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Integrating Multi-Variable Driving Factors to Improve Land Use & Land Cover Classification Accuracy using Machine Learning Approaches: A Case Study from Lombok Island

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Abstract

Accurate classification of land cover is essential for effective land management and environmental monitoring. This study aimed to enhance land cover classification for Lombok Island using advanced machine learning algorithms. The models employed include Random Forest, Gradient Boosting, Decision Tree, and Naive Bayes, integrating a wide range of variables, such as Landsat satellite imagery, spectral indices, physiographic, climatic, and socio-economic data. Among these, Random Forest demonstrated the highest model accuracy at 82%, followed by Gradient Boosting at 80%, Decision Tree at 73%, and Naïve Bayes at 61%. In field validation assessments, comparing the predictions of these machine learning models with ground truth data, Random Forest was the most reliable, achieving an overall accuracy of 88%. This superior performance is largely due to the multi-variable approach, which allows the model to mitigate issues like cloud cover in satellite images. The key variables that significantly influenced the land cover classification on Lombok Island include proximity to settlements, temperature, and distance to roads. These results provide essential insights for land management strategies, enabling policymakers and stakeholders to make informed decisions on sustainable development, urban planning, and environmental conservation in rapidly changing landscapes.

Keywords: *land cover classification, machine learning, Random Forest, Lombok Island*

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Introduction

The rapid advancements in machine learning (ML) technologies have revolutionized various fields, including environmental science and land management. Accurate land cover classification is essential for effective environmental monitoring, sustainable land use planning, and conservation efforts (Vinaykumar et al., 2023). However, achieving high accuracy in land cover classification remains challenging due to the complex and dynamic nature of landscapes (Desjardins et al., 2023). Traditional methods often struggle to accommodate the variability in land cover types, leading to inaccuracies that can significantly impact decision-making processes (Gavade & Rajpurohit, 2021; Qichi et al., 2023).

Lombok Island, a region experiencing rapid urbanization, agricultural expansion, and environmental change, presents a unique case for studying land cover dynamics (Rahayu et al., 2023). The island's diverse ecosystems and the pressures from human activities require a robust and accurate classification system to manage and protect its natural resources effectively (Dewi & Sukmawati, 2020). The integration of ML approaches with multi-variable driving factors, such as climate data, topography, and socio-economic variables, offers a promising solution to improve the precision of land cover classification (Jaya et al., 2015; Mitra & Basu, 2023).

ML is favored over traditional methods because it automates data analysis, efficiently handling vast variables and generating new insights. Unlike classical techniques, which struggle with complex datasets, ML excels in processing and predicting outcomes from large, diverse data (Purnama et al., 2024). This automated approach allows for a more precise understanding of Lombok Island's land cover dynamics, offering greater value in environmental monitoring and decision-making compared to conventional methods.

This study explores the application of advanced ML algorithms, including Random Forest (RF), Gradient Boosting (GB), Decision Tree (DT), and Naïve Bayes (NB), combined with diverse variables such as satellite imagery, spectral indices, physiographic attributes, climate data, and socio-economic factors. By addressing limitations in traditional methods, such as cloud cover and lack of contextual data, this research enhances the accuracy of land cover maps for Lombok Island.

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Methods

Study area Lombok Island (Figure 1a), part of West Nusa Tenggara, Indonesia, spans approximately 4,739 km² with a population of around 3.3 million. The island features diverse land cover, predominantly agriculture (61.4%) and forests (25.8%). Significant land use changes, including deforestation and forest degradation, have transformed forest areas into agricultural land and shrubs (Kim, 2016). The island's varied topography, from the central volcanic range with Mount Rinjani (4,732 masl), the second-highest volcano in Indonesia, to coastal plains, adds complexity to land cover mapping efforts.

Software Several software tools were utilized for data collection, processing, and analysis. Google Earth Engine (GEE) was used for acquiring and processing satellite imagery (Qu et al., 2021). ArcGIS facilitated spatial data preparation and analysis (Çoban & Erdin, 2020). Spyder (Python 3 studio) was employed for data processing (Kadiyala & Kumar, 2017).

