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New Emerging and Comprehensive Land Mapping Unit at Detailed Scale: Integrating Random Forest Analysis and Remote Sensing Techniques for Sustainable Land Management

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Abstract

Precise and detailed land mapping is essential for sustainable land management, environmental conservation, and regional planning, especially in complex and diverse landscapes. This study aims to present an innovative framework for the development of Land Mapping Units (LMUs) at a detailed scale (1:20,000), through the integration of Random Forest (RF) analysis and high-resolution remote sensing data. This study was conducted in the South Malang Plateau, Indonesia (the area characterized by karst, tectonic, volcanic, and alluvial landforms) from June to December 2024. As part of the methodology, the study utilized a combination of geospatial data, including geological maps, DEM-derived topographical indices, and remote sensing indices (Normalized Difference Soil Index/NDSI, Soil Adjusted Vegetation Index/SAVI, Normalized Difference Water Index/NDWI, Modified Soil Adjusted Vegetation Index/MSAVI). A total of 10,903 field observation points were analyzed, with 70% used for model training and 30% for validation. The results show that RF-based LMUs achieved R^2 of 0.93 and Root Mean Square Error (RMSE) of 0.645, which is reliable to use. The LMUs provide a comprehensive understanding of landform-specific characteristics, including soil fertility linked to parent material, erosion sensitivity, and slope variability. These insights support applications in precision agriculture, disaster mitigation, and environmental planning. Moreover, the result can guide informed decision-making to prioritize sustainable land management that effectively prevents land degradation in the South Malang Plateau region, as stated in the Sustainable Development Goals (SDGs). The study demonstrates the potential of combining machine learning and remote sensing to refine spatial analysis and address the limitations of manual mapping methods. The proposed framework is scalable and adaptable to other diverse landscapes, making it a valuable tool for advancing sustainable land management in a rapidly changing world.

Keywords: geographic information systems; Land Mapping Units (LMU); machine learning; remote sensing; topography

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INTRODUCTION

Sustainable land management is the key to reduce the rates of land degradation and prevent desertification (Haregeweyn et al., 2023). Furthermore, sustainable land management is pivotal to the achievement of numerous objectives outlined in the Sustainable Development Goals

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(SDGs) including terrestrial ecosystem (SDG 15), food security (SDG 2) (Otekunrin et al., 2020), gender equality (SDG 5), and inclusive settlements and cities (SDG 11) (Zhan, 2023). However, effective and sustainable management requires accurate and detailed mapping of land resources to inform agricultural practices, environmental conservation, and regional development (Reddy and Singh, 2018; Mamo et al., 2022).

Mapping of land resources can usually be developed through Land Mapping Units (LMUs). LMUs play a principal role in understanding how landforms and natural resources are distributed over an area, providing key information about geology, terrain, hydrology, and soil properties. LMUs are useful for researchers, mapping experts, and policymakers as LMUs serve as a foundation for decision-making processes, however, the variability or homogeneity depends on the analysis scale and intensity (Dan et al., 2018; Zeraatpisheh et al., 2022). However, manual LMU mapping methods, specifically in Indonesia, frequently depend on manual digitization and coarse-resolution data (Mujiyo et al., 2018), such as soil maps at scales of 1:250,000 for regional and 1:50,000 for sub-regional planning (Brungard et al., 2015). Thus, limiting the ability to capture complex topographies and spatial variability, particularly in diverse landscapes, and also the subjectivity of the cartographer (Dan et al., 2018).

Advances in geospatial technologies, including Geographic Information Systems (GIS), remote sensing (Oyawale et al., 2020), and machine learning (Srivastava and Saxena, 2023), have significantly improved the accuracy and efficiency of land resource mapping (Bouguerra et al., 2023). These tools enable the integration of land elements derived from topographic and remote sensing data, enhancing the precision and scalability of LMU development (Bouguerra et al., 2023; Srivastava and Saxena, 2023). The integration of remote sensing and machine learning enhances environmental prediction by enabling large-scale, high-accuracy analyses (Ullah et al., 2024; 2025a). By offering finer spatial resolutions and integrating diverse data sources, it can address the limitations of manual LMUs (Wang et al., 2024), particularly in capturing the complexity of heterogeneous landscapes. Nikparvar and Thill (2021) emphasized the importance of handling spatial properties in machine learning, which aligns with this research integrating machine learning and high-resolution geospatial data for LMU classification in complex terrains. Trivedi et al. (2023) demonstrated the effectiveness of machine learning in land classification, particularly in heterogeneous landscapes. Their study highlighted the importance of feature selection and the integration of multisource remote sensing data to improve classification accuracy.

Among these techniques, the Random Forest (RF) algorithm has emerged as a robust machine-learning approach (Kasahun and Legesse, 2024). RF outperforms other machine learning algorithms in remote sensing, particularly for large and complex datasets. It achieves higher accuracy than Support Vector Machines (SVM) and Artificial Neural Networks (ANN), efficiently handles large data and requires minimal parameter tuning (Cracknell and Reading, 2014; Adugna et al., 2022). Its built-in feature selection improves classification accuracy, making RF a reliable choice for geospatial analysis. The approach is capable of effectively handling nonlinear relationships and processing large datasets, including the data derived from Digital Elevation Models (DEMs), geological maps, and vegetation indices (Phan et al., 2021; Aryal et al., 2023). Despite the significant potential, the application of RF for high-resolution (1:5,000 scale) LMU mapping remains underexplored, particularly in regions with diverse and complex landform characteristics, such as the South Malang Plateau.

The South Malang Plateau in East Java, Indonesia, is a distinguished area with geological and geomorphological diversity, including karst, old volcanic mountainous, tectonic, and alluvial landforms (Sahrina et al., 2022; Masruroh et al., 2024). Manual mapping techniques struggle to accurately delineate complex features, highlighting the need for innovative methodologies. This study aims to introduce a novel framework that integrates RF analysis with high-resolution remote sensing data to develop detailed LMU maps that are comprehensive, scalable, and application-specific. By addressing the limitations of manual approaches, the study supports sustainable land management practices. Focusing on the South Malang Plateau, the study provides actionable insights for precision agriculture, soil conservation, and environmental planning. The outcomes seek to bridge the gap between manual mapping techniques and modern demands for high-resolution and sustainable land management solutions.

MATERIALS AND METHOD

Study area

The study area was located in the South Malang Plateau which was included in the Southern Mountains Zone of East Java. Administratively, the research area is located in Malang Regency in the East Java Province, Indonesia or 112°17’ to 112°57’ west longitude and 7°44’ to 8°26’ south latitude and covers 99,642.01 ha. The average annual rainfall in the study area ranged from 0 to 314.60 mm and is included in type D climate based on the Schmidt-Ferguson classification system (Schmidt and Ferguson, 1951). The average annual air temperature ranged from 22.68 to 26.49 ℃ (on average 24.40 ℃) and had an annual average air humidity ranging from 58 to 97%.

Data collection

This research utilized multiple spatial datasets, including geological maps (Turen and Blitar sheets, 1:50,000), the national digital elevation model (DEMNAS, 8.25 m), and Sentinel-2 satellite imagery. The geological maps, published by the Geological Agency of Indonesia (https://geologi.esdm.go.id/geomap), provided lithological and structural information essential for landform classification (Bachri et al., 2023). DEMNAS, developed by Geospatial Information Agency (https://tanahair.indonesia.go.id/portal-web), integrated Interferometric Synthetic Aperture Radar (IFSAR) (5 m resolution), TerraSAR-X (5 m resampling resolution from the original 5 to 10 m resolution) and ALOS PALSAR (11.25 m resolution), offered high-accuracy elevation models (Patria and Putra, 2020). Sentinel-2 Level-2A imagery from the European Space Agency (https://browser.dataspace.copernicus.eu/) provided surface reflectance data across 13 spectral bands, with 10 m resolution for visible and near-infrared (NIR) bands, crucial for vegetation and terrain analysis (Wang et al., 2016). The integration of these datasets enhanced the precision of landform mapping, supporting high-resolution LMU classification.

