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Mesolandform classification and its relationship with smallholder coffee production in the Malang Regency, Indonesia

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ABSTRACT

Mesolandform analysis is necessary for smallholder coffee land management because it can clearly distinguish landform boundaries. Automatic mesolandform classification utilizes geographic information system (GIS) and remote sensing technology using the topographic position index (TPI), slope, curvature, lithology, land use, and normalized difference vegetative index (NDVI). This study aims to classify the mesolandform of smallholder coffee plantations and determine its relationship attributes with coffee production. The data included the Digital Elevation Model, lithology map, Sentinel 2 A harmonized image, and actual coffee production. The spatial analysis was performed using ArcGIS 10.8 and QGIS 3.1.6, and the statistical data analysis was performed using RStudio. Mesolandform affects coffee production ($p < 0.0001$) and was significantly related to it. The highest production was found on the open slope mesolandform, with coffee production ranging from 7.13 to 9.95 tons/ha. Mesolandform attributes have a significant effect on coffee production increase ($R^2 = 0.69$) on land characteristics with high coffee vegetation density (NDVI > 0.6), topographic position in open slope to flat (TPI 0–2), dominant slope is flat to undulating (<8%), and land curvatures are level or convergent foot slope (<2). The research results can support the sustainable management of smallholder coffee plantations based on mesolandform attributes.

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1. INTRODUCTION

Coffee plants are one of the export commodities in Indonesia (Zuhdi et al., 2021), along with cocoa, rubber, and palm oil plants (Darmanto et al., 2021). Smallholder plantations dominate coffee plantations in Indonesia (96%) (Krishnan, 2017; Tran et al., 2021). One of the largest coffee-producing provinces in Indonesia is East Java, which produces 45,914 tons of coffee beans and has a coffee plantation area of 89,219 ha (Ditjenbun, 2023). Malang Regency is the third coffee producer in East Java, after Jember and Banyuwangi (Munashiroh & Santoso, 2021; Utami & Bayu, 2022). One of the areas that cultivates robusta coffee is on the southern slope of Mount Kawi, precisely in the Kletek subwatershed. However, coffee production in this area started in 2019 at a low level (1,200 kg of coffee beans ha^{-1} $year^{-1}$). Low coffee production is caused by poor management and maintenance (Meirezaldi et al., 2022), poor coffee quality and quantity (Nabaasa et al., 2022), underutilization of mechanical technology (Tikuneh et al., 2023), lack of implementation of sustainable coffee farming (Tikuneh et al., 2023), lack of implementation of sustainable coffee farming (Kudama et al., 2021), low soil fertility (Wulandari et al., 2022), dan global climate change (Siles et al., 2022).

The Kletek subwatershed is a volcanic area with spatially diverse land characteristics influenced by a land physiography dominated by steep slopes (25-35°) (Bachri et al., 2023; Counts et al., 2018). Steep slopes in volcanic areas are

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associated with increased rockfall hazards, where slope geomorphology is crucial for determining slope stability (González de Vallejo et al., 2020). Coffee cultivation practices on steep slopes are incompatible with land characteristics (Nguyen et al., 2020). Although there are sustainable land management practices, such as the use of organic fertilizer, animal manure, and compost, there is a lack of sustainable land management practices (Byrareddy et al., 2019; Iskandar et al., 2019), shade tree planting (Ehrenbergerová et al., 2021; Piato et al., 2020), and application of soil and water conservation techniques (Amrulloh et al., 2024), coffee farmers tend not to apply these practices effectively (Mutolib et al., 2023) and tend to practice subsistence farming (Nazaruddin et al., 2020).

Many land management strategies have been implemented; however, landform characteristics have not been considered. Landform provides information on environmental conditions and natural resources (Du et al., 2019; Yulianto et al., 2019), predict, prevent, and mitigate natural disasters (Choudhury, 2024). Landforms can be analyzed based on their geomorphic features such as elevation, slope, aspect, and curvature (Dikau, 2020; Garcia & Grohmann, 2019; Janowski et al., 2022). Research conducted for landform classification using Digital Elevation Model (DEM) data modeled using the convolutional neural network method (Xu et al., 2022), analysis of terrain features, including slope, aspect, plan curvature, and profile curvature analyzed using Global Mapper (de Morisson Valeriano & de Fátima Rossetti, 2020), analysis of topographic position index (TPI) and slope index by automatic classification method (Ghosh & Bera, 2023), morphological analysis with supervised machine learning (Brigham & Crider, 2022). Using geographic information system (GIS) and remote sensing technology with automatic classification methods, this study analyzed the mesolandform using geomorphological variables, including morphology, morphometry, morphogenesis, and morpho arrangement.

The coffee yield is significantly associated with landform characteristics such as altitude, topography, and climatic conditions. Globally, the *Coffea canephora* (Robusta) plant thrives in the tropics at middle altitudes (300 - 900 above sea level), which gives it distinct flavor and yield characteristics (Campuzano-Duque & Blair, 2022). Topographical factors also affect the soil properties, soil moisture, and nutrient content that support coffee growth (Hameed et al., 2020). Geomorphological properties of coffee-growing regions can improve agricultural practices and crop yields.

Mesolandform can distinguish land characteristics at an area of 1 ha to 100 ha (MacMillan & Shary, 2009; Westoby et al., 2016). Mesolandforms play a role in determining the spatial distribution of ecosystems based on their components and position in the landscape (Chakrabarty & Mandal, 2018; Kim et al., 2021). Mesolandform characteristics consist of four aspects, including morphology (the arrangement of the natural shape of the land surface expressed in the form TPI) (Wang et al., 2020), morphometry (quantification of land surface expressed in terms of curvature and slope) (Sambodo & Arpornthip, 2021), morphogenesis (sequence of processes affecting landforms expressed in terms of different types of constituent rocks) (Cappadonia et al., 2016), and morpho-arrangement (the relationship of landform changes to objects on the land surface expressed in the form of land use and normalized difference vegetation index (NDVI)) (Tartila et al., 2019).