Variables The variables in this study were divided into dependent and independent variables. The dependent variable was the land cover class (Table 1), based on classifications from the Indonesian Ministry of Forestry and Environment (MoEF) (Direktorat Jenderal Planologi Kehutanan, 2015), reclassified into nine categories (Kim, 2016). Independent variables (Table 2) included satellite images, spectral indices, physiographic, socio-economic, and climate variables. These variables were chosen to capture the diverse factors influencing land cover changes and to enhance classification accuracy through ML models (Valdivieso-Ros et al., 2023).

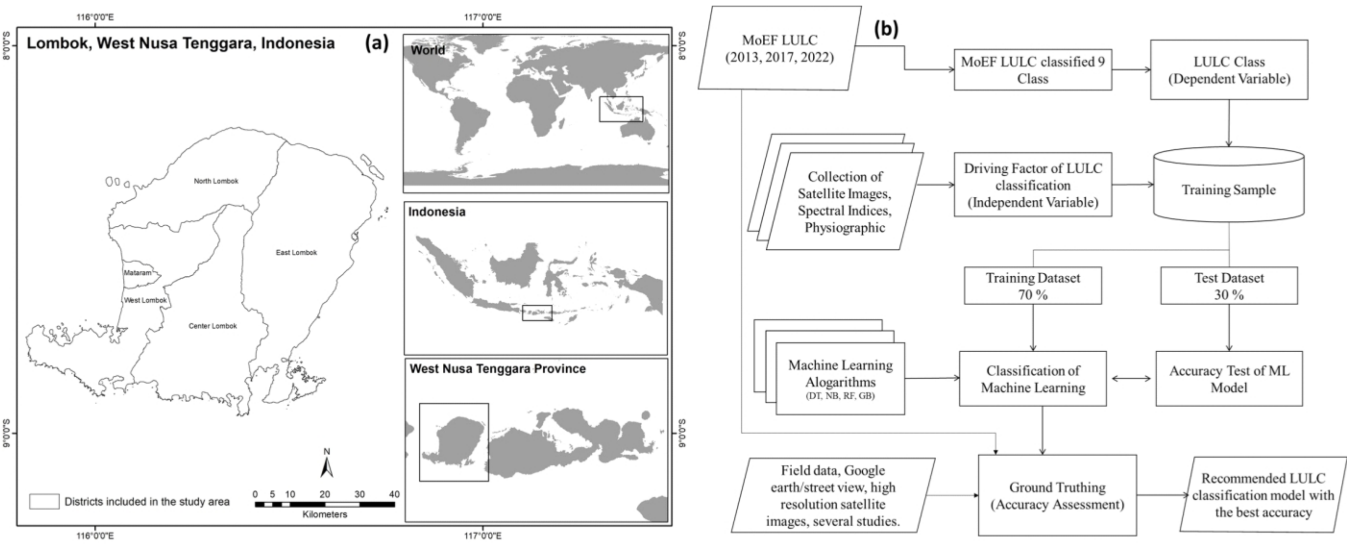

Figure 1 Study area (a) and flowchart of LULC classification and validation process using machine learning algorithms (b).

Table 1 LULC class code / dependent variable

New land use/land cover class	Land cover code (class) by Indonesia Ministry of Environment and Forestry	New class code
Primary forest	2001 (Primary dry land forest), 2004 (Primary mangrove forest)	1 (PF)
Secondary forest	2002 (Secondary dry land forest), 20041 (Secondary mangrove forest)	2 (SF)
Dry land agriculture	20091 (Dry land agriculture), 20092 (Mixed dry land agriculture/shrubs)	3 (DLA)
Paddy fields	20093 (Paddy fields)	4 (PFi)
Grassland/shrubland	3000 (Savanna/grassland), 2007 (Shrubs)	5 (GS)
Estate crop	2010 (Estate crop agriculture), 2006 (Estate crop forest)	6 (EC)
Wetlands	5001 (Water bodies), 20094 (Ponds)	7 (W)
Settlement/build up	2012 (Settlement), 20121 (Airport/port), 20122 (Transmigration)	8 (SB)
Other	2014 (Barren land), 20071 (Swamp shrubs), 20141 (Mines)	9 (O)

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Table 2 Variables independent of the driving factor

