} (x_b - m_{ib})^2} \quad (2)$$

where: x_b = pixel value in band b, m_{ib} = class mean for band b, n = number of spectral bands.

MDC is computationally efficient and accurate where class means are well separated but becomes less dependable under conditions of high spectral similarity since it does not take into account the variance and covariance of classes (Sharma Banjade, Rai and Subedi, 2023). PPC defines rectangular decision boundaries in spectral space using the minimum and maximum training values for each band in each class. A pixel x belongs to class i if (Eq. 3):

$$\min_{ib} \leq x_b \leq \max_{ib} \quad (3)$$

where: $\min_{ib}$ and $\max_{ib}$ are spectral limits for band b in class i.

PPC is quick and best for clearly defined classes with low internal differences but does not work well in complex plant patterns where there is high variation within the same group. Unlike supervised learning, the *k*-means clustering method falls under unsupervised classification. It does not need any training data. Method *k*-means simply breaks pixels into *k* groups based only on colour likeness, step by step reducing inside group difference (Eq. 4).

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \| X - \mu_i \|^2 \quad (4)$$

where: C_i = set of pixels in cluster i, μ_i = cluster centroid, $\| \ \|$ = Euclidean distance.

While *k*-means is rapid and valuable for exploratory mapping in data-poor contexts, it is prone to misclassification in heterogeneous landscapes, such as confusing sparse forest with open grassy areas, because it relies solely on spectral distance without spatial or contextual cues (Sari *et al*., 2023).

ACCURACY ASSESSMENT

For both supervised and unsupervised methods, the same set of 150 stratified random sample points was used for each year to ensure direct comparability of results. These points were evenly distributed across the five land cover classes, with 30 points allocated per class, irrespective of class area, in accordance with standard accuracy assessment procedures. The metrics are important in evaluating classification performance and have found application as standard metrics within remote sensing applications for this purpose (Shiraishi *et al.*, 2014; Sari *et al.*, 2023). Classification performance was evaluated using a confusion matrix (error matrix) for each classifier and year of cross-tabulating reference labels against classified labels. Four standard performance metrics were computed from this matrix: overall accuracy (*OA*), user's accuracy (*UA*), producer's accuracy (*PA*), and kappa coefficient (*KC*). The *OA* measures the proportion of correctly classified samples relative to the total number of reference points (Eq. 5):

$$OA = \frac{\sum_{i=1}^{k} n_{ii}}{N} \cdot 100 \tag{5}$$

where: k = number of class, n_{ii} = numbers of correctly classified samples for class i, N = total number of samples (150 in this study).

In the error matrix used, n_{ij} denotes the number of samples classified as class i (classifier output) while their reference or ground truth class is j. The *UA* for the class i expresses the probability that a pixel assigned to class i truly belongs to the class in the reference data, indicating commission error (Eq. 6). Conversely, *PA* for class i measures the probability that a reference pixel of class i was correctly classified, representing omission error (Eq. 7). Lastly, *KC* quantifies the agreement between the classification and the reference data while adjusting for agreement that could occur by chance (Eq. 8); where the expected agreement P_e is computed as in Equation (9).

$$UA_i = \frac{n_{ii}}{\sum_{j=1}^{k} n_{ij}} \cdot 100 \tag{6}$$

$$PA_i = \frac{n_{ii}}{\sum_{j=1}^{k} n_{ji}} \cdot 100 \tag{7}$$

$$KC = \frac{OA - P_e}{1 - P_e} \tag{8}$$

$$P_e = \frac{\sum_{i=1}^{k} \left(\sum_{j=1}^{k} n_{ij} \cdot \sum_{j=1}^{k} n_{ji} \right)}{N^2} \tag{9}$$

Generally, these metrics give a broad view of classification performance: *OA* is an overall measure of accuracy, *UA* gives the map reliability from the user's side, *PA* expresses completeness from the producer's point of view, and *KC* is a statistically adjusted measure of total agreement. Therefore, a stringent comparison of MLC, MDC, PPC, and *k*-means classification methods that will translate into which method brings out most reliably the vegetation change in diverse tropical landscapes within Raub District can be performed.

VEGETATION CHANGE DETECTION

Maps of 2000, 2010, and 2020 were compared pixel-by-pixel to detect change in an after-classification comparison using Equation (10) so as to be able to trace the dynamism of vegetation composition. For instance, it could easily be identified whether the land use was dense forest or had transformed into oil palm plantation; or from rubber plantation to open grassy area.

$$\Delta C_p = C_{p,t_1} - C_{p,t_2} \tag{10}$$

where: $C_{p,t1}$ = class label of pixel p at time t_1, $C_{p,t2}$ = class label of pixel p at time t_2, ΔC_p = change code (0 = no change, ≠0 = change type).

Meanwhile, matrices for change (as in Eq. (11) and Eq. (12)) were developed that summarised the area of transitions, and zonal statistics facilitated the provision of information on changes in hectares for every vegetation class.

$$A_{ij} = M_{ij} \cdot \text{pixel area} \tag{11}$$

$$P_{ij} = \frac{M_{ij}}{\sum_{i=1}^{k} \sum_{ij}^{k} M_{ij}} \cdot 100 \tag{12}$$

where: M_{ij} (for $i \neq j$) = changed pixels from class i to j.