The research gap is a landform analysis method based on geomorphological parameters, combining remote sensing and GIS technology and sustainable management of smallholder coffee plantations based on mesolandform characteristics. In the Kletek subwatershed, Malang Regency is an area with robusta coffee as its primary commodity. Coffee cultivation, especially its management, is dependent on mesolandform characteristics. Mesolandform classification is expected to be the basis of specific land management and can cover the area of smallholder coffee plantations to sustain robust coffee production. This research aims to classify mesolandforms on smallholder coffee plantations using automated classification while analyzing the relationship and influence of mesolandform attributes on robusta coffee production in the Kletek subwatershed, Malang Regency.

2. MATERIAL AND METHODS

2.1. Description of the study site

The research was conducted on smallholder coffee plantations on the southern slope of Mount Kawi, Kletek subwatershed, Malang Regency (Fig. 1), from October 2023 to June 2024. The research site has a focus area with a land-use type of smallholder coffee plantation. The area of the Kletek subwatershed is 17,845.97 ha, with an elevation of 178-2452 m above sea level. The climatic conditions of the research location have low rainfall in July - September (30 - 70 mm/month) and the highest rainfall in November - March (300 - 400 mm/month). In addition, the study area has an annual average air temperature of 22°C to 24°C. Rainfall data is processed from the Climate Hazard InfraRed Precipitation with Station (CHIRPS) spatial data, while air temperature uses the Copernicus' website.

2.2. Data Set

2.2.1. Topographic Position Index (TPI)

TPI uses DEM data analyzed using GIS (Chowdhury, 2023). It determines the difference in height at the center point (Z0) and the average height within a certain radius (Zn). Figure 2 illustrates TPI conditions. The formula of TPI is expressed as Equation 1.

$$TPI = Z_0 - Zn \quad [1]$$

2.2.2. Geology

The geological map was prepared based on the 1992 geological map (1:100,000) of Kediri (42-1508-3), Turen (45-1607-4), and Blitar (1507-6) sheets, and the 2012 geological map (1:50,000) sheets of Kandangan (1508-32), Kepanjen (1607-43) and Wlingi (1507-64). The data obtained were delineated in the research area (Erharter et al., 2023).

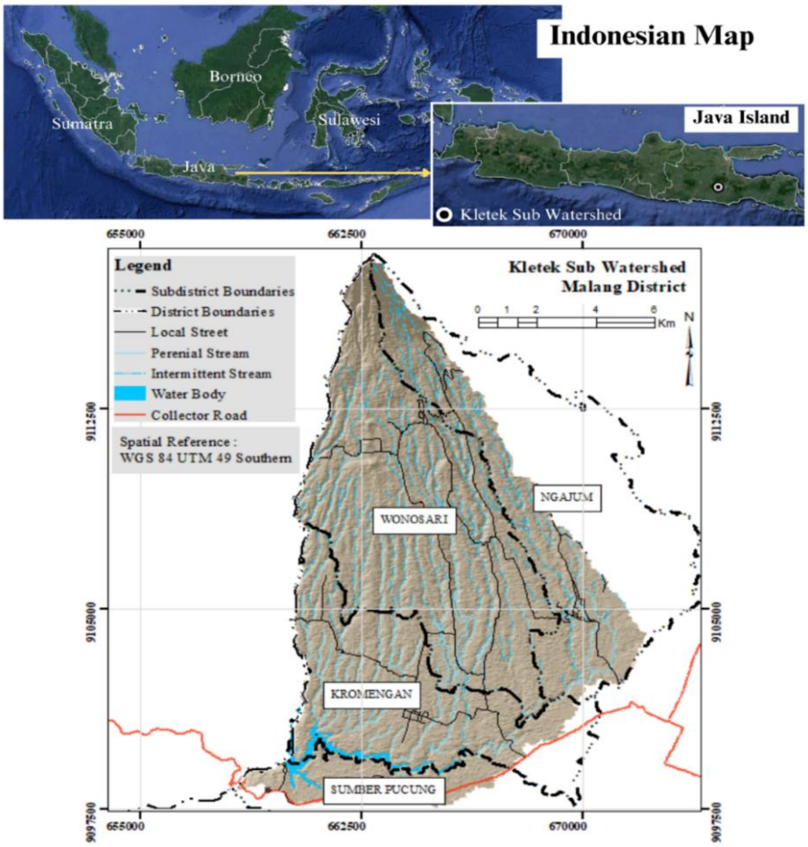


Figure 1. Reserach location Map

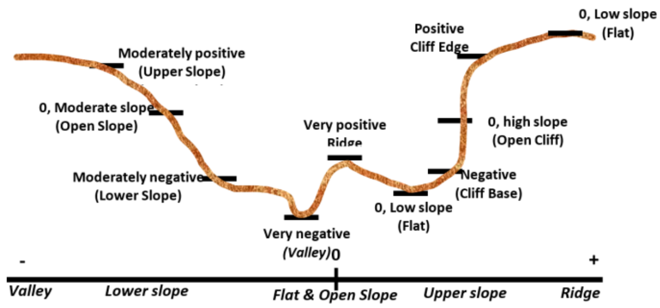


Figure 2. Illustration of TPI (Weiss, 2001)

2.2.3. Slope

The slope is a quantitative land morphology indicating the land degree. Slope analysis was conducted using the surface raster tool in ArcGIS (Ba et al., 2018). Then, reclassify based on slope classification guidelines (Marsoedi et al., 1997).

2.2.4. Curvature

Curvature measurements are essential for characterizing objects shapes (Fathizadeh & Khalkhali, 2019). The curvature consists of profile and plan curvature (Fig. 3) (Çellek, 2024; Pennock et al., 1987). Curvature analysis was performed using the ArcGIS tool, i.e. the surface raster (Bartin et al., 2019).