Category	Variable	Source	Type and resolution	Refrences
Satellite images	Coastal aerosol Blue Green Red Near Infrared (NIR) SWIR 1 SWIR 2	Landsat 8 SR	All variables were uniformed into raster type files, and resampled to 30 meter resolution following the resolution of the Landsat 8 imagery	Khan et al. (2024); You et al. (2022)
Spectral indices	Normalized diference vegetation index (NDVI) Soil-adjusted vegetation index (SAVI) Normalized difference water index (NDWI) Enhanced vegetation index (EVI) Normalized difference built-up index (NDBI)	Landsat 8 SR		da Silva et al. (2020); Prasad et al. (2022); Singgalen (2024)
Physiographic	Elevation Slope Aspect Soil type	DEM FAO		Le et al. (2022); Qu et al. (2021)
Social-economic	Population density Near from road Near from seatleman Near from river Near from center government	Central Agency on Statistics Landform map of Indonesia		Gaur & Singh (2023); Herwirawan et al. (2017); Xie et al. (2023)
Climate	Average temperature Average precipitation	Terra Climate		Alzubade et al. (2021); Ibrahim and Ash'aari (2023)

Data querying/processing The target variable, i.e., land cover class data, is used as the *y* variable in the study. Independent variables are the *x* variables. The data obtained from the *x* and *y* variables was generated for each pixel by overlaying them in ArcGIS software and then using the 'Multiple Value Extraction to Points' tool to extract values per pixel. The overlay process in ArcGIS ensured all raster layers were harmonized spatially with consistent resolution and alignment, facilitating the accurate integration of dependent and independent variables. The resultant dataset, containing attributes for each data point, was then prepared for ML algorithms (Figure 1b). To ensure a robust evaluation of the models, the dataset was split into training and test datasets. The training dataset comprised 70% of the data, while the remaining 30% was used for testing. This division ensures that the models have enough data to learn from while retaining a sufficient portion for unbiased evaluation of their performance (Sulova & Arsanjani, 2020; Purnama et al., 2024).

For the ML models, several algorithms were employed due to their effectiveness in handling large and complex datasets. RF,GB, DT, and GB are non-parametric algorithms that do not assume a specific distribution for the data (Wedagedara et al., 2024).

Model evaluation The evaluation of the ML models was conducted using several performance metrics to ensure the accuracy and reliability of the land cover classifications. The primary metrics used were overall accuracy, precision, recall, and the F1 score (Sulova & Arsanjani, 2020; Purnama et al., 2024).

Overall accuracy measures the proportion of correctly classified instances among the total instances as shown in Equation *[1]*. Precision for each class is the ratio of true positive predictions to the total predicted positives for that class, as shown in Equation *[2]*. Recall/sensitivity for each class is the ratio of true positive predictions to the total actual positives for that class, as shown in Equation *[3]*. The F1 score for each class is the harmonic mean of precision and recall as shown in Equation *[4]*.

$$Overall\ accuracy = \frac{\sum_{i=1}^{9} TP_i}{\sum_{i=1}^{9}(TP_i + FP_i + TN_i + FN_i)} \quad [1]$$

$$Precision_i = \frac{TP_i}{TP_i + FP_i} \quad [2]$$

$$Recall_i = \frac{TP_i}{TP_i + FN_i} \quad [3]$$

$$F1\ score_i = \frac{2.Precision_i \times Recall_i}{Precision_i + Recall_i} \quad [4]$$

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note: *TPi* is true positive value for each class *i*, *FPi* is false positive value for each class *i*, *FNi* is false negative value for each class *i*, and *TNi* is true negative value for each class *i*.

K-fold cross-validation was used to ensure robustness and generalizability (Equation *[5]*). The dataset is divided into k subsets, and the model is trained and validated k times (Darapureddy et al., 2019), each time with a different subset as the validation set. Receiver operating characteristic (ROC) curve and the area under the ROC curve (AUC) (Equation [6]) were used to evaluate the model's ability to distinguish between classes (Tougui et al., 2021). The ROC curve plots the true positive rate (TPR) against the false positive rate (FPR), while AUC provides a single scalar value summarizing the model's performance across all thresholds. Feature importance (Equation *[7]*) was analyzed using Scikit-learn, ranking variables based on their contribution to the model's decisions. Higher importance values indicate a greater impact on the model's predictive capability (Zhang et al., 2023).

$$\textit{Cross-validation accuracy} = \frac{1}{k}\sum_{i=1}^{k} Accuracy_i \qquad [5]$$

$$AUC = \int_0^1 TPR(FPR)\mathrm{d}(FPR) \qquad [6]$$

$$\textit{Feature importance } (FI) = \sum_{t\in T}\frac{N_t}{N} \times \Delta_i(t) \qquad [7]$$

note: is set of all DTs in the model, *t* is a specific node in a tree where the feature is used, *Nt* is the number of samples that reach node *t*, *N* is the total number of samples in the dataset, and $\Delta i(t)$ is the decrease in impurity (e.g., Gini impurity or entropy) at node *t* due to the split on the feature.