Mapping units

This study tested two different mapping unit methods: 1) manually delineated LMUs and 2) units described using RF analysis. The overall workflow with analysis steps is illustrated in Figure 3.

LMU classification

The classification of LMUs adhered to established guidelines, incorporating both the sub-landform codes and their corresponding names. This process was conducted following the classification standards outlined by the Center for Soil and Agroclimate Research in 1997. For instance, in “V.1 Volcanic Intrusion of Plains, a” where V.1 represents the code, Volcanic Intrusion of Plains is the name, and “a” indicates the relief type.

Manual LMU

Creating a manual LMUs in the South Malang Plateau area, a map of land characteristics was integrated. This method was carried out by overlaying or superimposing the three maps and manual delineation. The manual LMU delineation process involved interpreting topographic maps, aerial photographs, geological maps, and climate maps to define the boundaries of LMU. In detailed mapping, boundary lines were drawn in the field based on soil properties, environmental factors, and changes in slope, land use, or vegetation. In semi-detailed mapping, delineation was conducted on topographic maps or aerial photographs supported by geological and climate maps (Sukarman and Ritung, 2013).

The overlay method was carried out by grouping areas that show similar characteristics into the same land unit. This overlay method facilitated the combination of several thematic maps, such as geology, slope, and relief maps, in one unified coordinate system. This approach allowed the integration of diverse data sets, resulting in more comprehensive and accurate land classification. The LMUs produced by this manual method were used to determine the observation point. This observation point was used as material in running the next LMUs analysis model using the RF method. Observation points were spread across each boundary in various landforms with a total of 10,903 points, karst 41.35%, tectonic 18.03%, volcanic 39.42%, and alluvial 1.20% (Figure 1).

LMU using RF analysis

The next method for creating LMUs was through RF analysis. This method required a set of input layers for segmentation. Geological data, DEM-derived data (relief, slope, and curvature), remote sensing-derived data (Normalized Difference Soil Index/NDSI, Soil Adjusted

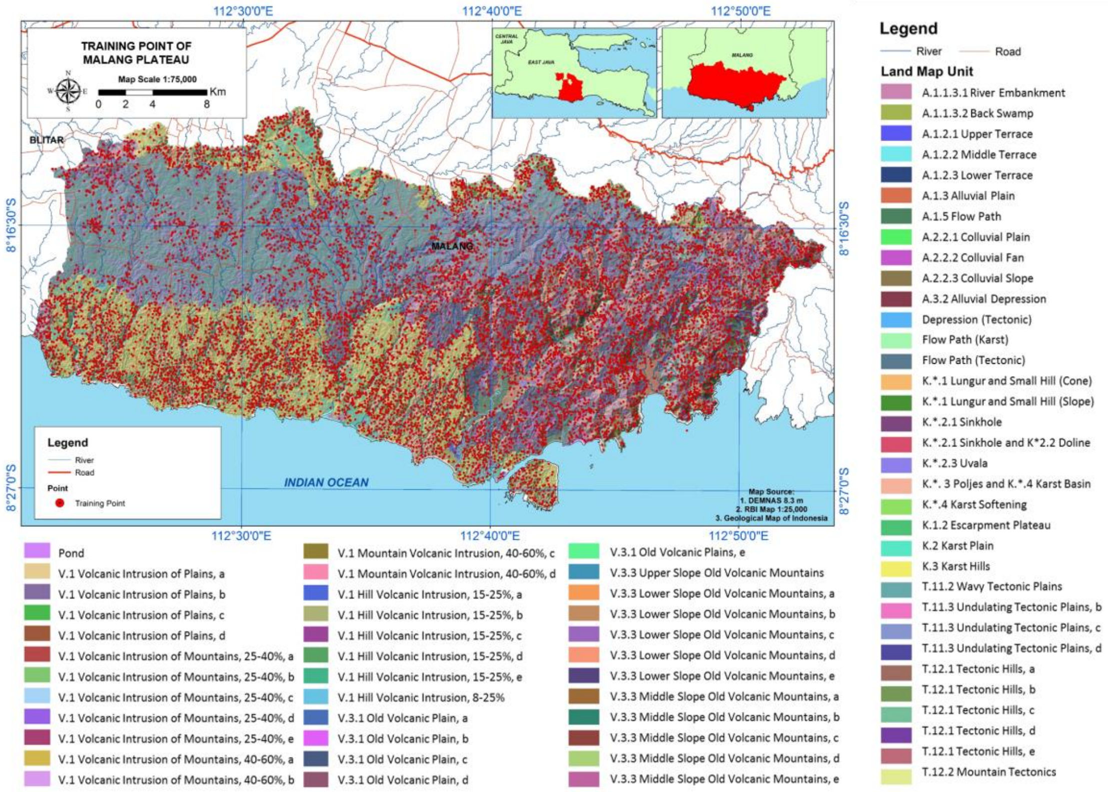


Figure 1. The distribution of observation points for training the model

Vegetation Index/SAVI, Normalized Difference Water Index/NDWI, and Normalized Difference Vegetation Index/NDVI) as well as landform identification observation points in the field were subjected to multicollinearity analysis in RF algorithm. Topographic Position Index (TPI) or relief slope, and curvature (DEMNAS) data were derived from DEMNAS data, which were obtained using the TPI (Weiss, 2001) and Spatial Analyst method. Four transformation indices derived from satellite imagery in the form of NDSI, SAVI, Modified Soil Adjusted Vegetation Index (MSAVI), and NDWI were used in this research (Figure 2). This transformation indices analysis was carried out using ArcGIS 10.8 software. The formulas for NDSI, SAVI, NDWI, and MSAVI are expressed by Equations 1, 2, 3, and 4, respectively.

