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Land suitability assessment for agricultural crops in Enrekang, Indonesia: combination of principal component analysis and fuzzy methods

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ABSTRACT

Land suitability assessment is essential for the efficient use of diminishing fertile agricultural land. Assessment parameters include soil texture, pH, the sum of basic cations, base saturation, cation exchange capacity, organic carbon, soil depth, slope, and mean annual temperature and precipitation data. Results showed that 76.28% and 23.26% of the total area were optimally and moderately suitable for coffee growth, respectively; 9.6% and 90% were optimally and moderately suitable for cocoa growth, respectively; 1.98%, 78.74%, and 19.26% were optimally, moderately, and marginally suitable for clove growth, respectively; and 6.68%, 86.89%, and 6.41% was optimally, moderately, and marginally suitable for pepper growth, respectively. The final land suitability index (LSI) was strongly influenced by the threshold values used by the researcher and the quality of the land indicator itself. Plant threshold values differed due to variations in plant recruitment. The main limiting factors were mean annual temperature <26°C, acidic soil pH, and low CEC. This study showed that the fuzzy method is ideal for converting the numerical data of various magnitudes into membership function values and representing land suitability. The principal component analysis is an effective method to determine the weights of multiple factors in a systematic and objective manner. The linearity test found a correlation between LSI and production with f = 0.00, indicating that the applied model can predict agricultural production and is applicable to other agricultural land management.

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1. INTRODUCTION

Sustainable agriculture is defined as a comprehensive system of crop production practices with site-specific applications that will persist in the long term (Siebrecht, 2020). According to Pan et al. (2022), sustainable agriculture ensures the most efficient use of agricultural resources. One of its main goals is to ensure that agriculture does not deviate from the natural system itself. Land suitability evaluation is one of the keys to designing sustainable land use. Land suitability is the eligibility of a specific type of land for a specific purpose (Mugiyo et al., 2021) and is determined by evaluating the climate, soil, and topographical components and understanding the biophysical constraints. Assessing the capability and suitability of land is required to address current and future food security through the efficient use of land resources. According to Taghizadeh-Mehrjardi et al. (2020), the evaluation of agricultural land suitability is critical to increasing production and planning a sustainable agricultural system. This assessment is also useful in aligning agricultural land use and assisting agricultural land use planning decisions to overcome the competition between various possible land uses so that land can be used efficiently. Furthermore, appropriate land suitability for certain agricultural activities will encourage production. Agricultural production is closely related to farmers' income and influences farmer decisions to support sustainable agriculture (Piñeiro et al., 2020).

Recent technological advances in Geographic Information System, Remote Sensing, Decision Support System, and web-based applications have enabled powerful, highly accurate, and long-term interventions in agriculture in terms of where to farm and which plant is the best fit. Land suitability assessment is commonly referred to as multicriteria (MC) evaluation due to the large number of factors considered in the process. Information on climate, hydrology, topography, vegetation, and soil properties should be considered in this analysis (Yang et al., 2021). Land suitability assessment with MC evaluation is a tool that deals with decision problems related to conflicting criteria and is classified into two categories, namely, multi-attribute decision-making (MADM) and multi-objective decision-making (MODM) (Kumar et al., 2017; Sheikh et al., 2021). Land suitability assessment with MADM is suitable for decision-making using discrete criteria where the importance between attributes is determined by the decision maker. The criteria in MADM are usually filtered, prioritized, and finally ranked by the decision maker (Gebre et al., 2021). Some examples of land suitability assessment using MADM are pairwise comparisons such as analytic hierarchy process (AHP) and value or utility functions such as MAVT, MAUT, and SAW (Liu et al., 2013; Zhang et al., 2015). For instance, Barati et al. (2019) integrated AHP and matrix cross-reference multiplication methods to determine key agricultural strategic factors. Devi and Yadav (2013) combined fuzzy elimination with elimination and choice translating reality method to optimize plant location. Rajabi and Mousavizadeh (2015) used the technique for other reference by similarity to ideal solution method to rank candidate locations for agricultural industries in Iran. The problem often faced in land suitability assessment using MADM is the strong subjectivity of researchers in determining the importance of land attributes. To solve this problem, researchers used principle component analysis (PCA) in land suitability assessment to examine the interests of many conflicting land attributes. In contrast to MADM, land suitability assessment using MODM is a decision-making method using criteria whose degree of importance is not predetermined. The importance between criteria in MODM is not discrete but is continuously described as an unbroken set of observations. MODM often uses mathematical modeling to determine the importance of the attributes (Gebre et al., 2021). Nasrollahi and Razmi (2021) suggested the use of multi-objective mathematical programming model for location optimization and capacity planning in future research.