All spatial analyses and area calculations were conducted using QGIS.

SOFTWARE AND TOOLS

Geospatial tools were many within the workflow for this analysis. Image correction and classification were performed in ENVI. Spatial analyses and visualisations took place in QGIS. Statistical computation and classification performance evaluation occurred in Python using libraries including Rasterio, NumPy, and scikit-learn. Google Earth Pro was extremely helpful for both ground-truth validation and comparison of historical imagery.

RESULTS AND DISCUSSION

COMPARISON OF CLASSIFICATION PERFORMANCE

The classification performance over three study years 2000, 2010, and 2020 using user accuracy (*UA*), producer accuracy (*PA*), overall accuracy (*OA*), and kappa coefficient (*KC*) clearly brought out the differences between these four classifiers: maximum likelihood classification (MLC), *k*-means, minimum distance classifier (MDC), and parallelepiped classifier (PPC) (Tab. S1). In 2000 MLC attained the highest *OA* of 86.80% with a balanced *UA* of 80.66% and *PA* of 81.17%, supported by an appropriately strong kappa value of 0.86. Class-wise is also performed best toward the identification of dense forest (*UA* = 90.00%, *PA* = 100.00%), oil palm plantation (*UA* = 90.00%, *PA* = 90.00%), and open grassy area (*UA* = 80.00%, *PA* = 100.00%). The results obtained by *k*-means are significantly lower, with an *OA* are 72.00% and a mean of *UA* with approximately 71.50%. There was misclassification between oil palm (*UA* = 66.00%, *PA* = 62.50%) and rubber plantation (*UA* = 64.00%, *PA* = 66.00%) in the study. This misclassification was mainly attributed to spectral overlaps as noted by Othman *et al.* (2019). MDC generated an *OA* equal to 61.5%, with *UA* near about 57.09%, and *PA* near about 74.74%, and kappa equal to 0.58, accompanied by high omission errors for the rubber plantation, where *UA* equalled only 54.55% and *PA* just reached up to 60.00%. PPC achieved a classification accuracy of 65.10% based on the *OA*, with a kappa value of 0.59. However, the model showed significant omission for certain classes, particularly rubber plantation, where both the *UA* and *PA* were zero.

By 2010, MLC stayed on top with *OA* = 91.30%, *UA* = 77.33%, *PA* = 87.83%, and *KC* = 0.82. It got the perfect score for open grassy area (*UA* = 100.00%, *PA* = 100.00%) and high marks for rubber plantation (*UA* = 90.00%, *PA* = 100.00%). Method *k*-means increased to *OA* = 83.30% (*UA* = 69.16%, *PA* = 73.33%, *KC* = 0.58) but still had trouble clear of oil palm (*UA* = 67.00%, *PA* = 63.00%) from rubber plantation (*UA* = 65.00%, *PA* = 67.50%). MDC decreased to *OA* = 47.60% (*UA* ≈ 48.33%, *PA* ≈ 65.56%; *KC* = 0.43), showing big spectral errors, mostly between dense and thin woods, while PPC resulted an *OA* with approximately fifty-two percent only (*UA* ≈ 75.00, *PA* ≈ 45.00, *KC* = 0.46). In 2020, even with more land cover breakup, MLC is still on top of *OA* = 92.70%, *UA* = 79.48%, *PA* = 81.33% and *KC* = 0.79. It does very well for rubber plantation (*UA* = 70.00%, *PA* = 100.00%) and sparse forest (*UA* = 80.00%, *PA* = 72.73%). Method *k*-means gets its best *OA* at 85.30% (*UA* = 68.82%, *PA* = 70.68%, *KC* = 0.61) but still mixes up oil palm (*UA* = 65.00%, *PA* = 60.50%) and rubber plantation (*UA* = 63.5%, *PA* = 65.0%). MDC gives *OA* = 48.9% (*UA* ≈ 49.38%, *PA* ≈ 60.83%; *KC* = 0.44), does very badly for oil palm (*UA* = 100.00%, *PA* = 25.00%). PPC gets *OA* at 72.60% (*UA* = 65.00%, *PA* = 49.67%, *KC* = 0.69) but misses out totally on oil palm plantation (*UA* = 0.00%; *PA* = 0.00%).

MLC minimised both commission (high *UA*) and omission (high *PA*) errors across the three-time frames. It worked better for spectrally similar tropical land cover classes, e.g., oil palm and rubber plantation. An increasing trend was consistent with *k*-means but hampered by some basic problems of unsupervised clustering, mainly confusion between certain types of vegetation that are spectrally overlapping, as discussed by Sari *et al.* (2023). A method dependent only on simple Euclidean distance is not appropriate for heterogeneous landscapes, such as MDC; while spectral boundaries are too rigid leading to severe omission errors even when purity is quite high for certain classes, such as PPC, according to Zhang Liu and Biljecki (2023). This finding falls among recent research advocating hybridisation of the statistical strength of MLC with contextual and object-based fine-tuning towards maximising accuracy combined with flexibility under highly dynamic tropical settings.