$$\text{NDSI} = \frac{\text{G-R}}{\text{G+R}} \quad (1)$$

$$\text{SAVI} = \frac{\text{NIR-R}}{\text{NIR+R}}\ (1+\text{L}) \quad (2)$$

$$\text{NDWI} = \frac{\text{G-NIR}}{\text{G+NIR}} \quad (3)$$

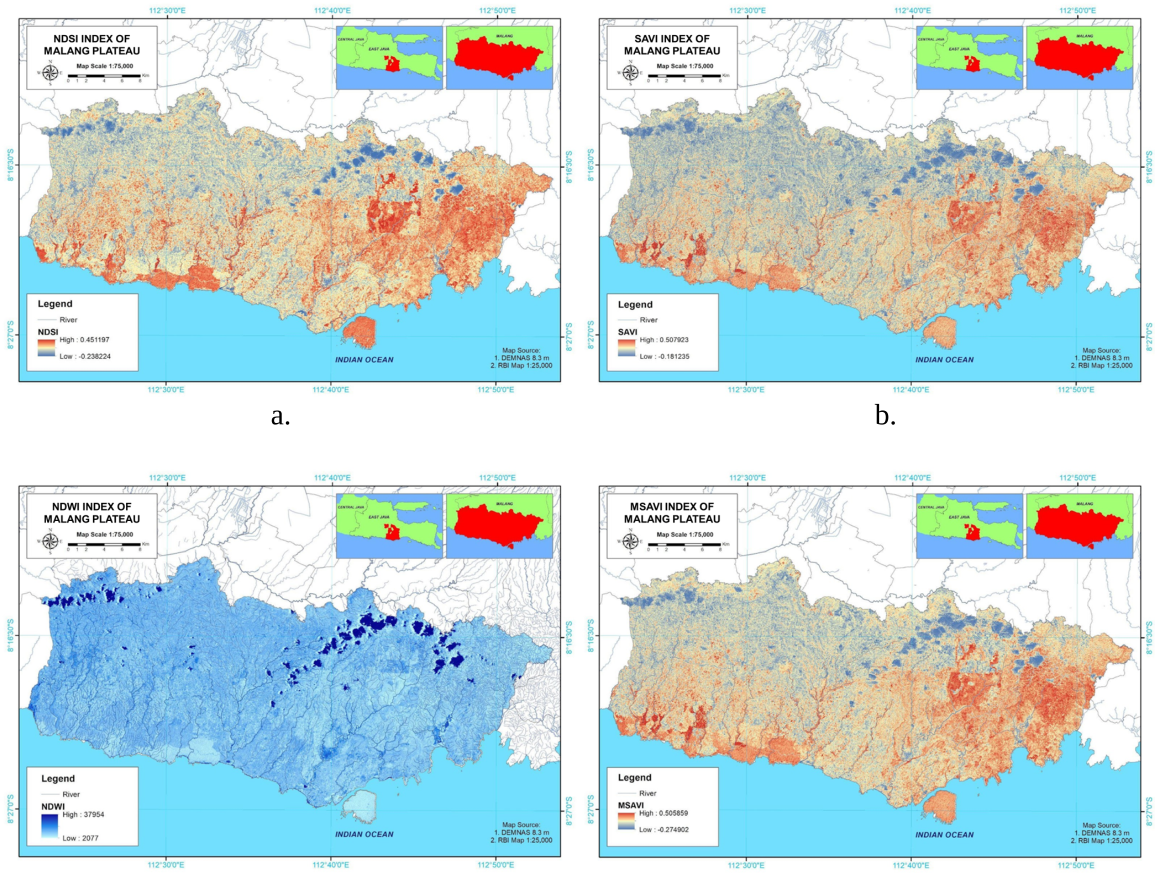
$$\text{MSAVI} = \frac{2\text{NIR} + 1 - \sqrt{(2\text{NIR}+1)^2 - 8\ (\text{NIR-R})}}{2} \quad (4)$$

Where G is the reflectance in the green band, R is the reflectance in the red band, NIR is the reflectance in the near-infrared band, and L is the soil brightness correction factor, commonly set to 0.5 for moderate vegetation density.

The identified points in the field were used to run the RF algorithm. As much as 70% of observation points were used for model development and 30% were used for model validation. This analysis was carried out using Forest-based Classification and Regression tools in ArcGIS Pro 3.4.0 software.

Contribution analysis of variables composing LMUs

To assess the relative contribution of each variable used in the delineation of LMUs, Principal Component Analysis (PCA) was done (Jolliffe and Cadima, 2016). PCA is a multivariate statistical technique commonly used to reduce data dimensionality while retaining most of the variation present in the dataset. The analysis



a. b.

c. d.

Figure 2. Transformation index of (a) NDSI, (b) SAVI, (c) NDWI, and (d) MSAVI

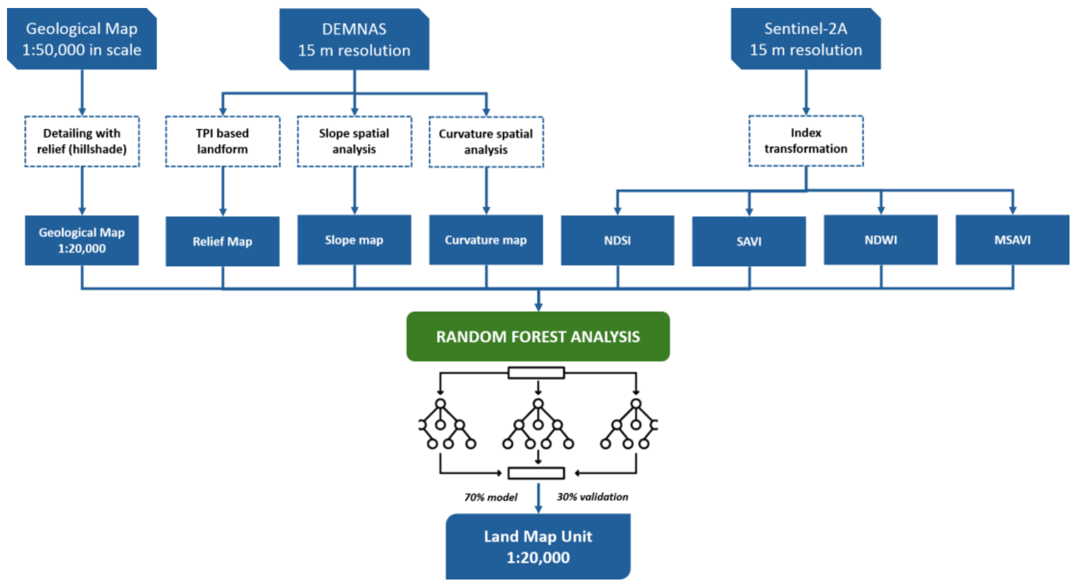


Figure 3. Research flow for compiling LMUs using a machine learning algorithm

was conducted using RStudio, which provides robust statistical tools and visualization packages for exploratory data analysis. In this study, the variables considered for PCA include geology, relief, slope, curvature (DEMNAS), NDSI, NDWI, MSAVI, and SAVI.

Accuracy assessment

Two performance measures, including R^2 and Root Mean Square Error (RMSE), were considered to ensure the model's stability and reliability. R^2 represents the percentage of variation explained by the model. Meanwhile, RMSE shows the overall accuracy of predictions. The formulas to calculate R^2 and RMSE are presented as Equation 5 and Equation 6.

$$R^2 = 1- \frac{\sum_{i=1}^{n}\left(Y_{actual}-Y_{predicted}\right)^2}{\sum_{i=1}^{n}(Y_{actual}-\bar{Y}_{actual})^2} \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{actual}-Y_{predicted})^2} \qquad (6)$$

Where $Y_{predicted}$ and Y_{actual} are the predicted and observed proportions of dye-stained areas, n is the number of samples, and $Y_{predicted}$ and Y_{actual} are the means for the predicted and observed proportion of dye-stained areas. A good model typically has an R^2 close to 1 and an RMSE of almost 0 (Wang et al., 2018).

RESULTS AND DISCUSSION

Formation process of the South Malang Plateau and its effect on sustainable land management

Land formation in the South Malang Plateau has undergone a series of uplift, erosion, and sedimentation over millions of years ago, resulting in a complex topography. The South Malang Plateau area is dominated and initiated by tectonic influences, which are marked by the presence of several faults. Tectonic activity is estimated to have started in the Late Oligocene when this area was still land or shallow sea. Followed by magmatic activity which is thought to have occurred due to the subduction between the Indian Ocean Plate under the Southeast Asian Continental Plate, so that the layers of sedimentary rock and tuff are composed of the Mandalika and Wuni Formations.

The South Malang Plateau area continued to undergo sedimentation until the Late Miocene, accompanied by the formation of carbonate sediments forming the Wonosari Formation, which is composed of limestone, coral, and claystone. At the end of the Tertiary, tectonic uplift occurred, causing the entire surface area to be elevated, accompanied by faulting and mild folding. Erosion by river flow continued to occur on old rocks up to the Wonosari Formation, resulting in alluvium deposition. The river flow in the South Malang Plateau area is generally trellis-type, with relatively wide valleys and cliffs that vary from steep to gentle. The trellis river flow pattern is typically found in areas with layers of folded mountain sediments with large slopes, characterized by channels that are parallel in pattern, flowing in the direction of the slope and perpendicular to the main river (Lihawa, 2017).