Land suitability assessment with multiple criteria must consider two main things: equalizing the unit of assessment and evaluating conflicting interests between multiple attributes. Membership values and weight of indicators play an important role in the final result of land suitability assessment using MCDM (Giordano & Liersch, 2012; Liu et al., 2013). Researchers employed a combination of fuzzy and PCA as a solution to these two main issues. Fuzzy is used to standardize attributes, and PCA is applied to assess conflicting interests between attributes. To date, fuzzy inference has been developed by many experts. Fuzzy method is a development of the Boolean method, which is considered too rigid and standard and has only two values, true and false (0 or 1). Fuzzy methods allows membership values to be transformed to 0 up to 1; in land suitability assessment, the closer an index value is to 1, the better the land suitability. According to Qiu et al. (2014), land suitability maps generated using this method are informative and accurate. Many studies used fuzzy methods for land use optimization (Akbari et al., 2019; Arabsheibani et al., 2016). For instance, Nabati et al. (2020) used a fuzzy inference system to identify land capabilities according to agroecological zoning. Feizizadeh and Blaschke (2013) used the fuzzy set method to standardize the criteria for land suitability assessment in Iran by applying a scale of 0 to 1. Owing to the wide variety of soil properties, intercorrelation can cause multicollinearity issues. Bernardi et al. (2016) pointed out that multivariate statistical approaches could be used to solve these problems and assist in land management, resulting in improved land ecosystem services (Montanaro et al., 2017). PCA is another well-known multivariate statistical technique that displays the relative positions of data points in few dimensions while retaining as much information as possible and investigates relationships between dependent variables. Ranjbar et al. (2016) compared the ability of various multivariate methods in analyzing the soil physicochemical properties for wheat to determine the importance of this parameter. They found that by using PCA, the relationship between the results and other parameters could be accurately interpreted. PCA can also effectively determine the weighted value to achieve a desired result (Basu et al., 2022). According to PSU (2018), PCA is traditionally used to identify which variables have the most influence on a process and to simplify the data into multiple PCs that account for most of the variability in the data. Ghaemi et al. (2014), Nguyen et al. (2020), and Said et al. (2020) used PCA to reduce dimensional data into few factors. However, Ranjbar et al. (2016) pointed out that not reducing data is the most accurate method for evaluating land quality and providing consistent results. Hence, the current study used PCA only to determine the importance of soil attributes without reducing it to a few data.

To date, fuzzy combined with MODM for land suitability assessment has not been widely adopted. Most researchers combined fuzzy and MADM such as AHP (Keshavarzi et al., 2020; Kılıc et al., 2022; Mosadeghi et al., 2015; Nasery et al., 2021; Paul & Ghosh, 2022; Sengupta et al., 2022; Zalhaf et al., 2021) due to the simple application and easy implementation. However, in fuzzy–MADM, the weight of the indicator is usually determined subjectively by the researcher or in accordance with expert opinions. The most often encountered problem is the differences of opinion among several experts, causing bias and confusion for researchers. Most studies directly provided value ranges based on relevant studies. In addition, the effect of a land trait on other land properties for an area is not always the same as that for other areas. This difference is caused by many factors, including the way farmers cultivate crops and the characteristics of the soil in the area itself. Using the assessment of the degree of importance of soil properties in land evaluation for a specific from previous research on different areas can lead to bias. Maddahi et al. (2014) and Luan et al. (2017) pointed out that the weight between land assessment indicators must be considered objectively according to the data or characteristics of the area itself for accurate evaluation. In land suitability assessment, the assignment of land characteristics should be based on data. Therefore, the current work aims to analyze land suitability using fuzzy–PCA as a new approach to address the above problem. With the proposed method, the importance of land attributes can be determined objectively on the basis of the characteristics of the research area itself.