Field assessment The field assessment aimed to validate the accuracy of the land cover classifications generated by the ML models. The process involved selecting sample points for each land cover class using a stratified random sampling approach. For each land cover class, 30 sample points were selected to ensure adequate representation and reliable validation. The accuracy of the land cover classifications was evaluated using the following metrics (Khaldi et al., 2024); Overall accuracy (OA) (Equation *[8]*) measures the proportion of correctly classified instances among the total instances, Producer's accuracy (PA) (Equation *[9]*) measures the accuracy from the perspective of the ground truth (how well each reference class is classified), and User's accuracy (UA) (Equation *[10]*) measures the accuracy from the perspective of the classifier (how reliable the classification is for each class).

$$OA = \frac{\sum_{i=1}^{n} Mii}{N} \qquad [8]$$

$$PA = \frac{Mii}{\sum_{i=1}^{n} Mij} \qquad [9]$$

$$UA = \frac{Mii}{\sum_{i=1}^{n} Mji} \qquad [10]$$

note: *Mii* is the count of correctly classified instances for class *i*, *Mij* is the count of all actual instances of class including both correctly and incorrectly classified instances, *Mji* is the count of all instances classified as class by the model, including both correctly and incorrectly classified instances, *n* is class count, and *N* is count of all actual instances. The confusion matrix elements *Mii*, *Mij*, and *Mji* represent the counts of correct and incorrect classifications, allowing for a detailed assessment of the model's performance for each land cover class.

Results

Characteristics of the dataset The distribution of the land use and cover (LULC) dataset extracted from the MoEF land cover shows significant variation, with Dryland Agriculture and Rice Fields as the most dominant classes, covering 36.7% and 32.3% of the dataset respectively. Primary and Secondary Forests also hold considerable portions, with 17.4% and 10.3%. The dataset incorporates crucial driving factors, including satellite imagery, climate data, physiographic attributes, and socio-economic variables. Spectral indices from Landsat imagery provided key insights into vegetation density and water presence (Rajeswari & Rathika, 2024), while climate data, with an average precipitation of 5.58 mm day^{-1} and temperature of 28.21°C, emphasized environmental variability. Physiographic factors like soil type and elevation further illustrated the region's diverse topography, and socio-economic variables highlighted significant spatial and demographic disparities. These combined factors are essential in analyzing the complex interactions driving land cover changes, offering a comprehensive perspective for predictive modeling and sustainable land management (Sithole & Odindi, 2015; Yang et al., 2015).

Accuracy of ML algorithms The performance of the ML algorithms in classifying LULC on Lombok Island was rigorously evaluated using multiple metrics (Table 3; Figure 2). RF emerged as the most accurate model, achieving an overall accuracy of 82% and a Kappa coefficient of 0.76, indicating strong agreement with the ground truth data (Ao et al., 2019). The GB model also performed well, with an accuracy of 80%, though slightly lower than RF, this is likely due to GB's sequential learning, which can make it more sensitive to noise, whereas RF's ensemble approach is more robust to variability in the dataset. DT and NB models lagged behind, with accuracies of 73% and 61%, respectively. K-fold cross-validation was revealed that RF consistently outperformed the other models across all folds, further solidifying its reliability. ROC curve analysis provided additional insights into the models' performance. The RF model demonstrated exceptional discriminatory power across all land cover classes, with AUC values close to 1 for most classes, indicating near-perfect classification capabilities (Chicco & Jurman, 2023). The ROC/AUC graphs for RF clearly highlight its ability to separate positive and negative classes effectively, showcasing its superior performance across diverse land cover categories. In contrast, GB, while still effective, showed slightly lower AUC values in some classes, reflecting its sensitivity to complex data patterns. DT and NB exhibited significant drops in performance, particularly for more complex classes, as evident from their flatter ROC curves, indicating poorer class discrimination. This comparison highlights RF's superior ability to distinguish between different land cover types on Lombok Island. The analysis of feature importance underscored the critical factors influencing the models' predictions. In the RF model, variables such as temperature and settlement proximity were identified as the most influential, reflecting their significant role in determining land cover patterns.