VEGETATION COVER DISTRIBUTION AND CHANGE PATTERNS

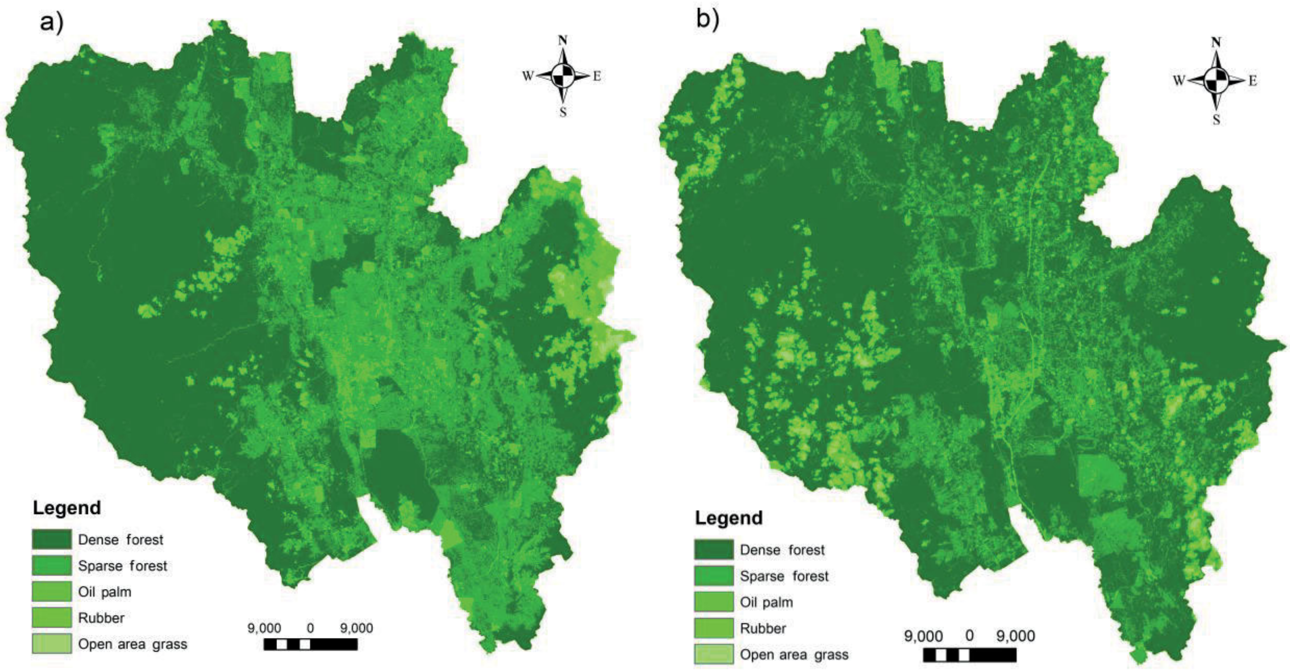
Table 3 in the temporal analysis captures major landscape changes between 2000 and 2020 in Raub District, with explicit results of human activities. It is an alarming trend under all four classification methods that dense forest cover is decreasing concomitant with increasing oil palm plantations and open grassy areas. Dense forests have recorded reductions across all classifiers. For instance, *k*-means results revealed that in 2000 (Fig. 2a), an estimated area of 115,000 ha was reduced to 84,000 ha by 2020 (Fig. 2c); thus proposing a net loss of about 31,000 ha (27%) (Fig. 2a–c), MLC records decline from 118,200 ha to 86,100 ha within the same period (Fig. 3a–c). This pattern reflects much wider regional trends toward deforestation elsewhere in Southeast Asia as a result of agricultural expansion, in particular oil palm cultivation, and infrastructure development. The dense forest decline signifies not only habitat loss but also carbon storage, hydrological regulation, and biodiversity integrity (Curtis *et al.*, 2018). Oil palm plantations have been expanding massively during the two decades; *k*-means results highlight that they were only 22,000 ha in 2000 but reached 41,500 ha by 2020 (88.6% increase) (Fig. 2a–c). MLC has similar growth patterns (21,100–40,300 ha) (Fig. 3a–c) and MDC (20,900–40,200 ha) (Fig. 4a–c). Malaysia is a global leader in palm oil production hence such expansion reflects sustainability issues on greenhouse gas emissions from peatland draining and threats to biodiversity as highlighted by Meijaard *et al.* (2020). The fast pace of replacing forests with oil palms signals economic resilience taking precedence over ecological considerations.