2. MATERIALS AND METHODS

This study was conducted in Enrekang, one of the districts in South Sulawesi, Indonesia. Administratively, this district consists of 12 subdistricts with an area of 1,786.01 km² and has a varied topography comprising hills, mountains, valleys, and rivers at elevations ranging 47–3293 meters above sea level. The land use is dominated by forest and plantation areas (25.3% of total area). Astronomically, Enrekang is located between 3°14'36" and 3°50'0" South Latitude, and between 19°40'53" and 120°06'33" East Longitude. Four cultivated plants (coffee, cocoa, pepper, and cloves) in the study site were analyzed and compared. Guidelines for land suitability assessment were adopted from Technical Guidelines for Land Evaluation of Agricultural Commodities by Ritung et al. (2011) and guidelines by Sys et al. (1993) on Land Evaluation Part III on Plant Requirements. The three main variables used in the assessment were climate, topography, and soil, with a total of 10 indicators. The variables are listed in Table 1.

2.1 Field Sampling and Laboratory Analysis

Some land attributes can be estimated or measured directly in the field, and some must be assessed in the laboratory. Here, field observations included soil depth and slope measurements, and other soil variables were analyzed in the laboratory. A land unit map of the research area (Figure 1) consisting of 15 land systems was used as reference for soil sampling. This map combines information of the ecological principles related to rock types, hydroclimate, landforms, soil, and organisms (Gharechelou et al., 2016). According to Juergensmeyer and Roberts (2013) survey results, including the unit map, could be used as a basis for land evaluation. Soil samples were randomly collected from each land unit. Undisturbed soil was selected in this study to provide an overview of the physical properties of the soil on a plot of land with a relatively homogeneous area. Some of the requirements were as follows: not burial ground, not in residential areas, not plantation areas, and not areas managed by the community.

Thirty soil samples were obtained from top (depth 0–25 cm) and subsoil (depth > 25 cm) from 15 land units. Subsoil samples were used for texture and cation exchange capacity (CEC) analysis, and topsoil samples were subjected to pH, basic cation (including Ca, Mg, K, and Na), and base saturation analysis. Texture, CEC, pH, sum of basic cations, base saturation, and C-organic content were analyzed in the laboratory. These factors were examined using the following approaches: pipette method for texture analysis, 1:2.5 soil–water suspension for pH analysis, Walkley–Black method with 105°C dry soil samples for C-organic analysis, and cation exchange rate (NH_4-Acetat 1N, pH 7) in dry soil sample at 105°C for the analysis of sum of basic cations, CEC, and base saturation.

2.2 Terms and Stages of Land Suitability Assessment

Land suitability assessment was conducted using the fuzzy model by Zadeh (1965). The fuzzy set function can continuously analyze soil characteristics without categorizing them into different classes. In fuzzy analysis, land attribute values are converted to sustainable values ranging from 0 to 1. The purpose of using fuzzy sets in land suitability assessment is to provide solutions to the constraints created by Boolean logic, which only uses binary classification including "suitable" or "not suitable" categories. The fuzzy method in this study refers to the widely used semantic import model as illustrated in Figure 2.