The DT model (Figure 3a) classifies land cover classes based on variables such as proximity to settlements,

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Table 3 Accuracy of LULC model classification

LULC classification models	Accuracy of machine learning algorithms					Field assessment accuracy			
	Accuracy	Kappa coef.	Precision	Recall	F1-Score	Overall accuracy	Producer's accuracy	User's accuracy	Kappa statistic
Random Forest	0.82	0.76	0.82	0.82	0.81	0.88	0.85	0.84	0.86
Gradient Bost	0.80	0.72	0.78	0.79	0.78	0.75	0.70	0.69	0.72
Decision Tree	0.73	0.66	0.73	0.74	0.73	0.65	0.68	0.68	0.61
Naïve Bayes	0.61	0.50	0.61	0.61	0.60	0.46	0.51	0.69	0.39
MoEF (Control)						0.80	0.74	0.72	0.77

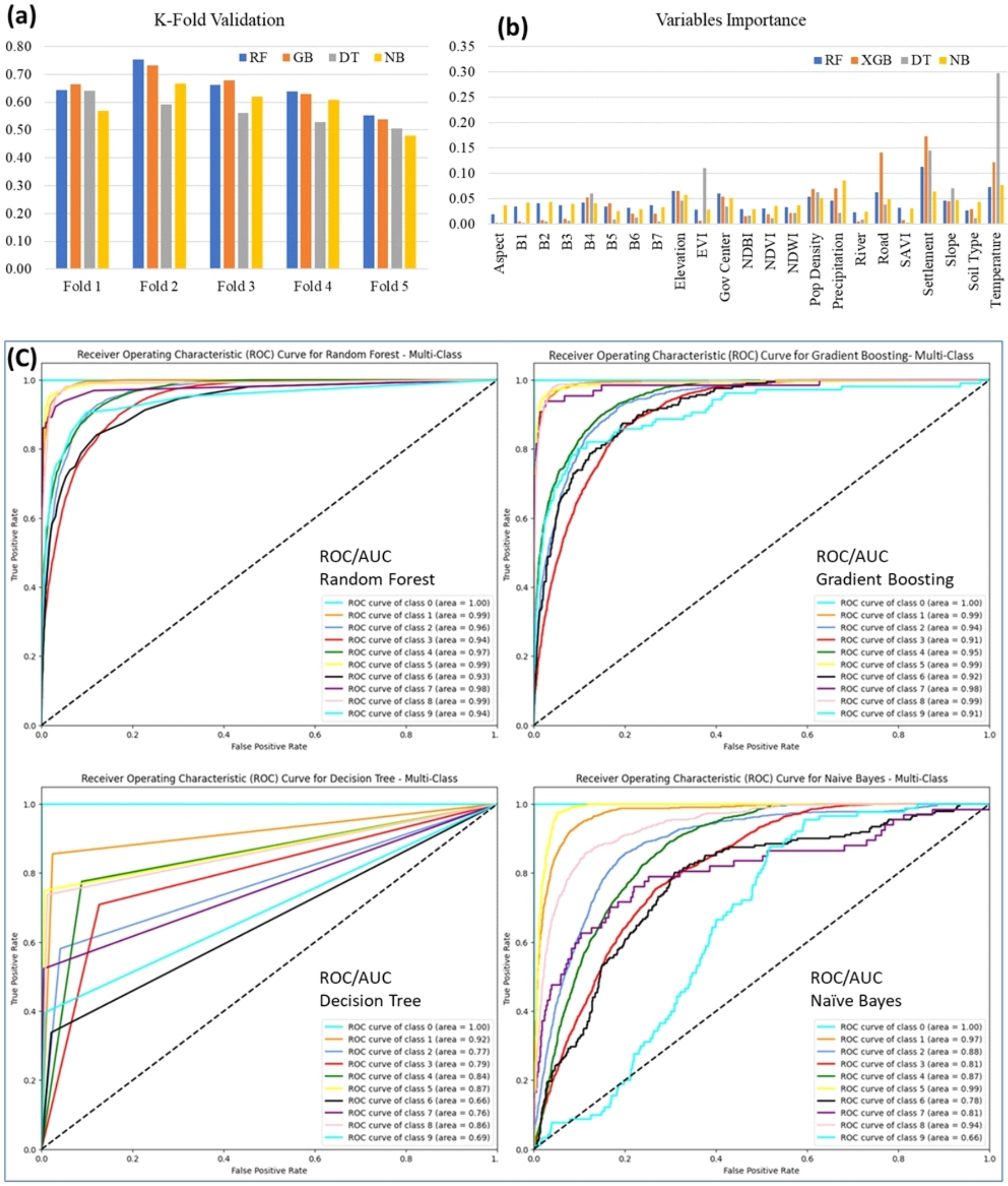

Figure 2 Accuracy assesment results: K-Fold validation (a), Variables importance (b), ROC/AUC curves (c).

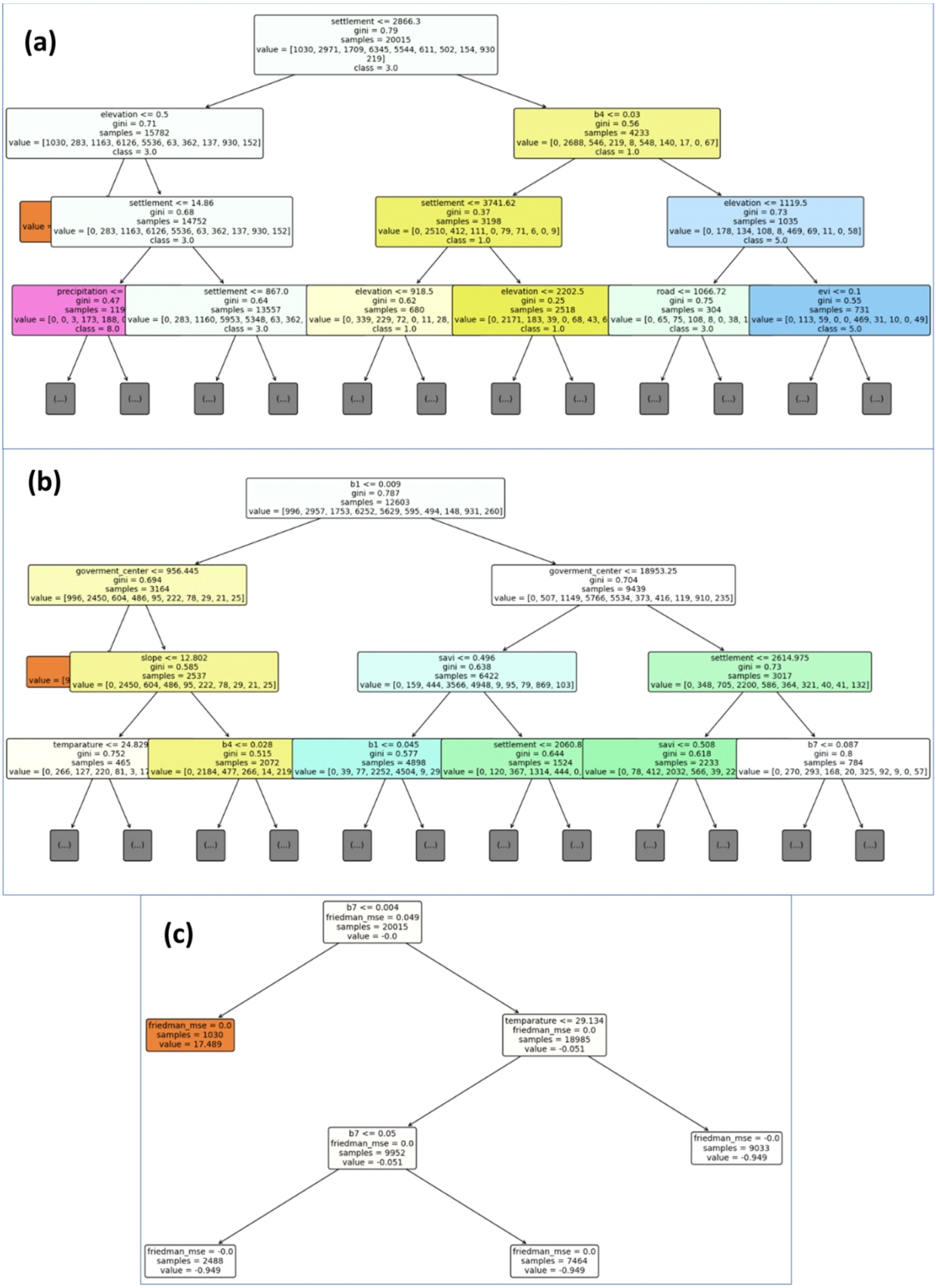

Figure 3 Examples of branches on a decision tree (a), One of the decision tree (branch) examples in Random Forest (b), One of the decision tree examples in Gradient Boosting (c).