The study highlighted that the South Malang Plateau has unique characteristics shaped by its formation process, including shallow soil depth, which makes it vulnerable to water scarcity. Few cash crops can thrive in this region, and the area faces a significant risk of desertification. As a result, many residents migrate to larger cities, leaving the South Malang Plateau as an underdeveloped area. Despite its low soil fertility due to its shallow depth, this karst region is strategically important as a coastal area and provides valuable ecosystem services. This is in line with a previous report by Soedwiwahjono and Pamardhi-Utomo (2020) that karst is a strategic area due to it has economic, scientific, and humanitarian values related to livelihoods for sustainable land management. Even though the karst ecosystem provides essential ecosystem services, including habitat for terrestrial and aquatic biodiversity (tree cover, ponds, and caves), it is increasingly threatened by limestone mining, agriculture, and large-scale infrastructure development. The rapid expansion of tourism infrastructure has intensified environmental pressures (Reinhart et al., 2023). Therefore, conducting detailed land mapping and obtaining accurate mapping data by understanding and considering the processes of landscape formation are essential. These efforts can guide informed decision-making, prioritize sustainable land management, and effectively prevent land degradation in the South Malang Plateau region.

Geology of the South Malang Plateau and its effect on sustainable land management

The geological distribution map in the South Malang Plateau was made based on the detailed 1:100,000 scale geological sheets of Turen and Blitar (Table 1). The geological formations in the South Malang Plateau area consist of various types of rocks and formations that form in various landforms. The Wonosari Formation is the dominant geological formation in the Malang Plateau, covering an area of 33,572.85 ha (33.72%) and composed of rocks, namely limestone, sandy marl, and claystone inserts. The Wonosari Formation is found in karst landforms that are identical to limestone. Limestone is a rock that is easily dissolved, resulting in the presence of holes around the body of the rock (Figure 4).

Soil geochemical and physical properties are strongly influenced by geological parent material,

Table 1. Geological data of the South Malang Plateau

Geology	Abbreviation	Area coverage	
		ha	%
Alluvium and Beach Sediment	Qal	486.60	0.48
Swamp and River Sediment	Qas	1,377.65	1.38
Campurdarat Formation	Tmcl	3,817.17	3.83
Nampol Formation	Tmn	29,013.87	29.14
Wuni Formation	Tmw	6,365.65	6.39
Wonosari Formation	Tmwl	33,572.85	33.72
Intrusive Rock	Tomi	2,087.37	2.09
Mandalika Formation	Tomm	16,120.04	16.19
Mandalika Formation Tuff Member	Tomt	6,713.39	6.74
Total		99,554.59	100.00

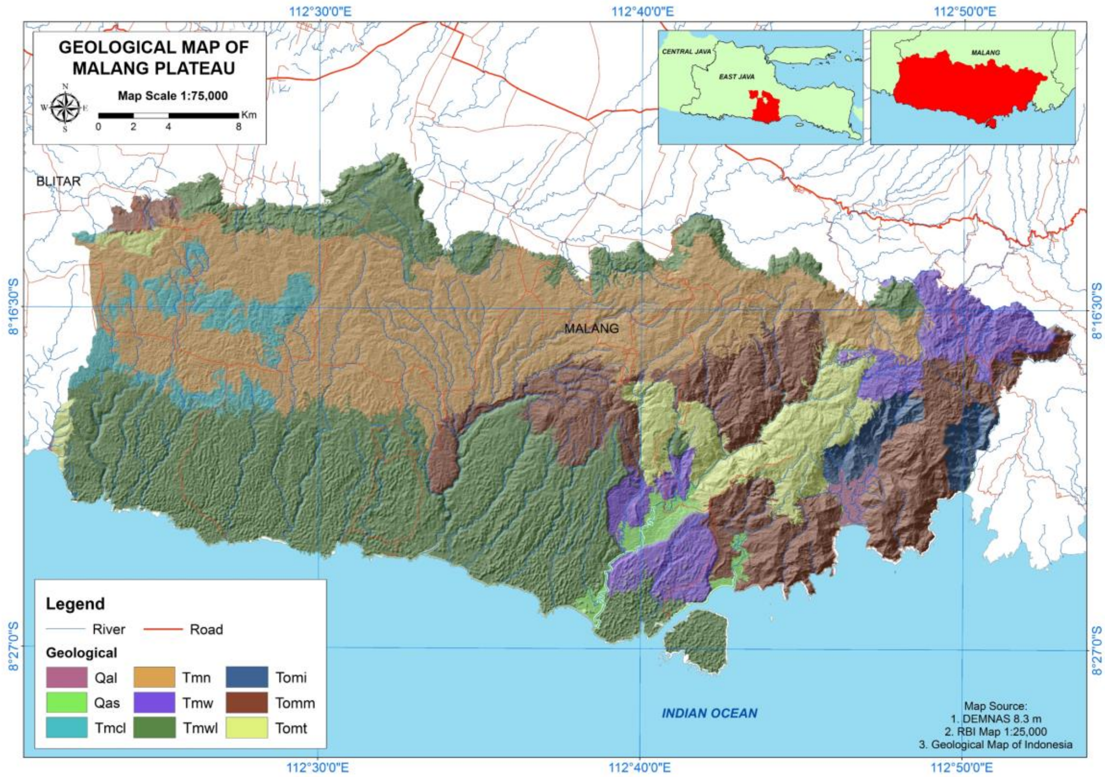


Figure 4. Geological map of the South Malang Plateau

making geology a crucial determinant of soil characteristics (Simon et al., 2021). Thus, geological maps are often utilized to infer soil properties. Similarly, previous studies such as Barré et al. (2017) highlighted the influence of geology on soil organic matter and nitrogen stocks, and Kirkpatrick et al. (2014) demonstrated the predictive value of geological data for regional soil chemical properties. These findings underscore the impact of geological conditions on soil variability, providing essential insights for integrating geological data into sustainable land management. Additionally, the relationship between geology and soil extends to water quality, as catchment geology often determines nutrient concentrations in headwaters, aiding in the identification of environmentally sensitive areas (Djodjic et al., 2021).

This study highlights that LMUs at a detailed scale can provide a comprehensive representation of the geological characteristics of the South Malang Plateau. This enables in-depth analysis of the geology and supports planning efforts by providing critical information on soil fertility and its relationship to parent material, as well as assisting in disaster mitigation and identification of safe zones for disaster preparedness on the South Malang Plateau. For example, Mandalika Formation covers 16.19% of the South Malang Plateau, an area vulnerable to water scarcity and erosion, low soil depth, and high soil fertility. In addition, Wonosari Formation covers 33.72% of the area, which is predominantly a high-slope area with high erosion sensitivity. These special areas required special management. The detailed-scale LMU provides crucial data for sustainable soil and land management, supporting multiple SDGs. With rising demands on land resources, integrating LMU data into a systemic research framework enables targeted management, innovation, and policy support. This approach promotes sustainable land use while balancing trade-offs and synergies (Löbmann et al., 2022).

Relief of the South Malang Plateau and its effect on sustainable land management

The relief conditions in the South Malang Plateau area exhibit unique characteristics ranging from flat to hilly. The relief map displays graphics and features of the earth's surface including curvature, slope, and landform. Relief mapping and classification in the South Malang Plateau were carried out using TPI (Table 2 and Figure 5). The most extensive relief category is class c (plains), covering an area of 56,807.8 ha across the region. The valleys in this area were formed by erosion processes and karst activity with steep scarp slopes and relatively flat bases. These valleys often serve as drainage pathways during the rainy season. The surrounding slopes, which are typically found along valley edges and ridgelines, are steep and sparsely vegetated, making them highly susceptible to erosion, particularly during periods of heavy rainfall. Plains in this area are relatively flat with little variation in height, often used for agricultural and residential activities due to easy access and lower

Table 2. Relief data of the South Malang Plateau

Class	Relief	Area coverage	
		ha	%
a	Valley	2,899.76	2.91
b	Slope	17,802.73	17.88
c	Plains	56,807.80	57.06
d	Hills/Mountains	17,078.22	17.15
e	Small ridges	4,966.08	4.98
Total		99,554.59	100.00