2.2.5. Landuse

Landuse analysis with supervised classification uses Sentinel 2A Harmonized imagery to obtain accurate classification. Next, a supervised classification method using maximum likelihood was applied to categorize land cover types based on spectral signatures (Hashim et al., 2019).

2.2.6. NDVI

The NDVI is a vegetation density index that provides an overview of vegetation cover on the land surface. Land attributes shape the dynamics and arrangement of objects on the land surface (Gomes et al., 2019). The Raster calculator tool in QGIS to compute the NDVI using NIR and red band. Mathematically, NDVI is expressed as Equation 2.

$$NDVI = \frac{\lambda NIR - \lambda Red}{\lambda NIR + \lambda Red} \quad \text{[1]}$$

2.2.7. Semi-Automated Mesolandform Classification

Mesolandform analysis uses vector data and then intersects (overlays) all mesolandform attributes. Before overlaying, each data set must be classified according to Figure 4. Furthermore, land attributes can be named using ArcMap in the attribute table by labeling all mesolandform attributes with a unit area of 2.5 ha. Furthermore, the attribute name of each land unit is given (Ghosh & Bera, 2023).

2.2.8. Smallholder Coffee Plantation Classification

The supervised land-use classification method was enhanced using the Multiple Endmember Spectral Mixture Analysis method to classify the details of smallholder coffee plantations. This method can retrieve specific land cover information based on multispectral and hyperspectral image data. MESMA assumes that the image consists of many different end members based on spectral differences. MESMA analysis was conducted using the application of QGIS 3.1.6 (Van der Sluijs et al., 2023).

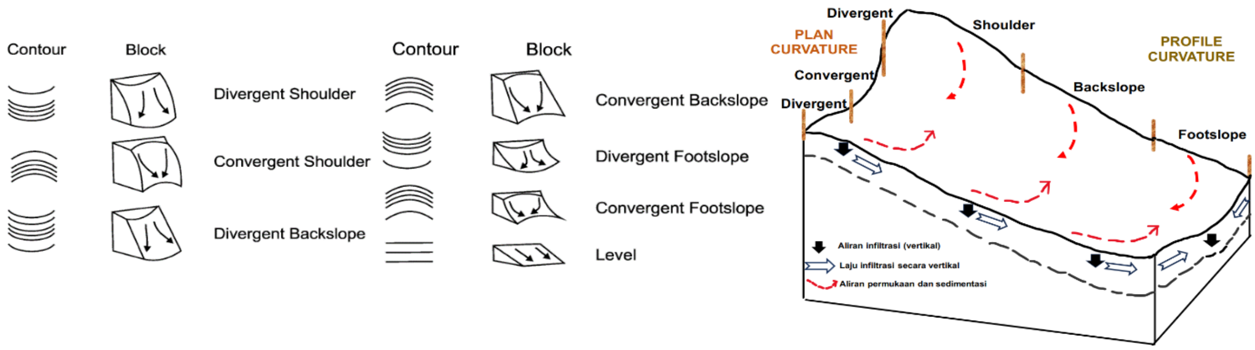


Figure 3. Curvature concept on landform

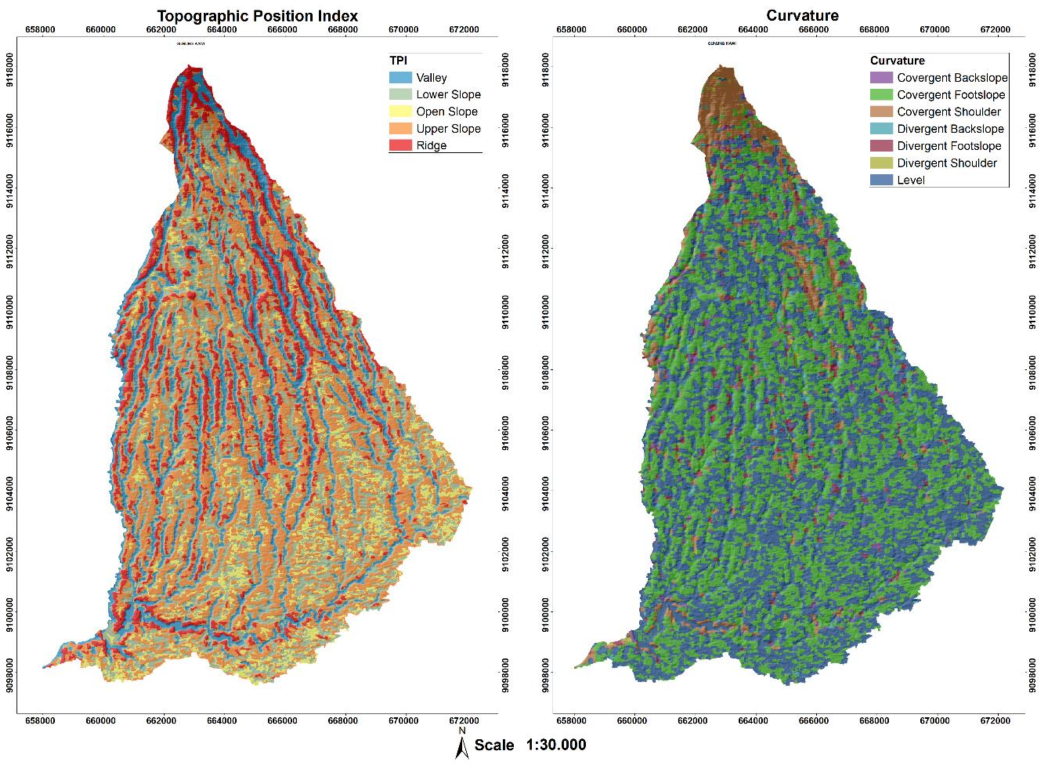


Figure 4. Mesolandform attribute (TPI (left); Curvature (right))

2.3. Data collection and analyses

Production data were collected using the physiographic method based on map unit boundaries in the mesolandform (Risamasu, 2023). There are eight mesolandforms on smallholder coffee plantations, which take five observation points/mesolandforms. Observation points were determined using the stratified random sampling method based on accessibility, productive age of coffee plants, and coffee cultivation land area >0.25 ha. Spatial data was processed using GIS applications such as ArcGIS 10.8 and QGIS 3.1.6. Statistical analysis was conducted using the 5% analysis of variance test, 5% Duncan's test, correlation, and multi-linear regression using RStudio (Grömping, 2015).