Table 3. Area distribution by vegetation class

Vegetation class	Area (ha) in the year		
	2000	2010	2020
***k*-means**			
Dense forest	115,000	96,000	84,000
Sparse forest	45,000	52,500	48,300
Oil palm plantation	22,000	31,200	41,500
Rubber plantation	25,000	30,100	28,600
Open grassy area	6,500	10,200	15,400
MLC			
Dense forest	118,200	98,700	86,100
Sparse forest	42,800	50,300	46,800
Oil palm plantation	21,100	30,700	40,300
Rubber plantation	24,600	28,500	27,000
Open grassy area	5,900	9,800	14,200
MDC			
Dense forest	113,500	95,200	83,500
Sparse forest	43,200	51,000	47,200
Oil palm plantation	20,900	30,500	40,200
Rubber plantation	24,400	28,900	27,300
Open grassy area	6,100	9,700	14,600
PPC			
Dense forest	114,200	96,300	84,800
Sparse forest	43,500	51,300	47,400
Oil palm plantation	21,200	30,800	40,400
Rubber plantation	24,700	29,000	27,400
Open grassy area	6,000	9,600	14,500

Explanations: MLC = maximum likelihood classification, MDC = minimum distance classifier, PPC = parallelepiped classifier.
Source: own study.

Sparse forest area exhibits fluctuating patterns, increasing from 2000 to 2010 and then decreasing by 2020. For example, under MDC it was 43,200 ha in 2000 and increased to 51,000 ha by 2010 and then reduced to 47,200 ha by 2020. This might be indicative of a forest degradation pathway land cover mosaic where the sparse forest is first created and then later converted



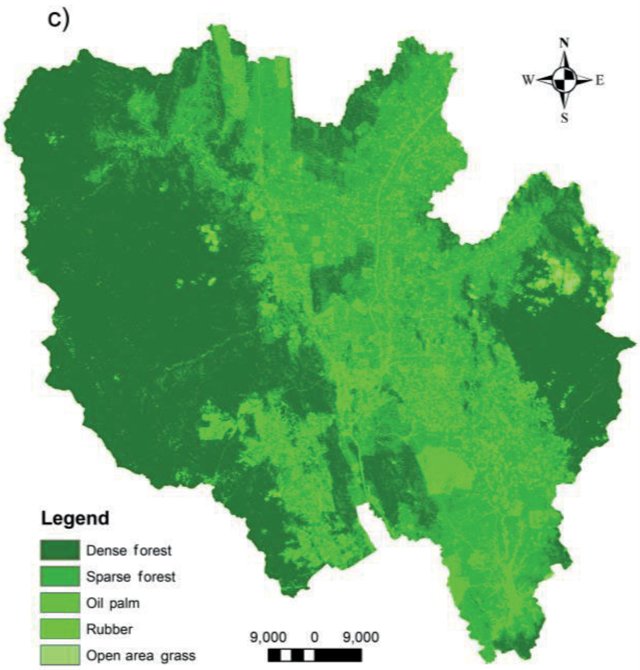


Fig. 2. The *k*-means classification results for images: a) 2000, b) 2010, c) 2020; source: own study

into plantations. Such landscapes have been described as being in an ecologically vulnerable state which is likely to be further degraded if not managed with restoration interventions (Maxwell *et al*., 2020). Open grassy areas about doubled their size under most classifiers. Under PPC they increased from 6,000 ha in the year 2000 to 14,500 ha by the year 2020 (Fig. 5a–c). This could be interpreted to be an increase in the abandonment of lands that have been degraded probably due to overexploitation or else cleared for new agricultural use. Though they do deliver some ecosystem services, grassy areas are much less biodiverse than the forests they replace and might indicate a wider ecological decline. Trends match well between classifiers but with small differences in area estimates that show methodological sensitivities. MLC always gives slightly higher dense forest areas than *k*-means because of its probabilistic pixel classification advantage in distinguishing spectrally similar classes. Consistency across methods actually aids in making such observed patterns; it suggests that the detected land cover transitions are not some artefacts of the classification technique but rather genuine land use/land cover change. At the broadest level, over two decades Raub's, changing vegetation type distributions reflect the replacement of forest-dominated landscapes with agro-industrial systems. This shift may advance economic development goals but comes at a considerable ecological cost. They underscore the need for balanced land use planning, taking into consideration development and environmental sustainability. They also prove the valuableness of remote sensing technologies in guiding and directing decisions regarding land management, particularly in tropical regions that possess high biodiversity where rapid transformations of lands are taking place.