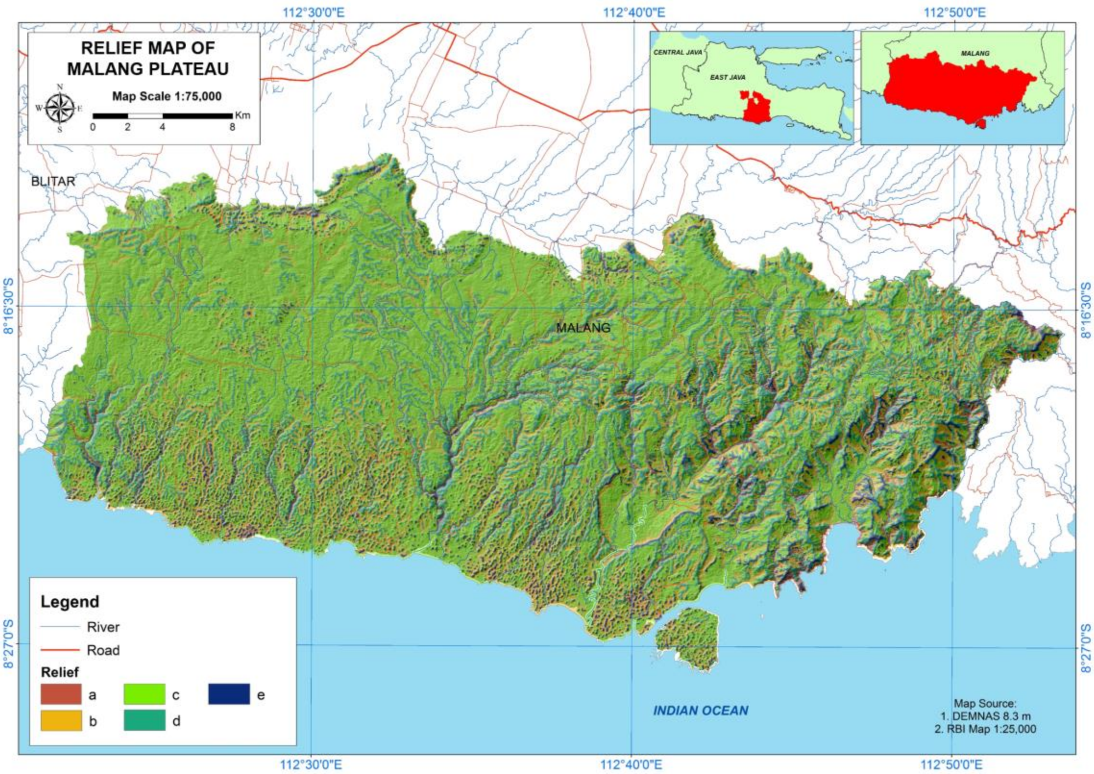


Figure 5. Relief map of the South Malang Plateau; a) valley; b) slope; c) plains; d) hills/mountains; e) small ridges

risk of erosion. Hills/mountains have moderate to high slopes and are usually covered with denser vegetation. Small ridges in this area have varying slopes and are often covered with dense vegetation. Ridges serve as water flow dividing lines in this area.

Relief is a key factor in defining soil properties and in shaping sustainable land management strategies. Variations in terrain, such as steep slopes and mountain relief, often lead to soil erosion, reducing soil depth, compromising structure, and diminishing fertility, thereby hindering vegetation growth and land productivity (Fidelus-Orzechowska et al., 2021). On flatter terrains, relief affects water and sediment flow, influencing soil horizon development and soil quality (Woś and Pietrzykowski, 2021). This study revealed that even though the South Malang Plateau is mainly a plain area (57.06%), improper land management in the upper watershed area leads to degradation. For example, the expansion of oil palm plantations in the area can exacerbate water scarcity, as oil palms require substantial amounts of water for their growth and development. Previous studies present both advantages and disadvantages regarding the expansion of oil palm plantations in the area (Sumarmi et al., 2022; Wicaksono et al., 2023). Thus, providing LMUs at a detailed scale at the South Malang Plateau by integrating RF analysis and remote sensing techniques can map the area that should be developed or maintained as a conservation area according to its relief, particularly in a rapidly changing world. This study aligns with a previous study by Mersha et al. (2024) who emphasized that effective land use planning and conservation strategies are crucial for ensuring the long-term sustainability of ecosystems.

Slopes of the South Malang Plateau area and its effect on sustainable land management

The South Malang Plateau area has various slope conditions ranging from flat to hilly slopes (Table 3 and Figure 6). The slope of the South Malang Plateau has different levels in each landform. However, it can be seen that the dominant slope is relatively flat. Tectonic and alluvial landforms are dominated by flat slopes (0 to 3%) to gentle slopes (8 to 15%) with an area of 2,556.39, 13,089.78, and 25,299.36 ha, respectively, so quite a lot of these areas are used as optimal land use, for agricultural activities, settlements, and infrastructure development. In contrast, volcanic landforms, which are dominated by slightly steep slopes (15 to 25%) to steep (25 to 40%) with an area of 28,184.85 and 20,390.05 ha, reflect the presence of active geomorphological processes, such as uplift and volcanic activity in the past. For agricultural development, the area requires thorough exploration to assess and enhance its agricultural resilience, ensuring sustainable and adaptive practices for future challenges (Rozaki et al., 2023). This condition generally produces a more dynamic topography with a higher potential for disasters and land management that needs to be considered. The slope is stated as one of the factors that influence the variation of landforms in various regions, with a value of 38.46% recorded throughout the Malang Plateau region. The slope of the land in this area is often not too steep, but its wavy and hollow surface makes the karst area require proper management to be optimally utilized, especially for agriculture and infrastructure development.

Accurate LMUs developed through the integration of RF analysis and remote sensing, as demonstrated in this study, offer significant potential for future advances. With the methods used here, scientists can further develop predictive models to simulate the movement of soil materials, including the transport of organic carbon. Such models will improve understanding of soil dynamics, particularly how the redistribution of organic carbon affects soil fertility. This approach can serve as a critical tool for improving soil management practices and ensuring long-term agricultural productivity and ecosystem sustainability. For example, in Southeast China, the integration of RF and Deep Learning successfully provides accurate soil type maps that are an important basis for agricultural decision-making and land degradation control (Bao et al., 2024).

Table 3. Slope data of the South Malang Plateau

Class	Slope	Area coverage	
		ha	%
0–3	Flat	2,556.39	2.56
3–8	Slightly gentle	13,089.78	13.14
8–15	Gentle	25,299.36	25.41
15–25	Slightly steep	28,184.85	28.31
25–40	Steep	20,390.05	20.48
40–60	Very steep	8,223.25	8.26
> 60	Rough	1,808.94	1.81
	Total	99,554.59	100.00