3. RESULTS

3.1. Mesolandfrom attributes of smallholder coffee plantations

Mesolandfrom attributes consisting of the TPI, slope, curvature, geology, land use, and NDVI were prepared in the study area (Fig. 4, 5, 6). Morphology is the natural arrangement of objects on the earth's surface that form a landscape, and it is represented by the TPI (Huggett & Shuttleworth, 2022). The TPI can distinguish land on an upper slope (5465.93 ha), a lower slope (3439.65 ha), a valley (2445.30 ha), a ridge (1983.79 ha), or an open slope (1249.90 ha) position. Volcanic areas have a topographic position dominated by upslope and lower-slope areas.

The morphometric aspects can be reviewed based on curvature and slope analysis. Morphometry is the quantitative measurement and mathematical analysis of the physical characteristics of the Earth's surface and landforms, such as shape and size (Pande & Moharir, 2017). The curvature raster was classified into seven categories: convergent foot slope (6613.60 ha), convergent shoulder (1046.91 ha), convergent backslope (296,00 ha), level (6010.49 ha), divergent foot slope (301.64 ha), divergent shoulder (62.88 ha), and divergent backslope (253,09 ha). The slope at the study site is dominated by 15-30% (steep slope slope= 6494.89 ha), 8-15% (moderate slope = 4050.15 ha), 3-8% (gentle slope = 2492.12 ha), >30% (very steep slope = 1439.67 ha), and <1% (flat = 71.86 ha, as a water body).

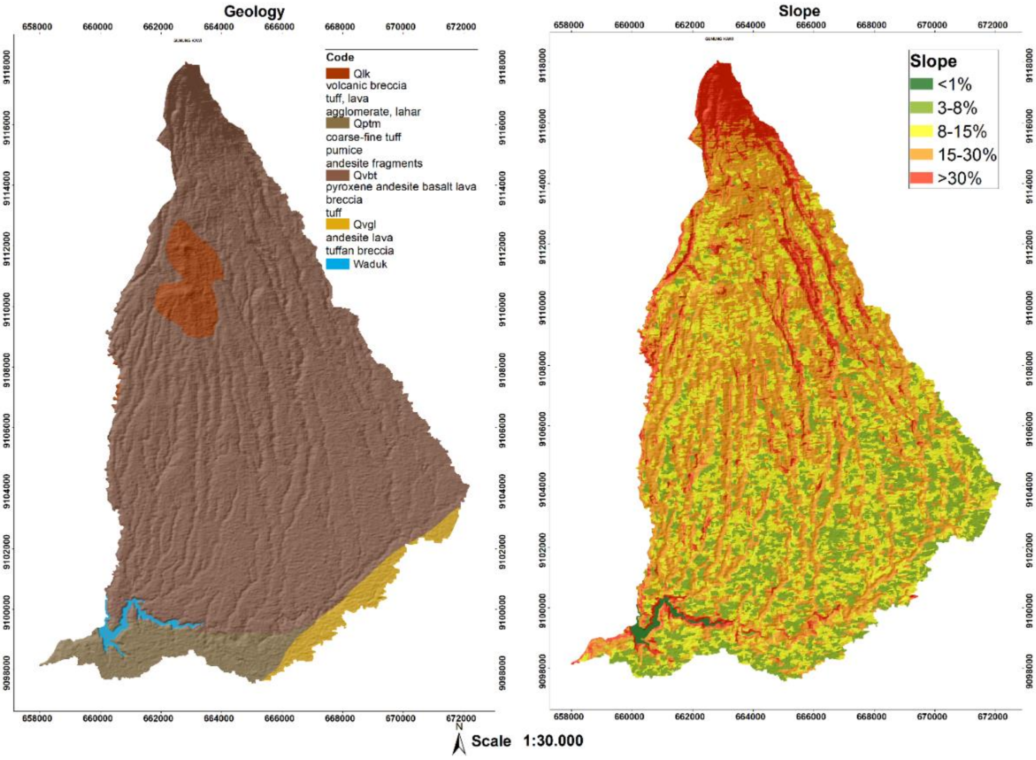


Figure 5. Mesolandform attribute (Geology (left); Slope (right))