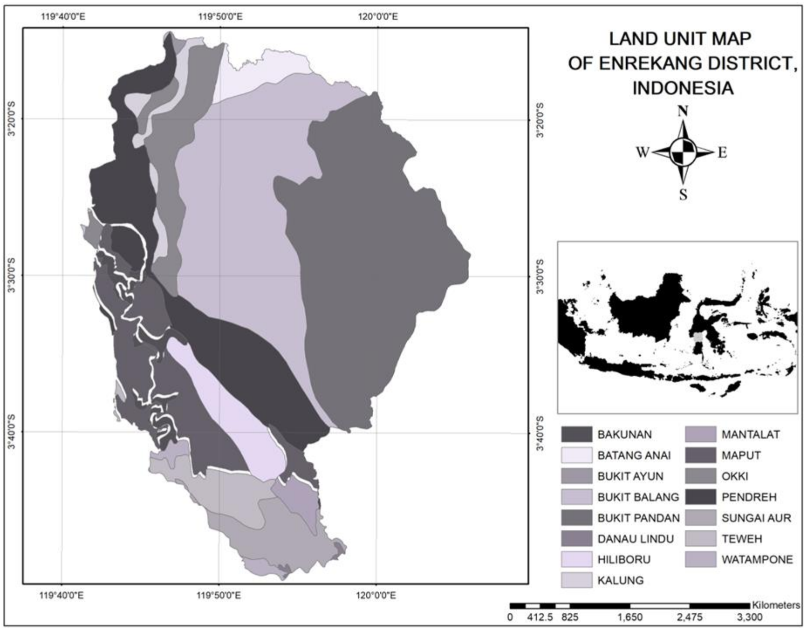

Figure 1. Land unit map of research area

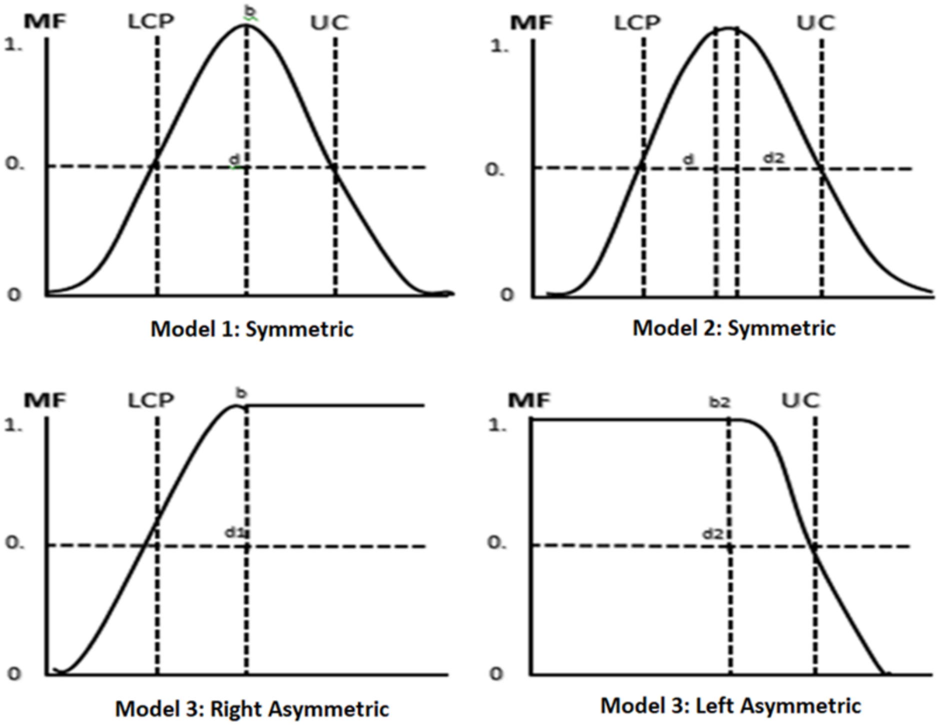

Figure 2. Fuzzy set model for land suitability assessment

Table 1. Source of data and description of research indicators

Indicator	Unit	Description	Data source
pH H_2O (V1)	-	The degree of acidity or alkalinity of the soil on a scale of 1–14	The results of laboratory analysis
Sum of basic cations (V2)	Cmol kg^{-1}	The number of basic cations that can be absorbed by the soil include elements of calcium (Ca), magnesium, potassium (K), and sodium (Na)	The results of laboratory analysis
Base saturation (V4)	Percent (%)	The ratio between the number of basic cations and all cations contained in the soil adsorption complex	The results of laboratory analysis
CEC (V4)	Cmol kg^{-1}	The number of cations that can be absorbed by the soil in 100 g	The results of laboratory analysis
Soil organic matter (V5)	Percent (%)	Soil material comes from the remains of living things that have undergone decomposition	The results of laboratory analysis
Soil depth (V6)	Centimeters	The depth of soil that can still be penetrated by roots	Field survey
texture (V7)	-	Comparison of the percentage of sand, silt and clay particles	The results of laboratory analysis
Annual precipitation (V8)	Millimeters (mm)	Total monthly rainfall in one year of observation	Central River Region Pompengan-Jeneberang
Annual temperature (V9)	Celsius (°C)	The average temperatures in one year of observation	Central River Region Pompengan-Jeneberang
Slope (V10)	Percent (%)	The degree to which a soil surface is inclined relative to the horizontal	Field survey