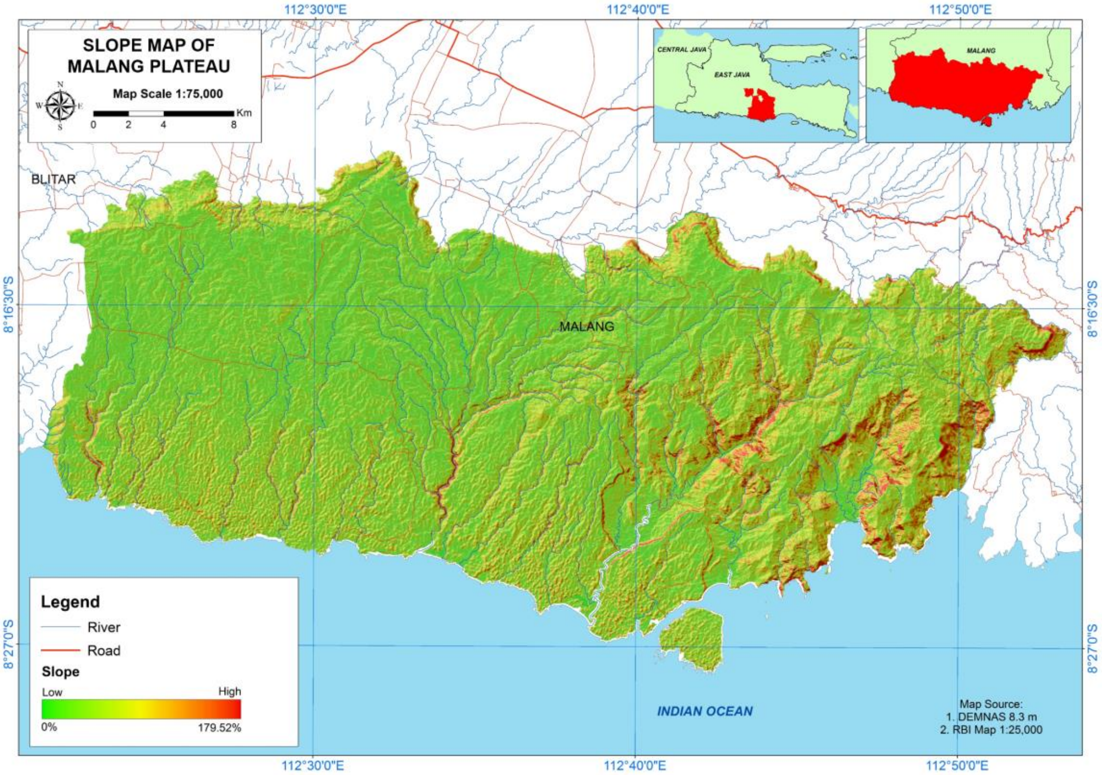


Figure 6. Slope map of the South Malang Plateau

Manual LMU and its limitation for sustainable land management

LMUs of the Malang Plateau were divided into four different landforms, namely alluvial, karst, tectonic, and volcanic (Figure 7). Manual LMUs based on factors such as climate, topography, parent material, geology, soil, and vegetation, often operate at coarse scales, typically at 1:1,000,000 for national mapping. Conversely, the integration of RF and remote sensing can develop LMUs at a detailed scale, 1:20,000 in this study. In the manual method, the map only provides broad geographic coverage and consistent data representation, and this is unable to reflect detailed spatial variability, particularly regarding soil parent material and related attributes in regions with complex landscapes. In Indonesia, where diverse topography and high soil heterogeneity prevail, such coarse-scale mapping proves inadequate for addressing localized land management challenges. This lack of precision limits the implementation of sustainable, data-driven land-use strategies, emphasizing the need for more detailed and region-specific mapping approaches (Heung et al., 2014).

LMU using RF analysis and its pivotal benefit for sustainable land management

The result of this study emphasized that in karst landforms, RF can detect complex boundaries and inconsistencies in manual delineation, identify small hills (conical hills) and sinkholes, and detect errors when data information is lost (Figure 8) faster and more accurately than the manual method. The LMUs developed in this study demonstrated high accuracy, with an R^2 of 0.93 and an RMSE of 0.645.

In the tectonic landforms, located on the central and northern South Malang Plateau, the RF algorithm used in this study effectively identified various landform features, refined inaccurate boundaries, and enhanced the distinction of sequential landforms and generalized relief features, resulting in smoother and clearer representations compared to manual methods (Figure 9). Also, the results closely aligned with manual delineations for river sections, with minimal discrepancies, confirming the reliability of mapping fluvial features.

In alluvial landforms located on the southern part of the South Malang Plateau, the RF used