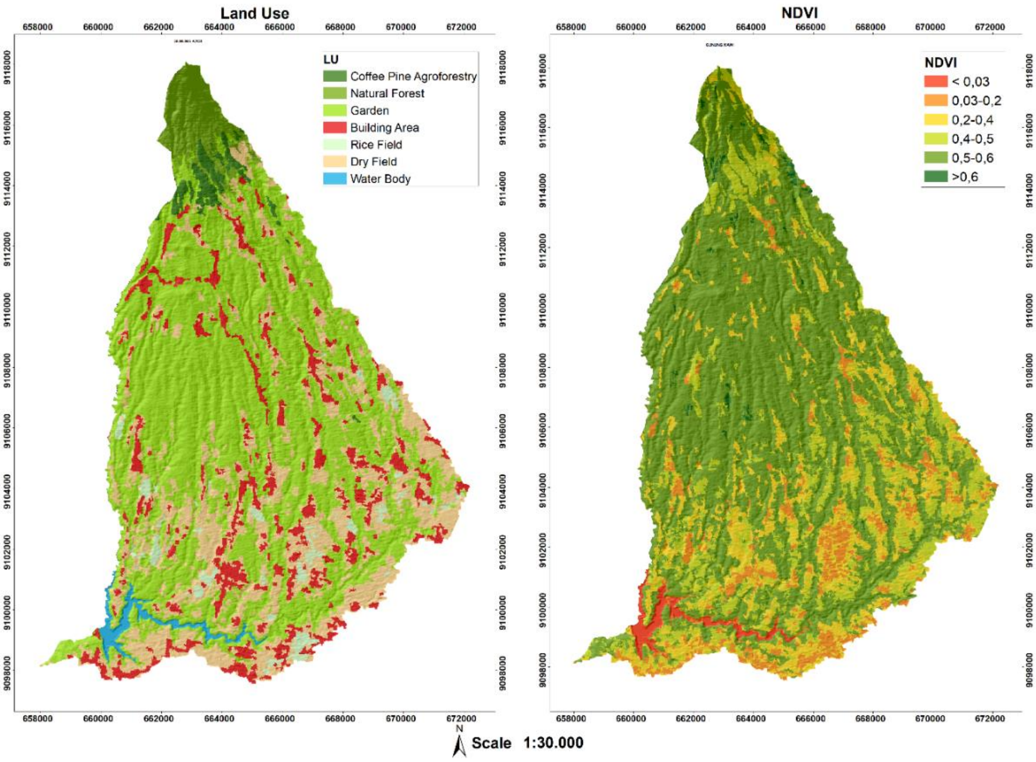


Figure 6. Mesolandform attribute (Land use (left); NDVI (right))

Morphogenesis is the sequence of processes that shape the land as a process of land geomorphology, such as the type of rocks and endogenous and exogenous processes (Shvarev et al., 2022). The rock formations comprising the parent material at the research site are Qvbt (pyroxene andesite basalt lava, breccia, & tuff = 12,563.24 ha), Qptm (coarse-fine tuff, pumice, & andesite fragments = 931.56 ha), Qlk (volcanic breccia, tuff, lava, agglomerate, and lahar = 565.46 ha), and Qvgl (andesite lava & tuff breccia 422.03 ha). The geological composition and structure of rocks play crucial roles in determining landforms and landscape transformation (Skentos, 2018).

Morpho-arrangement is the relationship between landform changes in one space on the earth's surface. Changes in conditions on the earth's surface are related to land use and cover changes (Tartila et al., 2019). The study site consists of coffee-pine agroforestry (236.07 ha), natural forest (582.10 ha), garden (8363.38 ha), rice field (336.81 ha), dry field (3391.78 ha), building area (1485.25 ha), water body (189.84 ha). The NDVI class at the research site was divided into 6 classes with an interval value of 0.5-0.6. (high density = 9033.31 ha), 0.2-0.4 (low density = 2221.88 ha), 0.4-0.5 (moderate density = 2076.83 ha), 0.03-0.2 (very low density = 954.24 ha), <0.03 (without coverage = 206.66 ha), and >0.6 (very high density = 92.31 ha).

3.2. Mesolandform classification

The mesolandform classification of smallholder coffee plantations in the Kletek subwatershed, Malang Regency is divided into eighrt landforms (Table 1): a canyon and deep inside stream (682.16 ha), midslope drainage and shallow valley (2310.29 ha), upland drainage and headwater (1308. 66 ha), u-shape valley (1533.38 ha), open slope (545.70 ha), upper slope and plateau (1407.48 ha), local ridge hill in the valley (1227.74 ha), and midslope ridge and a small hill in the valley (1227.74 ha). The research location generally has two other mesolandform classes: plain & mountain top and high ridge. However, these two mesolandforms are not used for coffee cultivation in smallholder coffee plantations because coffee plants are cultivated on land with a slope of >3%. The top of the mountain is a natural forest area. Mesolandform attributes compiled based on supervised classification and overlaid based on geomorphological aspects can provide an overview of detailed land conditions. Validation of the actual condition of the characteristics of each mesolandform refers to the classification presented in Table 1 using the sample points. Each mesolandform unit was ground-truth at five observation points representing all mesolandform units. Land use type was determined in the form of smallholder coffee plantations. The mesolandform map and the actual condition of the coffee plantation are presented in Figure 7.

The results showed that mesolandform attributes significantly relate to the physiographic conditions of smallholder coffee plantations. Morphology, morphometry, and morpho arrangement are geomorphology aspects that play a role in the preparation of mesolandform. The mesolandform variations of smallholder coffee plantations are influenced by TPI (morphology), slope and curvature (morphometry), and NDVI (morpho-arrangement) (Fig. 8). The formula for preparing the mesolandform of smallholder coffee plantations based on the four attributes in the form of $\hat{Y}$ =-2.26TPI+47.76NDVI-3.87Curvature-0.10Slope+8.55 (R^2_{adj} = 0.67). TPI is an algorithm used to measure the topographic position of land and can analyze landforms automatically (Vinod, 2017). In local geometry, the curvature values indicate the geomorphological characteristics (Dikau, 2020). The slope is the relief condition of land; slopes with flat and steep classes have different values (Schlögel et al., 2018), and are related to the water flow process (Guo et al., 2020). Curvature reflects land surface flow conditions through convexities and depressions that impact flow dynamics and heat transfer (Dinler et al., 2018). Quantifying the spatial heterogeneity of NDVI shows how natural and anthropogenic interact to influence vegetation dynamics, resulting in changes in object's on the land surface (Gao et al., 2021).

3.3. Relationship between mesolandfom and coffee production

Coffee production was obtained by collecting old coffee beans from each tree in one observation point. Coffee production differed significantly between the mesolandforms, as shown by the relatively diverse box plot graph (Fig. 9). The lowest average production was found in the canyons and deeply incised streams, with a production range of 2.01-3.70 tons ha^{-1}. The highest production was found on the open slope mesolandform, with coffee production ranging from 7.13 to 9.95 tons ha^{-1}.