The following important values are shown in the modeling of Figure 2: b, which is the value of a land attribute at the ideal point; lower crossover (LCP) and upper crossover (UCP), which are the lower and upper thresholds/margins of a land attribute, respectively, based on conditions where the land attribute is considered to be at a critical level for certain crop productivity; and d, which is the width of the transition zone based on the optimal value minus the threshold value. In the fuzzy model 1, an optimal point is used to assess soil attributes with one ideal point but two critical threshold points (upper and lower). The fuzzy 2 model has an optimal point consisting of a range of values from points b1–b2, so it can be divided into two asymmetric models. The fuzzy model 3 can be interpreted as follows: the higher the attribute value of a land, the better. In this model, the soil attribute has only one optimum point with a lower threshold point. In the fuzzy function model 4, land characteristics are interpreted as follows: a smaller a land characteristic, the better. This trend is similar to the slope level. The research control points in Table 2 were arranged according to the agricultural land evaluation criteria of Ritung et al. (2011) and Sys et al. (1993), fuzzy modeling in Figure 2, and land characteristics of the research site.

One of the main stages of this research is to determine new factors or variables that have been considered for inclusion in land suitability assessment. For this reason, factor analysis was carried out using PCA to group the land attributes that were considered to have the same characteristics into one new factor/variable (Hotelling, 1933; Karl Pearson, 1901). Many studies used PCA as a data reduction technique. However, the current work used the total data set principle and did not require any reduction in land attributes. Thus, PCA was used only to analyze the correlation between land attributes and then classify them into new factors without reducing them. This goal was achieved by creating new uncorrelated variables that successively maximize variance. As a result, good data interpretation was obtained. PCA components with one or more eigenvalues were retained (Figure 3). The number of indicators for each component or factor is same as that for the analyzed land, but each component/factor will only maintain one or more indicators with a maximum corresponding load. The variance of each component/factor explains the contribution of the component in interpreting data as a whole, and the corresponding load explains the extent of correlation between the indicator and component (Armenise et al., 2013; Mukherjee & Lal, 2014). In principle, PCA can produce as many components (factors) as the indicators included in the analysis. However, only components with eigenvalues >1 were retained for the next analysis. According to this rule, four factors were maintained and labeled as factor 1, factor 2, factor 3, and factor 4. These factors can be defined as the correlation of each land attribute with the component. The first factor defines the most variance, and the last factor defines the least. Therefore, the first factor defines the most weight, and the last factor defines the least. Beginning with the first one, each component was obtained partially out of the previous component. On the basis of PCA analysis, four new factors were added to the calculation of land suitability index (LSI) (Figure 3 and Table 4).

After the soil attributes were determined and new variables were created, the next step was to standardize the land attributes to equalize the unit of assessment using a value range of 0 to 1 from Equation 1.

$$MF(xi) = [1/(1 + \{(xi - b)/d\}2] \quad [1]$$

$$MF(xi) = 1, \text{ if } (b1 + d1) \le xi \le (b2 - d2) \quad \text{(fuzzy model 2)},$$

$$MF(xi) = 1, \text{ if } xi > b \quad \text{(fuzzy model 3)},$$

$$MF(xi) = 1, \text{ if } xi < b \quad \text{(fuzzy model 4)}.$$

Another important step in this research is the objective weight assessment. Weight was calculated using simple mathematical modeling (Equation 2). The assigned weight ranged from 0 to 1. For the weight of a factor (Wf) and an individual land indicator (Wi), the following must be considered: loading factor of each indicator (yi), total loading factor (Σy), variance component of each factor (m), and total variance component (Σm).

$$Wi = (|yi|)/(\Sigma |y|) \quad [2]$$

$$Wf = (|m\_i|)/(\Sigma |mi|) \times 100$$

Join membership function (JMF) calculation is also one of the most important stages of this research. According to factor analysis, four new factors were included in the land suitability assessment. JMF, which reflects the quality of the land, was calculated for each factor. A high JMF indicates a good land quality. JMF was calculated using Equation 3:

$$JMF(Xi....z) = \Sigma\_(i=1)^n [Wi (MFi)] . \quad [3]$$

LSI was calculated after all of the parameters of land suitability assessment were determined. For LSI calculation, the JMF of each factor was then integrated with the weight of the factor (Wf) using Equation 4:

$$LSI = \Sigma\_(i=1)^n [Hfi (JMFxi)] . \quad [4]$$

3. RESULTS

3.1 Land Properties in the Study Area

Some of the land characteristics in the research location are summarized in Table 3. Soil pH in the study area is acidic with minimum of 4.56 and maximum of 6.04. The basic cations used are calcium (Ca), magnesium (Kolesnikov et al., 2013), potassium (K), and sodium (Na). The sum of basic cations found in top and sub soil layers in all land systems is quite high for plantation plant growth with a range of 4.1–8.88 cmol kg^{-1}. The average value of base saturation in the top and sub soil layers is in the low-to-medium category. Base saturation values range from 28.54% to 46.30%. The CEC at the study site is classified as moderate with a range of 12.14–19.22 cmol kg^{-1}. In Bukit Ayun, Bukit Pandan, and Watampone land units, the C-organic content is extremely low at <1%. The highest C-organic content of 2.46% is found in Kalung land unit. Slope values obtained from the digital elevation model after 30 m SRTM image extraction range from 2% to >50%.

The annual precipitation in the research region is quite high, with annual average rainfall ranging from 1676 to > 2634 mm $year^{-1}$ and annual average temperature ranging from 21°C to 28°C. According to the field survey, the effective soil depth of the research location ranges 90–150 cm.

Table 2. Research control points for land suitability assessment

Commodity	Land indicators	LCP	b	d1	UCP	d2	Fuzzy Model
Coffee	pH H_2O	5.2	5.8–6.6	1.4	7.4	0.8	Model 2
	Sum of basic cations	2.8	6.5	3.7			Model 3
	Base saturation	35	50	15			Model 3
	CEC	15	24	9			Model 3
	Soil organic matter	0.8	2.5	1.7			Model 3
	Slope		8		18	10	Model 4
	Annual temperature	14	18–20	4	26	6	Model 2
	Annual precipitation	800	1400–1600	600	>2000	400	Model 2
	Soil depth	75	150	75			Model 3
	Soil texture		0		2	2	Model 4
Cocoa	pH H_2O	5.5	6–7	0.5	7.6	0.6	Model 2
	Sum of basic cations	2.8	6.5	3.7			Model 3
	Base saturation	20	35	15			Model 3
	CEC	15	24	9			Model 3
	Soil organic matter	0.8	2.5	1.7			Model 3
	Slope		8		18	10	Model 4
	Annual temperature	21	26–28	5	30	2	Model 2
	Annual precipitation	1200	1800–2000	600	3000	1000	Model 2
	Soil depth	75	200	125			Model 3
	Soil texture		0		2	2	Model 4
Clove	pH H_2O	4	6–7	2	8	1	Model 2
	Sum of basic cations	2.8	6.5	3.7			Model 3
	Base saturation	35	50	15			Model 3
	CEC	15	24	9			Model 3
	Soil organic matter	0.8	2.5	1.7			Model 3
	Slope		8		18	10	Model 4
	Annual temperature	21	26–28	5	30	2	Model 2
	Annual precipitation	1200	1800–2000	600	3000	1000	Model 2
	Soil depth	75	200	100			Model 3
	Soil texture		0		2	2	Model 4
Pepper	pH H_2O	4	6–7	2	8	1	Model 2
	Sum of basic cations	2.8	6.5	3.7			Model 3
	Base saturation	35	50	15			Model 3
	CEC	15	24	9			Model 3
	Soil organic matter	0.8	2.5	1.7			Model 3
	Slope		8		18	10	Model 4
	Annual temperature	19	24–26	5	30	4	Model 2
	Annual precipitation	1000	1600–1900	600	3000	1100	Model 2
	Soil depth	50	150	100			Model 3
	Soil texture		0		2	2	Model 4

3.2 New Factor Groups and Importance Weight

Each land attribute has the greatest load corresponding to each of the four factors. For example, slope is correlated at 0.898 with the first factor, 0.192 with the second factor, −0.147 with the third factor, and 0.069 with fourth factor. Each loading's square represents the proportion of variance (R^2) explained by a specific factor. For example, slope for factor 1, $(0.898)^2$ = 0.806 or 81% of its variance is explained by the first component. Subsequently, $(0.192)^2$ = 0.04 or 4% of the variance in slope is explained by the second factors. If the slope has a greater correlation to factor 1 than other factors, then the slope is classified as factor 1. This rule also applies to other land attributes. As previously explained, the weight of the land indicator (Wi) is the result of the corresponding load divided by the total corresponding load of the land attributes classified in that factor. Among the soil attributes included in factor 1, slope has the largest corresponding load. Therefore, the importance weight of the slope is greater (0.28) than that of the other land attributes included in factor 1. The total weight (Wi) of each factor is 1. This rule is also applicable to other land attributes. The following classification is based on the maximum corresponding