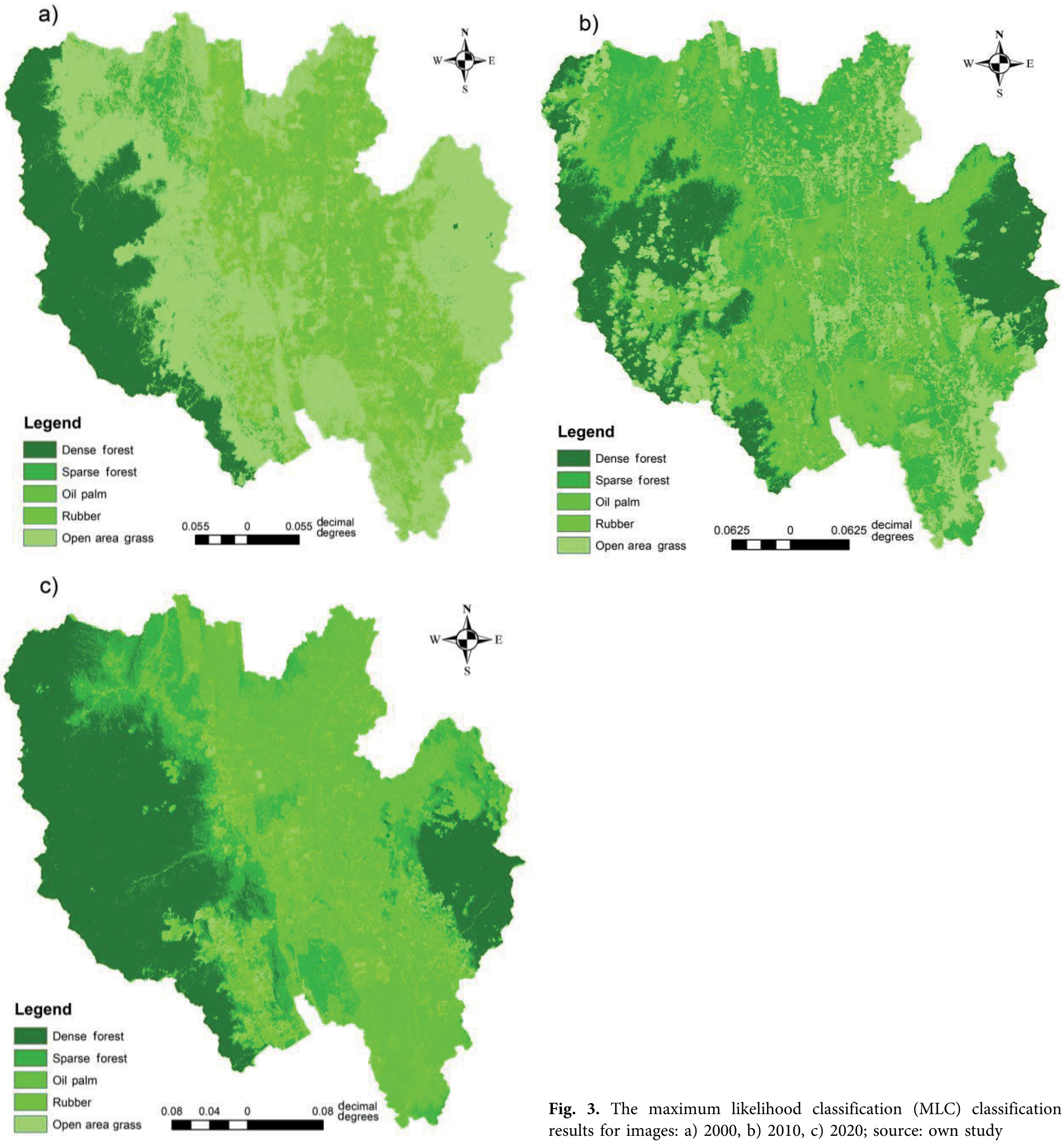


Fig. 3. The maximum likelihood classification (MLC) classification results for images: a) 2000, b) 2010, c) 2020; source: own study

CLASSIFIER STRENGTHS AND LIMITATIONS

Changes in vegetation vigour, which reflect variations in vegetation cover density and health, are influenced by the spatial extent and classification of land cover over time. These changes were derived from comparing classified maps from different years. Out of the three supervised MLC, MDC, and PPC as well as *k*-means clustering used, it has always been MLC that turned out to be the most accurate for all years. This basically gives an idea about the fact that as a supervised classification operating in a probability domain, MLC uses statistically representative training data to assign each pixel to land cover classes based on its probability of belonging to certain classes. The probabilistic approach assumes spectral signatures distribution for every class under normal conditions, something quite realistic in most applications of remote sensing, and enables detailed differentiation between spectrally similar vegetation types such as oil palm and rubber plantations or sparse forest and open grassy areas (Li *et al.*, 2012; Jensen, 2021). For example, linear plantation boundaries and transitional vegetation zones are delineated with high precision. Therefore, it becomes very useful in more detailed agricultural area expansion and forest fragmentation studies. The ability to model intra-class variability adds up to its good performance in areas where there is high spectral confusion due to overlapping canopy structures, or mixed landcovers prevalent in tropical landscapes (Foody, 2020). However, adequate, high quality, and representative training data, on which MLC is dependent, remains a handicap in remote and also cloud-prone