Table 1. Characteristic of mesolandform smallholder coffee plantation

No.	Landform Classification	Criteria
1	canyon and deeply inside the stream	Deep valleys are associated with rivers and are dominated by TPI valleys; steep walls (>30% slope), slope direction parallel to the river
2	midslope drainage and shallow valley	Slopes range from 8-15% and 15-30%; TPI is the open slope, upper slope, lower slope, and valley; curvature is divergent or convergent; associated with valleys and seasonal rivers
3	upland drainage and headwater	The TPI is upper slope; located at 8-15%, 15-30%, and >30% slope; curvature is convergent and level; associated with the river.
4	u-shape valley	The TPI is valley; land morphometry is basin; land slope is 3-8%, 8-15%, and 15-30%; associated with two hills.
5	open slope	TPI is an open slope present on all land slopes; land morphometry is level but can also be found in convergent (concave) morphometric conditions with slopes <15%.
6	upper slope and plateau	Located on the upper slope; TPI in the form of upper slope and ridge; slope <15%
7	local ridge hill in the valley	TPI in the form of ridge and valley or lower slope; land slope between 8-15% and 15-30%; located on a hill or peak but associated with the valley.
8	midslope ridge and a small hill in the valley	TPI in the form of ridge (15-30%), valley, or lower slope (8-15%)

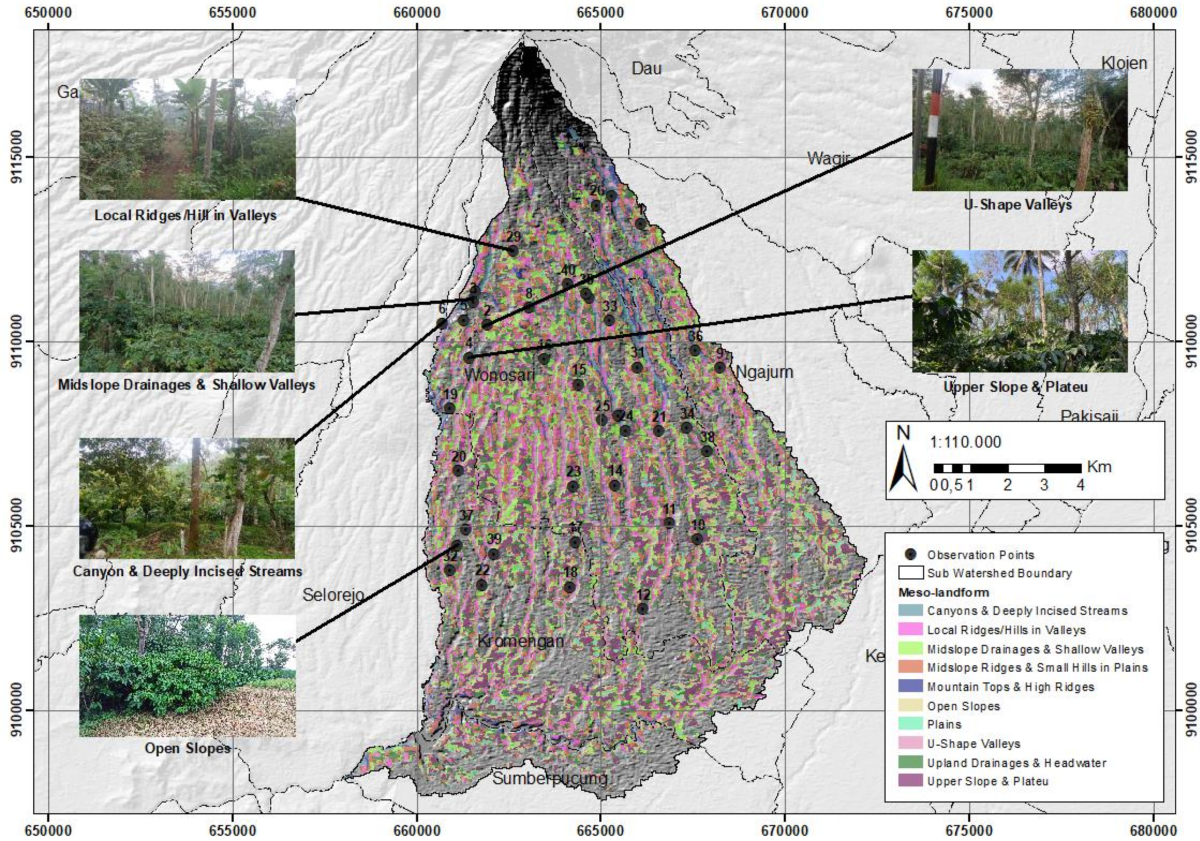


Figure 7. Mesolandform map and actual condition of smallholder coffee plantations in Kletek Subwatershed, Malang Regency