elevation, and Landsat band 4, which are selected step by step to effectively separate the data. For example, the elevation variable separates samples in the left branch to predict class 8, while Landsat band 4 in the right branch predicts class 1 with a clear separation. RF, consisting of many DTs (Figure 3b), is difficult to track in its entirety (Wang et al., 2009), but one example tree shows how variables like band 1, proximity to the government center, and slope are used to predict land cover classes, with each tree contributing to the model's complex decision-making. In GB (Figure 3c), one tree shows how the variables Landsat band 7 and temperature separate the data, with the model working to correct predictions from the previous tree step by step, achieving higher accuracy. Meanwhile, Gaussian NB is a parametric model that assumes Gaussian distribution and relies on parameters such as mean, variance, and class priors, where the Dry Land Agriculture class has the highest priority at 31.27%, influencing the model's tendency to predict classes with higher initial probabilities when feature information is not strong enough.

Field assessment of LULC predictive models Land use and land cover classification maps were generated using RF, GB, DT, and NB ML algorithms (Figure 4). These maps were created using rasterio, matplotlib and sklearn libraries, which allow ML algorithms to read and process raster data containing spatial information and produce prediction maps. Each map assigns a code between 1 and 9 to each pixel, representing the predicted land use class. The differences observed in these maps stem from the varying prediction capabilities and methodologies of each algorithm.

Discussion

The RF map stands out for its highest accuracy and reliability, displaying a more homogeneous color distribution that more accurately represents the actual land use classes. The GB map shows slightly more variability than RF, though it still maintains a similar level of accuracy. Some minor differences in predicted classes can be observed in certain areas when comparing GB to RF. The DT map, despite offering more detail, has lower accuracy and higher error rates, with more inconsistencies in color distribution compared to RF and GB. The NB map, having the lowest accuracy, shows a highly variable predicted class distribution and fails to correctly classify some areas.

In field assessments (Table 3), RF demonstrated the highest overall accuracy (0.88), followed by LULC MoEF (0.80), GB (0.75), DF (0.65), and NB (0.46). The results show that RF and GB have good accuracy, particularly for primary forest and paddy field classes, while DT and NB show lower accuracy. The RF model achieved superior performance over the LULC MoEF classification largely due to its ability to incorporate a diverse set of variables (Patil & Panhalkar, 2023) beyond just satellite imagery and spectral indices, which the MoEF model primarily relies on (BSN, 2020). Satellite imagery, while valuable, is often hindered by cloud cover, leading to gaps in data and less reliable classifications (Li et al., 2024). This limitation is particularly problematic for the MoEF model (BSN, 2020), which doesn't have additional variables to compensate for these gaps. In contrast, the RF model integrates a wide array of variables (Purnama et al., 2024), including climate, physiographic, and socio-economic factors. This multi-variable approach is a significant advantage because it allows the model to maintain accuracy even when one variable (Bin et al., 2016; Gavade & Rajpurohit, 2021), like satellite data, is compromised. For instance, if cloud cover obscures land features in the satellite imagery, the RF model can rely more heavily on other variables, such as elevation or proximity to human infrastructure, to inform its classifications. This flexibility and adaptability make the RF model more robust and accurate, as it can effectively use the available data to