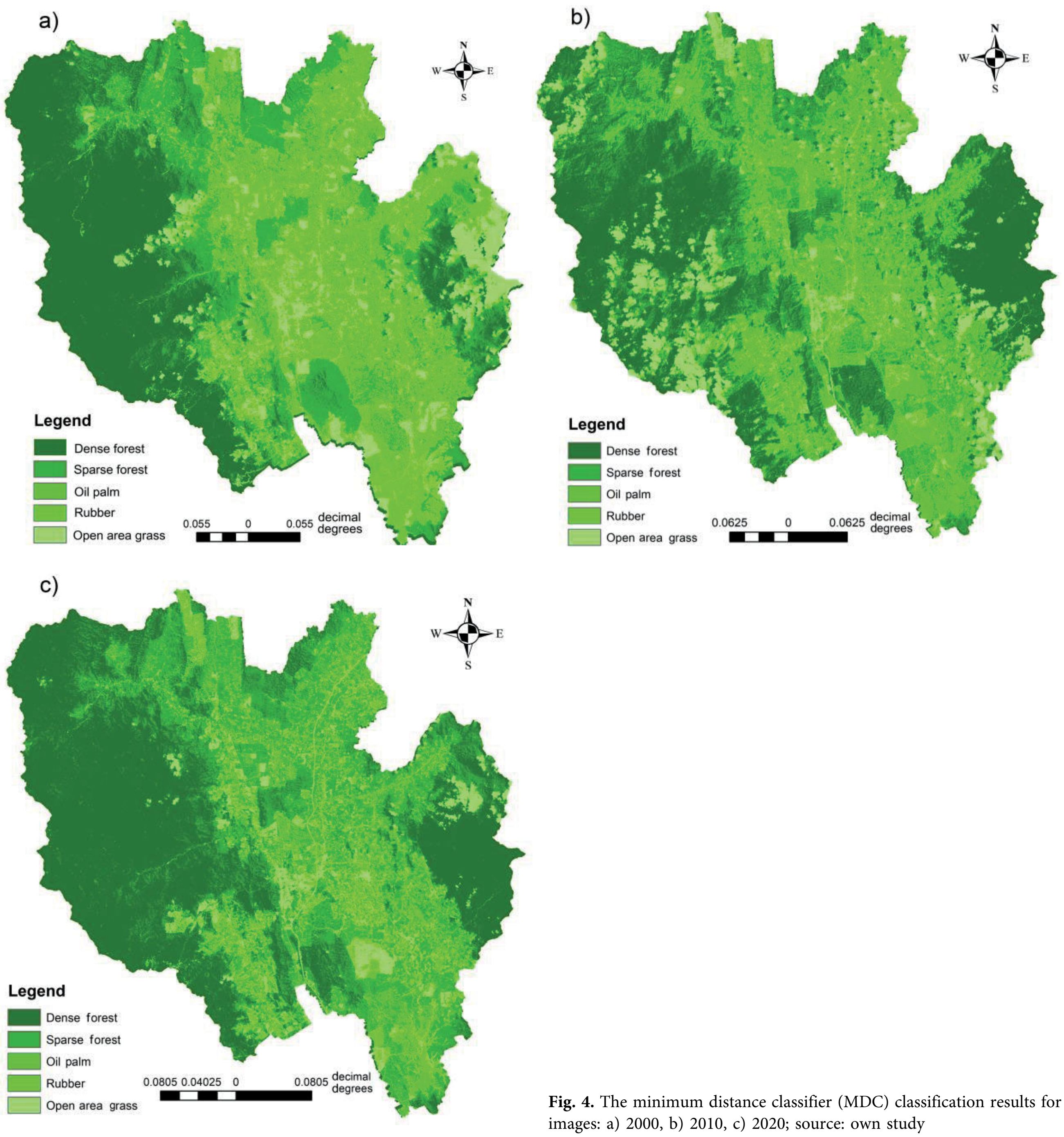
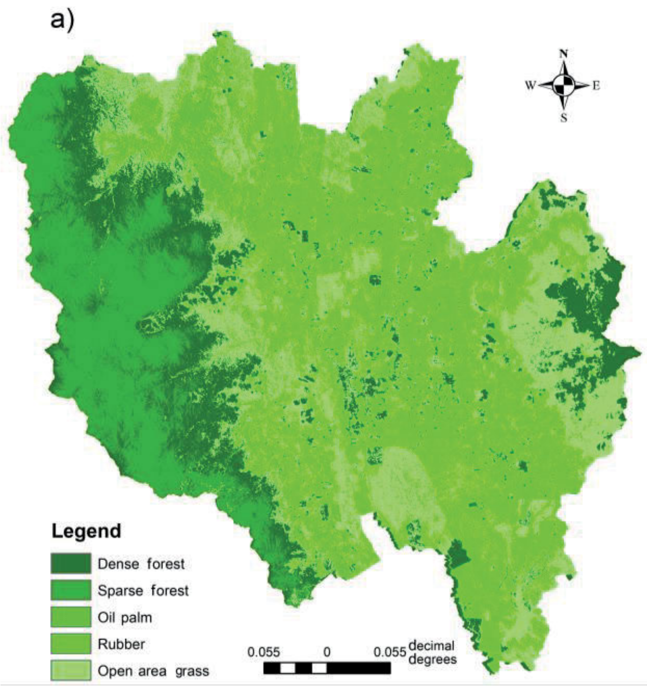
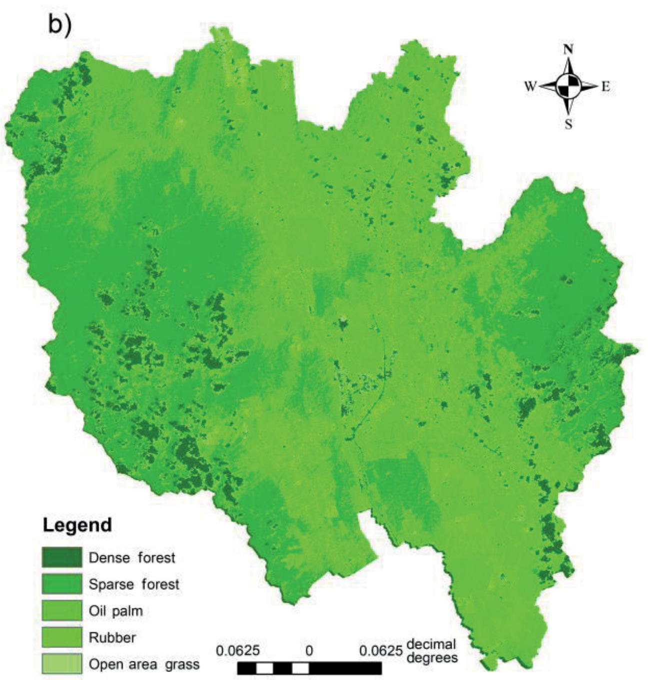