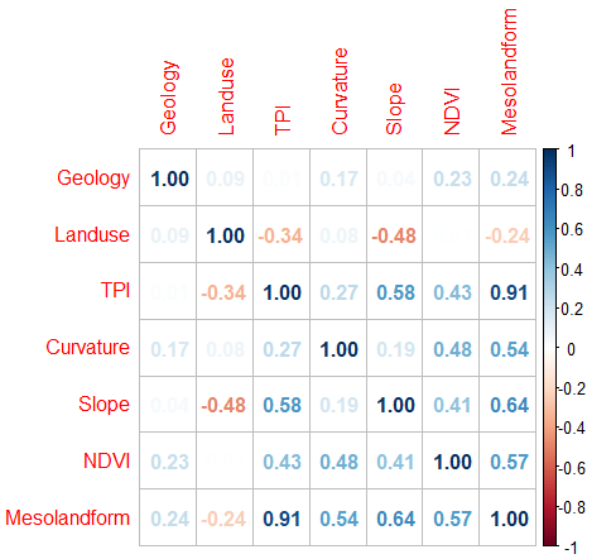
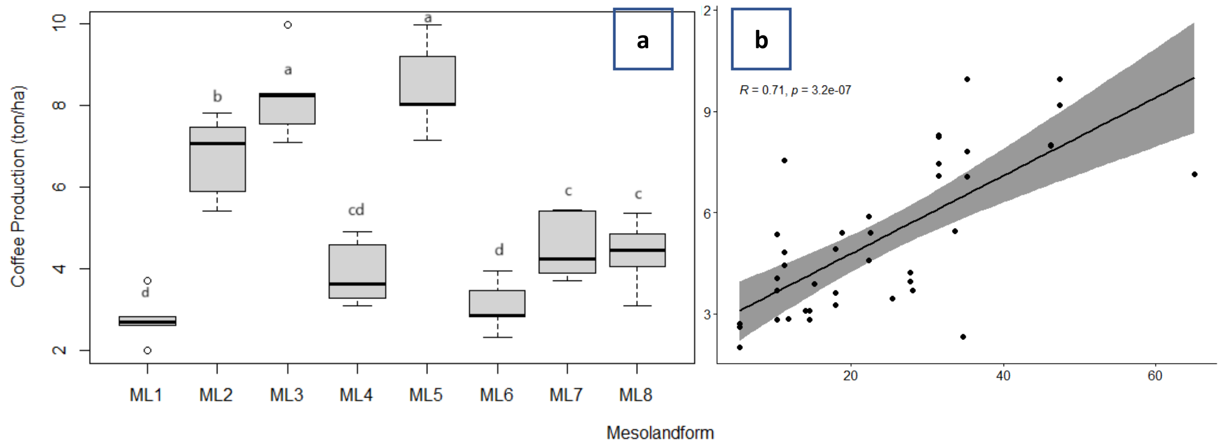


Figure 8. The relationship between mesolandform attributes score and mesolandfrom scores

The attributes and characteristics of each mesolandfrom influence differences in coffee plant diversity. The mesolandform attributes that have a significant relationship with coffee production are NDVI, TPI, slope, and curvature (Fig. 10). The relationship between mesolandform attributes (Xi) and coffee production (Y) was $\hat{Y}$ = 14.02 NDVI - 0.27 TPI + 0.03 Slope - 0.05 Curvature - 3.76 (R^2 = 0.69). The highest coffee production is found in the open slope mesolandfrom because the land attributes are suitable for coffee plant growth: TPI in the form of the open slope, curvature in the form of level or convergent, and slope <15%. These land attributes have a lower erosion potential than land with slopes >15% (Schwilch et al., 2015; Wang et al., 2019). The shape and position of the landscape strongly influence soil function because it directs the surface water and groundwater flow through convergent and divergent pathways. The convergent curvature can hold more water in the field and store it in the soil (Fan et al., 2020; Obi et al., 2014). Based on the characteristics of mesolandform attributes that act as a function of abiotic factors, coffee plants can be optimally utilized to support their growth. In addition, based on the NDVI analysis, the open slope was dominated by the density value, which averages 0.80. This value reflects coffee plants, and the canopy cover is sufficient to shade coffee plants. Land can serve as an alternative input variable, such as soil quality, topography, and microclimate, that enhances the efficiency of coffee production (Ngango & Kim, 2019) and the percentage of canopy cover (Etafa, 2022; Valente et al., 2022).

4. DISCUSSION

This study describes land on smallholder coffee farms based on mesolandform attributes in the Kletek subwatershed, Malang Regency. The mesolandform attributes with the most significant relationship with coffee production (Fig. 8) based on geomorphological approaches include morphology in the form of the TPI (r = - 0.71), morphometry in curvature (r = 0.39) and slope (r = - 0.43), and morpho-arrangement in the form of NDVI (r=0.79). Digital data from remote sensing, such as DEMNAS data and Sentinel 2A Harmonized image, can be used to identify the biophysical condition of the land surface.



ML 1 = Canyons & Deeply Incised Streams, ML 2 = Local Ridges/Hills in Valleys, ML 3 = Midslope Drainages & Shallow Valleys, ML 4 = Midslope Ridges & Small Hills in Plains, ML 5 = Open Slopes, ML 6 = Upland Drainages & Headwater, ML 7 = Upper Slope & Plateu, ML 8 = U-Shape Valleys

Figure 9. Distribution of coffee production (tons/ha) in each mesolandform (a) and it is relationship to coffee production (b)

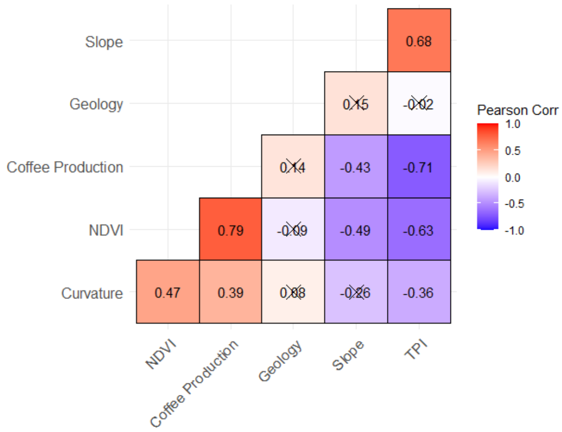


Figure 10. Correlation between the attribute of mesolandform and coffee production (tons/ha)

TPI values significantly affect increased production with interval values of 0-0.5 (flat) and 0.5-2 (open slope). This is a consideration for coffee plants to grow and achieve optimal production on flat, open slope land. The lower slope, upper slope, ridge, and valley TPI will reduce coffee production if coffee cultivation practices are not improved. This suggests that topography can provide important information on the distribution of cultivation suitability for specific crops (Lisso et al., 2024). TPI is a valuable tool in landform analysis, aiding in the classification and delineation of landscapes. TPI is commonly used in various studies for landform classification within GIS software, allowing for categorizing landscapes based on slope position and morphological classes (Argyriou et al., 2017). It is particularly beneficial in heterogeneous landscapes, offering a method to classify landform types that vary significantly in size (Kramm et al., 2017). Topographic, climatic, and soil factors influence the TPI and crop growth relationship. TPI is a quantitative measure that assists farmers and agricultural planners in identifying optimal land for cultivation based on its elevation relative to the surrounding landscape. TPI can indicate microclimate and soil conditions contributing to crop growth and yield, particularly affecting drainage, nutrient availability, and light exposure (Maestrini & Basso, 2018; Oliveira et al., 2022).