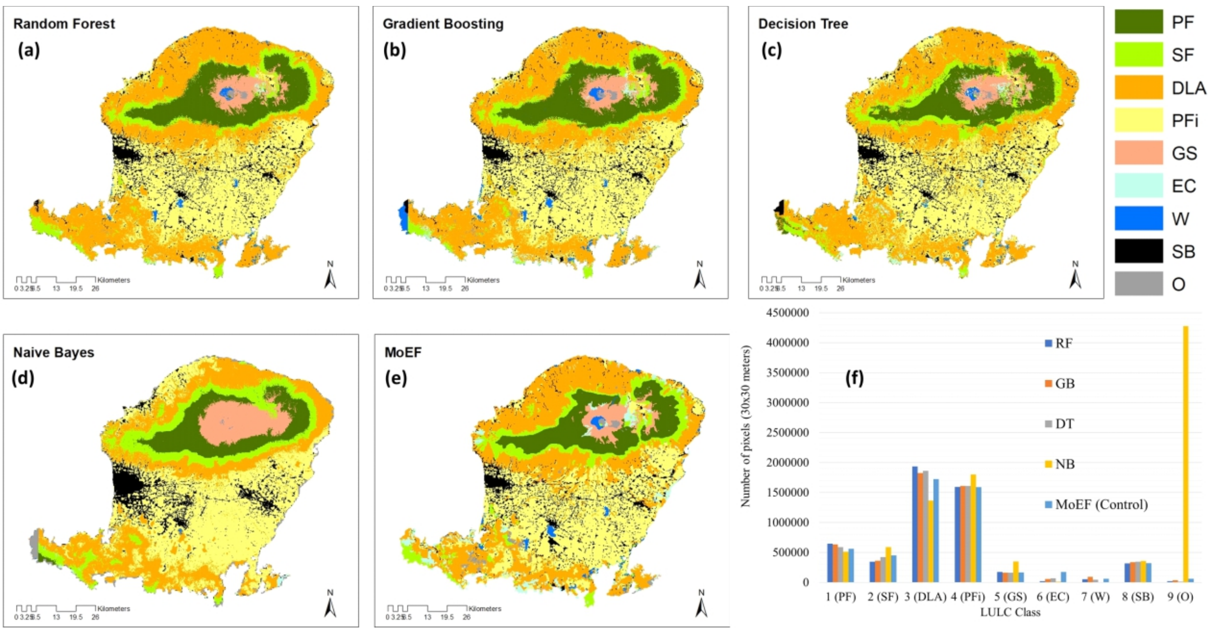

Figure 4 LULC class predictive model: Random Forest (a), Gradient Boosting (b), Decision Tree (c), Naïve Bayes (d), MoEF (e), proportion of the number of model pixels (f).

compensate for any missing or unreliable information from a single source (Wang & Ma, 2023). The ability of the RF model to leverage a diverse set of variables ensures that it can provide more accurate and reliable land cover classifications, overcoming the limitations that a narrower, single-source approach like the MoEF model faces. This multi-faceted approach explains why RF achieves higher overall accuracy and Kappa statistics, making it a more effective tool for land cover classification.

The findings of this study have significant implications for addressing global climate challenges, particularly in managing land cover changes like deforestation and agricultural expansion, which influence carbon dynamics. The use of ML with multi-variable datasets provides a robust approach for monitoring these changes. Identifying key factors like temperature and settlement proximity supports sustainable land use planning and adaptive management to mitigate climate impacts (Purnama & Çoban, 2024).

Conclusion

The results demonstrated that the RF model outperformed the other models as well as the LULC classification by the Ministry of Environment and Forestry, which relies solely on satellite imagery and spectral indices. The strength of the RF model lies in its ability to incorporate a diverse range of variables, including climate data, physiographic attributes, and socio-economic factors, allowing the model to maintain accuracy even when one or more variables are limited, such as the issue of cloud cover in satellite imagery. The RF model achieved the highest field assessment overall accuracy (0.88) with a high Kappa statistic (0.86), indicating excellent agreement between the model's predictions and ground truth data. This study highlights the importance of a multi-variable approach in ML models for LULC classification, which can significantly improve prediction accuracy by leveraging multiple data sources to overcome the limitations of relying on a single data source. Furthermore, these findings could influence local policies in Lombok by providing more accurate data to guide spatial planning, such as identifying areas for conservation, urban expansion, or agricultural development. Such data-driven decision-making supports sustainable land use management and environmental conservation efforts on the island.

Recommendation

It is recommended to integrate more diverse datasets, such as high-resolution temporal satellite data and detailed socio-economic indicators, to further enhance LULC classification accuracy. Additionally, exploring advanced ML techniques like deep learning could improve predictive capabilities in complex landscapes. For the Ministry of Environment and Forestry (MoEF), adopting a multi-variable with latest technology approach will significantly enhance the accuracy of land cover maps, leading to better land management and environmental monitoring across Indonesia.

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