Fig. 4. The minimum distance classifier (MDC) classification results for images: a) 2000, b) 2010, c) 2020; source: own study

areas. Any bias present in the training set will be carried into the classification itself.

The MDC is almost as good as the MLC. Mean values from reference samples are calculated and the spectrum's Euclidean distance for each class is determined. It runs fast and does not depend much on the assumption of normality (Sharma Banjade, Rai and Subedi, 2023). This method works well where spectral means between classes are distinct without much variance within classes. It will break down if there is spectral overlap between classes, such as might occur with rubber and oil palm plantations across a heterogeneous landscape like Raub, for example. Unlike the MLC, it does not use information on class variance and covariance; hence, it will be less robust under conditions of mixed pixels but better than most unsupervised approaches. In Raub, PPC's rigid boundary rules resulted in high omission errors, particularly for rubber plantations in 2010 and 2020, where spectral variability within plantation canopies fell outside the classifier's thresholds. This explains why PPC reported UA and PA values of zero for rubber plantations, highlighting its unsuitability for heterogeneous tropical mosaics (Shiraishi *et al.*, 2014). Classes that have tightly bounded spectral ranges and internal variability such as water bodies or bare land will work well but vegetation classes which typically have high intra-class variance may be misclassified. It is simple and hence fast but does not have the statistical strength of MLC nor adaptability of MDC and hence would rather be used for coarse classification tasks or perhaps as part of hybrid approaches.





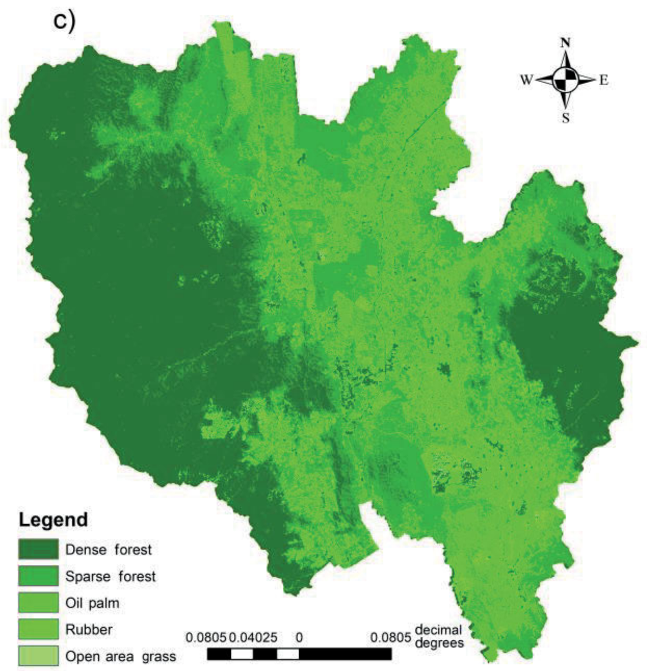


Fig. 5. The parallelepiped classifier (PPC) classification results for images: a) 2000, b) 2010, c) 2020; source: own study