The curvature has a significant effect on increasing coffee production. It indicates the specific shape of the land surface. The curvature shapes suitable for coffee plant cultivation are level (0-1) and convergent foot slope (1-2). The land curvature level can affect the water distribution on the land. In the curvature condition in the form of a level, the specific shape of the land surface is neither convex nor concave. The shape and roughness of the land surface can affect farmland quality by triggering the movement of nutrients, soil, water, and the area's geological structure (Zeraatpisheh et al., 2019). The curvature plays a crucial role in shaping landforms and influencing various geomorphological processes, such as vegetation patterning, sediment dynamics, and erosion rates (Baartman et al., 2018). The relationship between erosion rate and curvature over geologic time was explored, highlighting the impact of curvature on landscape evolution (Pelletier et al., 2018). Land curvature and crop growth suitability are important aspects of agricultural planning and land management, as well as in drainage, water retention, and soil stability. Research has shown that areas with concave curvature can support higher agricultural productivity because of increased soil moisture and nutrient availability (Ao et al., 2021). In addition to improving water retention, curvature can support the microclimate, which influences factors such as sun exposure and temperature, which are critical for crop development (Fan et al., 2020; Sun et al., 2021). Integrating curvature analysis into agricultural models explains how land morphometry affects crop growth. The curvature is strongly related to erosion processes and landform morphometry (Clubb et al., 2016). Digital geospatial data are crucial for characterizing landforms and investigating Earth's surface processes (Maxwell et al., 2023).

Slopes that have a significant influence on increasing production are in the flat (0-1%), slightly flat (1-3%), and gentle (3-8%) classes. Based on the land suitability class, coffee plants are suitable on slopes <8%. Steep slopes can affect erosion rates and nutrient translocation. The slope critically influences landform development and various geomorphological processes. The relationship between slope and landform evolution has been extensively studied, with slope steepness and length affecting erosion processes and shaping the underlying surface (Liao et al., 2020). Moreover, changes in slope aspects have been observed to lead to modifications in habitat patterns and landform characteristics (Malatesta et al., 2019), such as parent material properties and slope, geological and climatic factors also play crucial roles in shaping slope landforms (Alijani & Sarmadian, 2015). Therefore, to optimize coffee production on slopes >8%, land management is needed in the form of terraces and covering the soil surface using litter or the addition of intercrops (Hombegowda et al., 2020).

NDVI is a crucial indicator of vegetation health and density. Land monitoring using NDVI data showed that high NDVI classes (>0.5) increased coffee production. This is because the higher greenness value displayed by NDVI indicates healthy plant conditions, so coffee production can be optimized (Bolaños et al., 2023). NDVI has been illustrated in assessing vegetation cover changes owing to anthropogenic activities, such as archaeological excavation, revealing how land use modifications can affect vegetation health and NDVI values (Rodrigo Comino et al., 2023). The relationship between NDVI and vegetation productivity was observed in different ecosystems (Lara et al., 2018; Sholikah et al., 2023). NDVI correlates to slope in certain mountainous regions, indicating a correlation between vegetation density and terrain steepness (Li et al., 2023).

Land management and coffee plant cultivation influence coffee production in each mesolandform (Ayele et al., 2021), and lower coffee productivity at higher altitudes may be attributed to suboptimal management practices, such as plant density and shade density, which can impact coffee productivity, especially at different altitudes (Anhar et al., 2020). Constructing terraces in coffee plantations can improve the quality and quantity of coffee, and terracing enhances the outcomes of coffee farming in steep terrains (Fernandez et al., 2024).

The study relied heavily on remote sensing data in the form of DEMNAS and Sentinel 2A Harmonized and landform attributes, which, while effective for broad-scale analysis, do not fully capture micro-scale variations in soil properties, farmer practices, or local climatic influences that affect coffee production. The accuracy of TPI, curvature, slope, and NDVI measurements can be affected by the resolution of digital data and potential processing errors, especially in hilly areas such as the Kletek subwatershed. There is a need to develop research using imagery with higher spatial resolution or aerial photography using drones. Research using very detailed remote sensing data is expected to cover the micro-scale of smallholder coffee lands. In addition, the study's focus on biophysical attributes may overlook socioeconomic factors, such as access to resources or market dynamics and the land management of smallholder coffee plantations. Although these findings suggest a strong relationship between mesolandform attributes and coffee productivity, further research is needed to validate this relationship across different watersheds and farming systems. Ground truth was used for validating remote sensing data and conducting detailed surveys of farmers' management practices and soil characteristics. Furthermore, conservation studies examining land management changes (terracing) and climate that affect NDVI and coffee yields over time could provide deeper insights into sustainable coffee farming in the same landscape. Until such comprehensive data are available, definitive conclusions regarding the optimal landscape attributes for coffee production in the Kletek subwatershed should remain tentative.

5. CONCLUSION

This study effectively classified mesolandforms to produce robusta coffee in the Kletek subwatershed. Eight mesolandform types, especially open slopes, were associated with higher yields (7.13–9.95 tons/ha) owing to the influence of suitable morphology, gentle slopes, and dense vegetation. The strong statistical correlation ($R^2 = 0.69$) demonstrates the importance of geospatial analysis in optimizing smallholder coffee plantations. By targeting land management that supports open slopes and terracing in steeper areas, farmers can sustainably increase productivity while supporting crop yields and ecological health.

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Declaration of Competing Interest

The authors declare that no competing financial or personal interests may appear to influence the work reported in this paper.

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