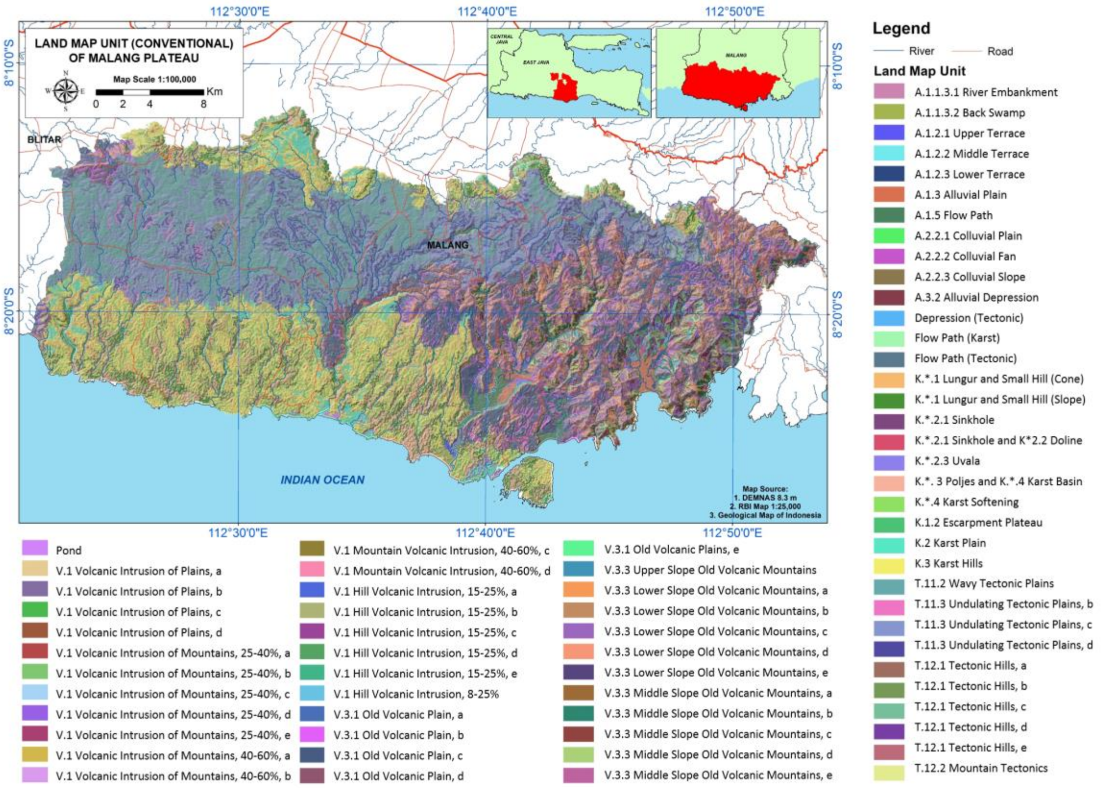


Figure 7. LMU result from manual analysis

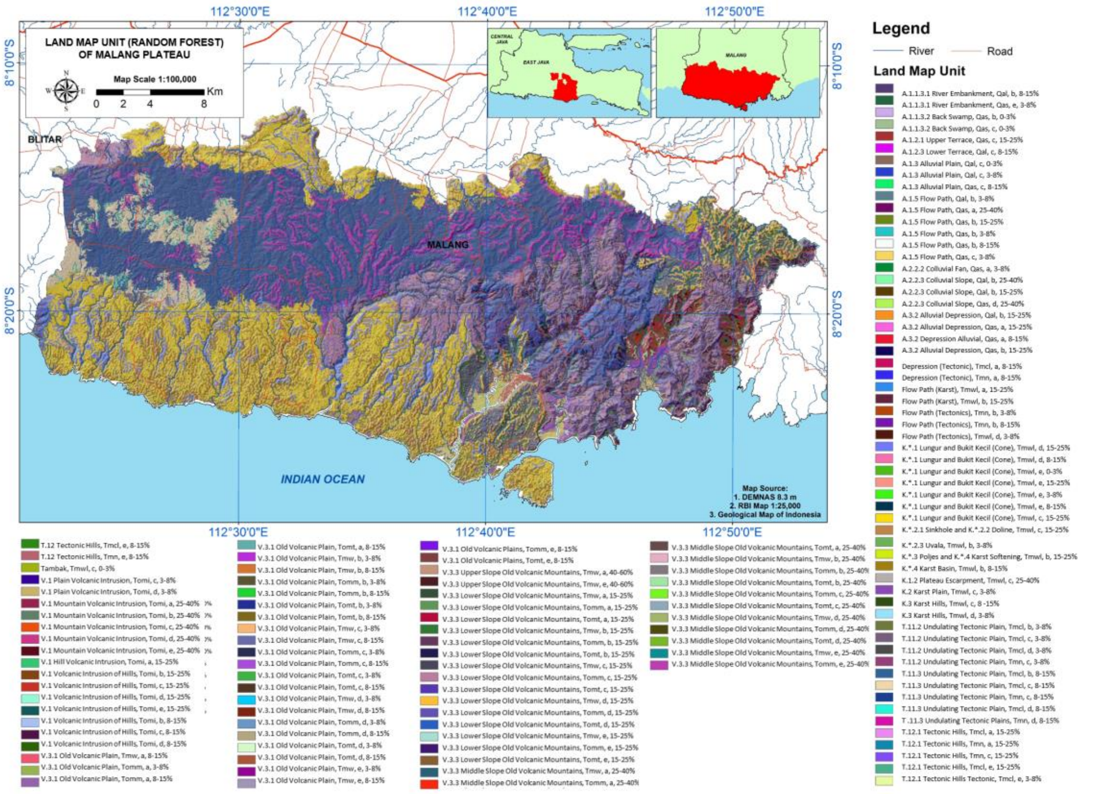


Figure 8. LMU result from RF analysis

in this study found high similarities in the division of river parts with manual digitization results. In addition, complex and unclear boundaries that result from manual delineation of slope differences are significantly refined using the RF system, improving mapping precision.

In old volcanic landforms on the eastern part of the South Malang Plateau, the RF algorithm used in this study demonstrated excellent capability in distinguishing topo-sequences, which is essential for further applications requiring detailed topographic data. In addition, RF can distinguish topo sequences in volcanic landforms, especially old volcanic areas, which are very much needed for further analysis. The ability to differentiate among upper, middle, and lower slopes, as well as plains, is particularly valuable for subsequent analyses. Moreover, RF-derived boundaries align closely with manually delineated contours, confirming the ability to enhance spatial accuracy and consistency.

The RF algorithm used in this study also corrects poorly defined or overly intricate boundaries often produced by manual delineation methods. This study aligns with a previous study by Kuhn and Johnson (2013), who reported that RF has a high level of sensitivity to uninformative data so that errors in the data can be reduced. Also, this study revealed that in regions like sloping plains, distinctions in slope and slope positions are often overlooked when using manual delineation techniques. However, the RF algorithm may produce slightly different boundaries because it clusters objects with similar characteristics into a single unit.

This study proved that RF classifier provides significant advantages for mapping applications, which is in line with a previous study by Heung et al. (2014), especially when dealing with complex and heterogeneous datasets, thus, improving the precision and reliability of spatial predictions, such as soil taxonomic units and parent materials. The scalable application of this study is not limited to mapping karst landforms with their unique features such as conical and sinkholes, but also to vegetation mapping such as plant invasive species (Matyukira and Mhangara, 2024; Zaka and Samat, 2024). The advances of this study need to be further extended, particularly in the context of soil properties, to develop accurate soil mapping. Such mapping is crucial for improving agricultural productivity, land use planning, ecosystem conservation, and environmental management, especially in complex karst landscapes where soil properties significantly influence land management practices.

Contribution of geology, slope, and relief indexes to the development of LMUs

PCA analysis revealed important insights into the contribution of different variables to the principal components and their potential impact on LMU prediction using RF analysis (Figure 10). The first principal component (PC1) accounted for 99.97% of the variance, highlighting that most of the data variability was captured along this axis. DEMNAS (curvature) and slope were highly aligned with PC1, making them the most influential variables in explaining the overall variance. This underscores their important role in LMU prediction, as topographic features such as curvature and slope are known to determine water distribution, soil characteristics, and vegetation suitability, which are important in land management.

In contrast, NDSI and geology contributed predominantly to PC2, explaining only 0.02% of the variance. Although their overall effects are smaller than those of PC1, these variables likely capture local or context-specific variation that is relevant to LMU delineation. For example, geological features have a significant impact on soil composition and fertility, while soil indices such as NDSI are particularly important in regions where soil affects vegetation and water availability. Vegetation indices such as MSAVI, SAVI, and NDWI, on the other hand, negatively affected PC1, suggesting that they may have a smaller impact on broad patterns of variability. However, these indices are critical in small-scale predictions, particularly for understanding vegetation health, biomass, and water content, which are often important in agricultural and ecological assessments.

Interestingly, the relief showed minimal influence on PC1 and PC2, indicating its limited contribution to variance in this dataset. This may indicate that while it plays a role in certain contexts, relief is not the primary driver of LMU prediction here. This PCA insight aligns closely with the RF variable importance metrics, where DEMNAS (curvature) and slope are expected to emerge as top predictors due to their dominant variance contributions. In contrast, variables such as relief may play a smaller role, and vegetation indices, despite their lower PCA contributions, may improve LMU prediction in areas with dynamic vegetation patterns.

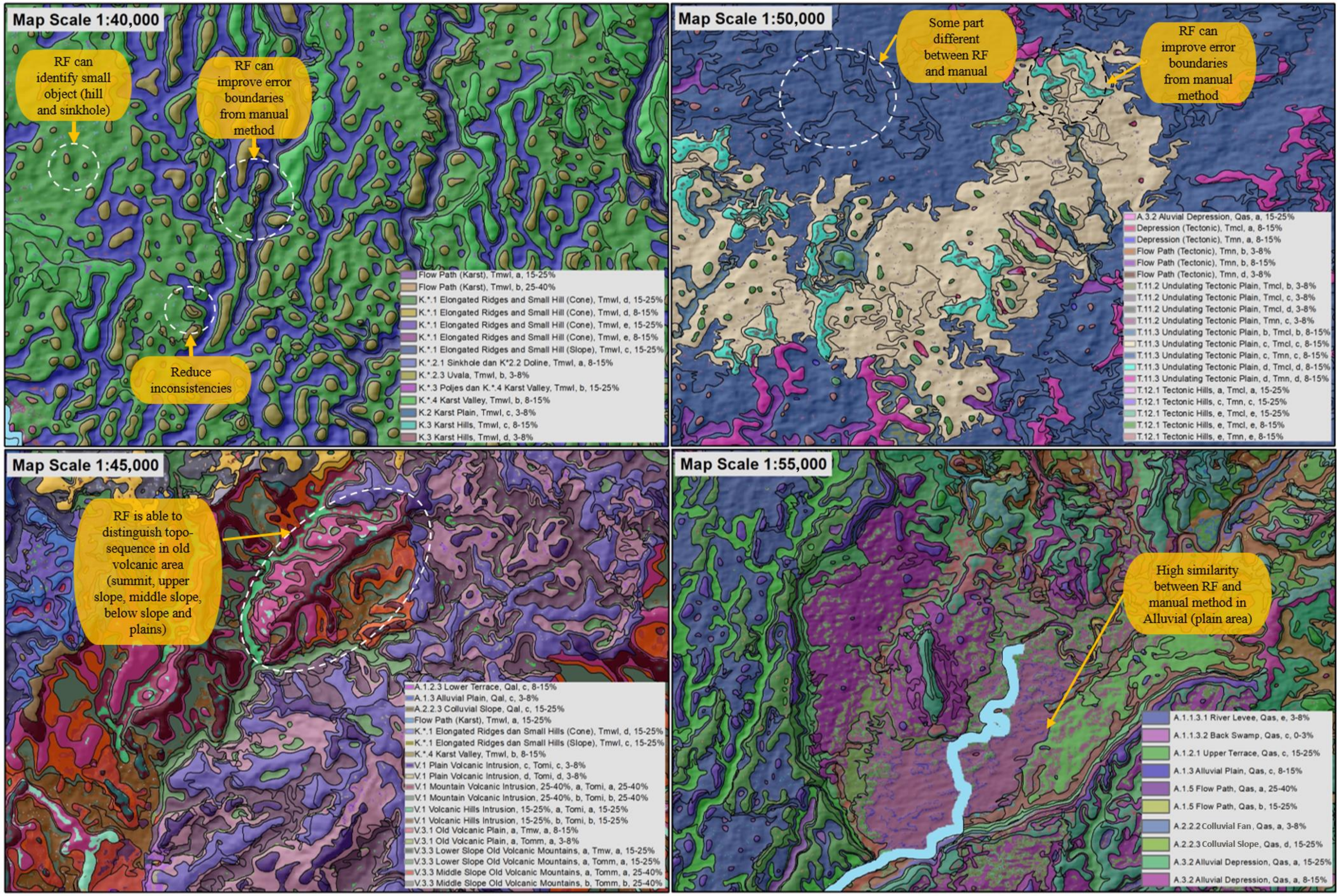


Figure 9. Advantages and limitations of the RF analysis for LMU

The implication of study and recommendation for future sustainable land management in diverse and complex landforms