Method *k*-means being of an unsupervised nature does not necessarily need labelled training data. It is a process where spectrally similar pixels are grouped into classes and then manually assigned to vegetation classes. Therefore, this algorithm can be optimally applied for quick surveys or exploratory mapping tasks and when no ground truth data are available (Jensen, 2021). But the method is fraught with some problems over heterogeneous landscapes, such as typically confusing sparse forest with open grassy areas and difficulty in separating out rubber plantations from other woody vegetation. This is because its determination strictly depends on spectral distance metrics, i.e., without consideration of any contextual or spatial information, leading to instability within mixed-pixel zones which are exactly the areas of interest in degradation and regeneration monitoring (Foody, 2020). Besides, subjectivity introduced by manual labelling after clustering may reduce temporal consistency. In comparative evaluation, the overall ranking of performance in the Raub case study goes as: MLC > *k*-means > MDC > PPC. Long-term detailed monitoring requiring policy relevance prefers MLC due to its statistical rigor and adaptability when the training data is available; meanwhile, systems offering a simpler structure with rather high accuracy in situations where spectral overlap is not so wide are preferred. Where class boundaries are well defined, PPC can provide quick classifications that are less useful in cases of vegetative mapping with complex spectral information. The unsupervised *k*-means approach retains some utility in rapid-resource-limited assessments or even as a preliminary step before application of more robust supervised methods. Method *k*-means as exploratory analysis, followed by MLC for fine mapping, with MDC or PPC as possible stopgaps between degrees of data availability and landscape heterogeneity, will synthesise toward strong monitoring praxis. This steps the line between best praxis in tropical forestry monitoring whereby method choice is subordinated to resource context and desired degree of classification accuracy (Edwards *et al*., 2019; Maxwell *et al*., 2020).

IMPLICATIONS OF VEGETATION CHANGE

A twenty-year comparison of vegetation change in Raub District from four classifying methods: MLC, MDC, PC, and *k*-means clustering; reflects major ecological transformations that bear equally great policy consequences. The dominant trend common to all classifiers is the high magnitude of reduction in dense forest cover from more than 113,500–118,200 ha in 2000 to only 83,500–86,100 ha by 2020. This reflects general Southeast Asian trends in deforestation where large tracts of forests are cleared for oil palm and rubber monocultures (Dhandapani, Yule and Drewer, 2024; Saharudin, Jeswani and Azapagic, 2024). Tropical forests are important in the sequestration of carbon, climate regulation, hydrological balance, and biodiversity conservation. Removal of these forests leads to habitat fragmentation and consequently resilience attributed to ecological strength when it comes to adjustments under climatic conditions. The conversion increases the aboveground biomass carbon stocks lost which puts Malaysia as a nation at a disadvantage in fulfilling its international commitments related to climate change. These plantations contain more carbon than open land; however, they can never carry out the intricate ecological functions fulfilled by a complete forest. Besides, such monoculture systems are further intensified by mechanical clearing, chemical input, and hydrological modification, simplifying habitat structure, hence narrowing niche diversity and restricting native species persistence.

By 2020, it also noted about a threefold increase of open grassy areas consistently across classifiers as an indication of degradation after clearing or conversion failure to productive plantations. Other such degraded land elsewhere in Malaysia was found to have low biodiversity value but high risks for erosion when rainfall is heavy (Sari *et al*., 2023). While ours is not a soil process classification, expansion of grassland area detected here in Raub does indicate increasing susceptibility to land degradation that will probably have downstream effects on water quality and local agriculture. From the wider social and economic perspective, this means that rural livelihoods and export revenues continue to be sustained by oil palm and rubber plantations expansion (Ahmad *et al*., 2024). However, these take place at the expense of forest-dependent communities alongside long-term ecological sustainability. This finding also supports further advocacy for the integrated land-use policy that introduces agroforestry systems together with a multifunctional landscape mosaic which contains natural corridors (Saharudin, Jeswani and Azapagic, 2024; Tiko *et al*., 2025). Another important lesson emphasised by this study is that method choices in vegetation monitoring have considerable effects on its reliability. As MLC generated results that were systematic and highly accurate, it thus becomes the most reliable method in providing estimates where decisions are extremely relevant to policies being developed. Other methods can complement roles as long as data or resource constraints exist.

CONCLUSIONS

The study of vegetation cover changes in Raub District, Pahang, Malaysia, can be divided into:

- selection of classification method: the choice of classification method is crucial for accurate vegetation cover change detection;
- best method: maximum likelihood classification (MLC) consistently performed best due to its ability to distinguish spectrally similar classes like oil palm and rubber plantations;
- minimum distance classifier (MDC) and parallelepiped classifier (PPC): MDC performs well when spectral means are well-separated but poorly when overlaps occur, while PPC is fast but less accurate in complex vegetation mosaics;
- *k*-means: *k*-means is quick and requires minimal data, but it has high error rates, particularly in open grassy areas;
- vegetation trends: all classifiers revealed that dense forests are being replaced by oil palm, rubber plantations, and expanding open grassy areas, reflecting broader deforestation and agricultural intensification in Southeast Asia;
- environmental impact: these changes lead to reduced biodiversity, disrupted hydrological systems, lower carbon storage, and increased land degradation risks;
- methodology recommendations: for long-term monitoring, multi-data classification (MLC) should be the default choice, with MDC or PPC as fallbacks, and *k*-means used only for preliminary assessments;
- policy implication: a tiered monitoring framework using these methods can support evidence-based land-use policies balancing economic development, biodiversity conservation, and climate resilience.

SUPPLEMENTARY MATERIAL

Supplementary material to this article can be found online at: https://www.jwld.pl/files/Supplementary_material_68_Shapiaai.pdf.

CONFLICT OF INTERESTS

All authors declare that they have no conflict of interests.

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