Landforms delineate spatial units that provide critical insights into ecological environments, natural resource distribution, and soil formation processes (Fang et al., 2019). Their importance in broader environmental systems and sustainability efforts is well-established. Modern studies have advanced landform identification using geomorphic attributes such as altitude, slope, aspect, and curvature, combined with artificial intelligence technologies. Machine learning models, including RF, have significantly improved the accuracy of landform mapping (Zhao et al., 2017; Du et al., 2019), with the RF method's ability to automatically select relevant features underscoring its utility in such studies.

This study successfully developed detailed LMUs at a scale of 1:20,000 for the South Malang Plateau, achieving over 93% accuracy by integrating RF analysis with high-resolution remote sensing data. The use of geospatial data, including geological and topographical features, enabled precise delineation of landforms such as karst, tectonic, volcanic, and alluvial landscapes. Karst landforms exhibited the highest mapping accuracy, while tectonic landforms were less precise due to DEM limitations. This study is supported by previous findings that using the combination of remote sensing and machine learning has proven to be a powerful approach for analyzing environmental prediction across different regions. For example, this approach has been successfully applied in Pakistan's Buner and Shangla Districts (Ullah et al., 2025b), Multan and Sargodha Cities (Zhang et al., 2025), and the Manchar Lake wetland complex (Chaoyong et al., 2024). These studies demonstrated how integrating satellite imagery with advanced computational models enables accurate monitoring of spatial and temporal patterns, which reinforces the effectiveness of remote sensing and machine learning in large-scale environmental assessments, providing valuable insights for sustainable land and resource management in various geographical settings.

Moreover, this study's findings underscore the critical role of accurate and detailed mapping for sustainable land management. LMUs provide essential information on soil

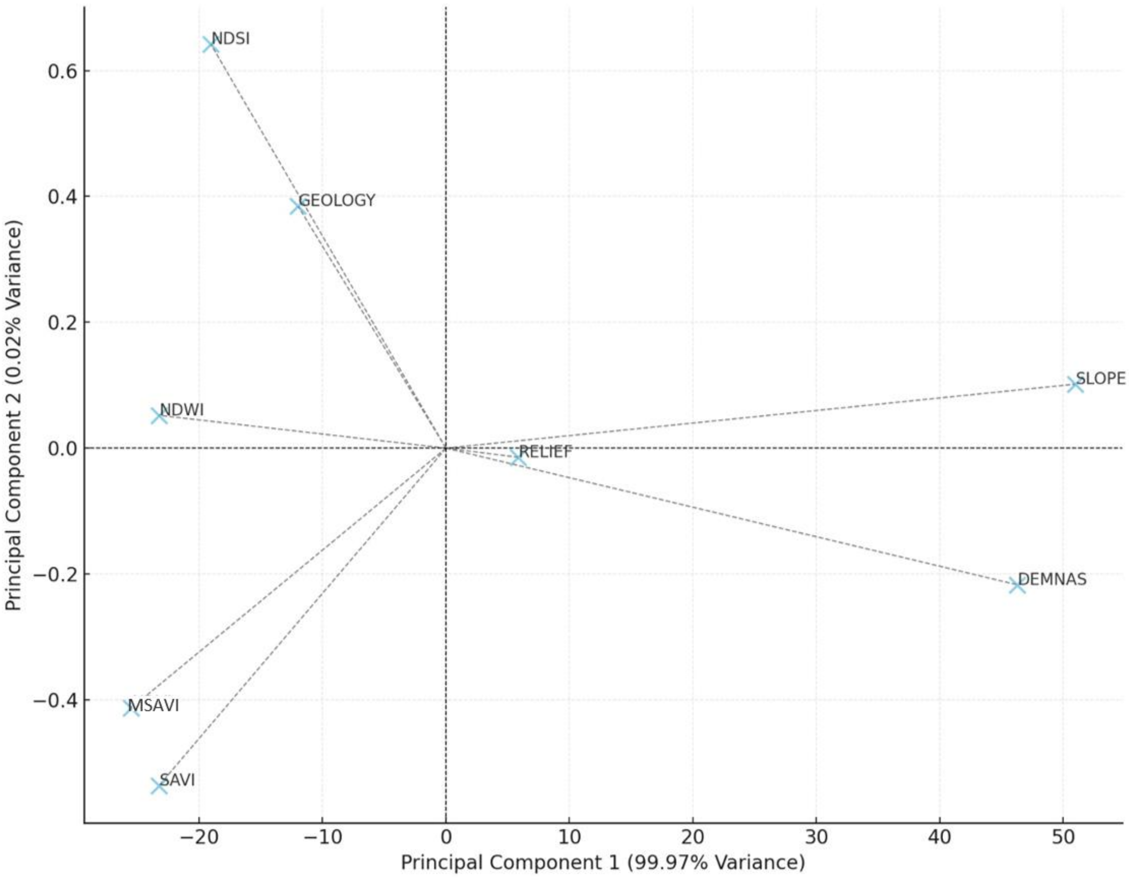


Figure 10. PCA of LMU using RF algorithm

fertility, erosion vulnerability, and landform-specific challenges, supporting applications such as precision agriculture, disaster mitigation, and environmental planning. For instance, karst regions with high slopes and erosion sensitivity require specialized conservation strategies, while tectonic areas need improved mapping techniques to ensure sustainable practices. Similar studies emphasized the importance of integrating geospatial technologies into land management. For instance, Reddy et al. (2018) demonstrated how RF and GIS analysis improved land resource mapping and agricultural land use planning, while Binte Mostafiz et al. (2021) highlighted the effectiveness of integrating topographic and vegetation indices for land suitability assessments. These studies also align with the findings of the present study, which suggested that incorporating geology, topography, and vegetation indices enhances decision-making in land management. To strengthen policy implications, this study recommends adopting LMU-based zoning regulations, incorporating LMU mapping into national land-use policies, investing in advanced mapping technologies, and strengthening land rehabilitation guidelines. Future research should incorporate additional environmental variables and advanced algorithms to improve the scalability and applicability of LMU mapping for diverse landscapes. This study's findings also highlighted the importance of advanced mapping techniques for post-mining rehabilitation, soil conservation, and water resource management, contributing to global sustainability goals and ecosystem restoration efforts.

CONCLUSIONS

The results of LMUs at a scale of 1:20,000 in the South Malang Plateau using the RF machine learning algorithm achieved a good accuracy, which is 0.93 for R^2 and 0.645 for RMSE. Curvature and slope are the variables with the highest contribution to the preparation of the LMUs map. This result could be a breakthrough in objectively compiling LMUs to replace the manual digitization that had been done less objectively. The result can guide informed decision-making to prioritize sustainable land management and effectively prevent land degradation in the South Malang Plateau region, as stated in the SDGs. Future research could incorporate a broader range of continuous and categorical covariates to further enhance mapping accuracy and efficacy. The limitation of this study was the inability to develop landform classes that were not captured by the available data, highlighting the need for additional data to improve model quality in future research.

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