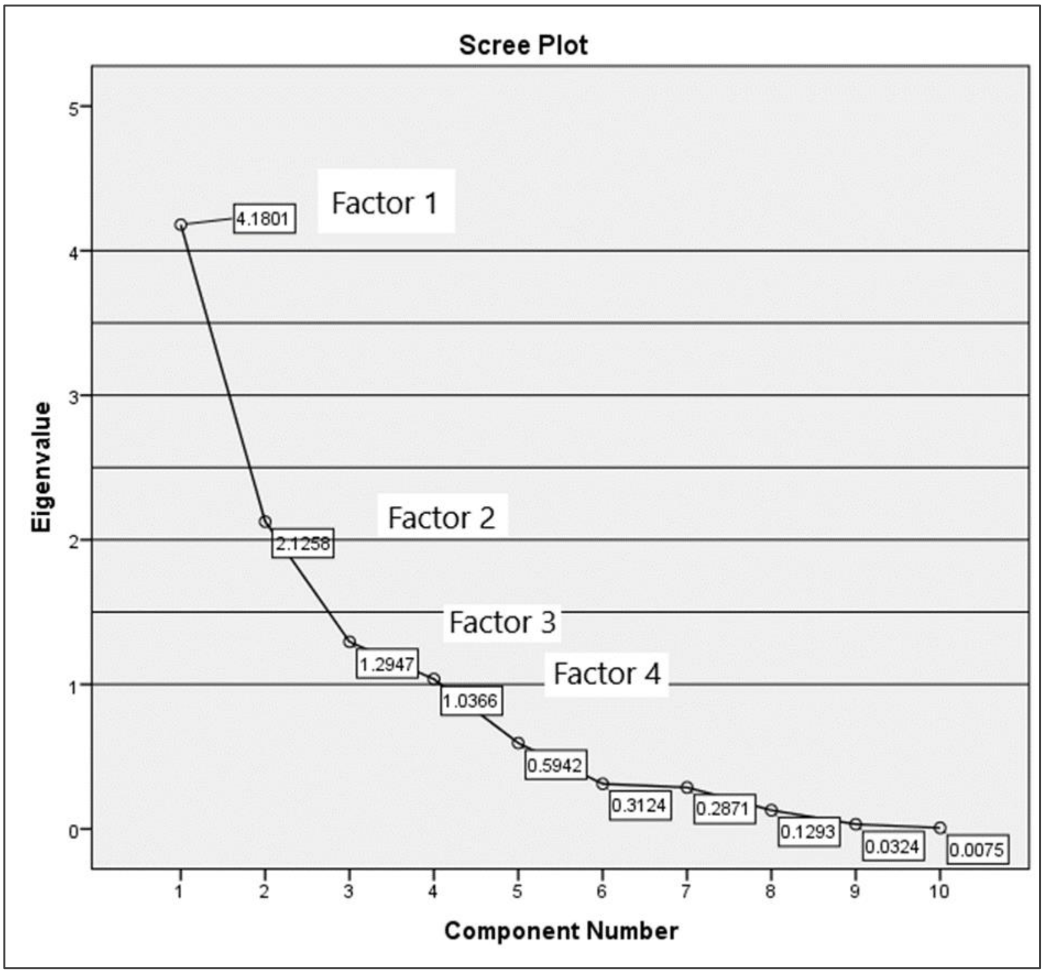

Figure 3. Scree plot of the eigenvalue by the component number

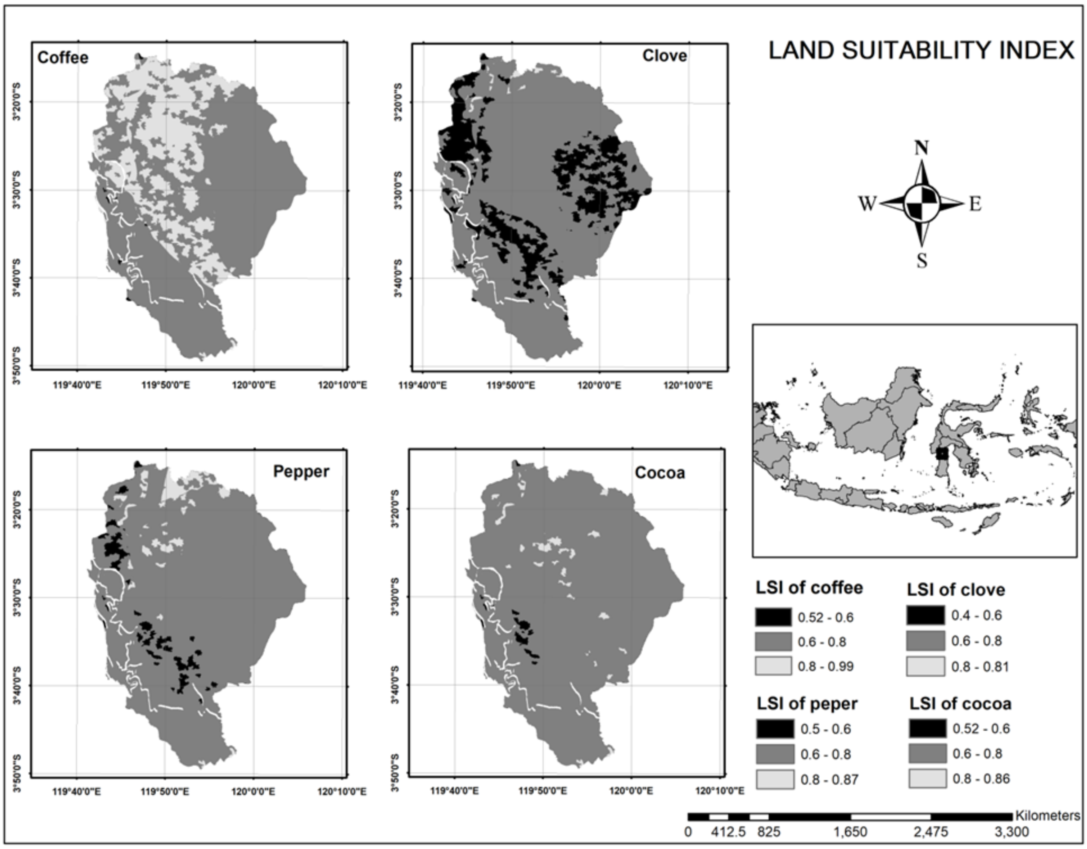

Figure 4. Land suitability index for plantation crops in research area

Table 3. Statistical description of land characteristics in the study site

Variable	Minimum	Maximum	Mean	S. E	Std. Deviation	Variance
pH H_2O	4.56	6.04	5.22	0.12	0.46	0.21
Sum of basic cations	4.15	8.27	5.14	0.27	1.05	1.11
Base saturation	28.54	46.30	33.96	1.41	5.48	30.01
CEC	12.14	19.22	15.66	0.54	2.08	4.33
C-organic	0.64	2.46	1.42	0.14	0.54	0.29
Slope	2.00	58.00	13.27	1.96	7.58	57.50
Annual temperature	21.00	28.00	26.07	0.45	1.75	3.07
Annual precipitation	1676.00	2634.00	209.98	11.60	432.23	186.14
Soil texture	0.00	2.00	0.80	0.22	0.86	0.74
Soil depth	90.00	150.00	120.00	5.26	20.35	414.29

Table 4. Rotation component matrix based on principle component analysis

	Factor							
	1		2		3		4	
Eigen values	4.18		2.12		1.29		1.03	
% Variance	41.80		21.2		12.94		10.3	
Factor weight (Hfi)	0.48		0.25		0.15		0.12	
Factor loading:		(W*i*)		(W*i*)		(W*i*)		(W*i*)
pH H_2O	−0.071		0.655	0.22	0.594		0.157	
Sum of basic cations	0.231		0.671	0.22	0.622		0.095	
Base saturation	0.089		0.115		0.945	1.00	0.106	
CEC	0.262		0.871	0.29	−0.194		−0.071	
C-organic	−0.027		0.830	0.27	0.303		0.060	
Slope	0.898	0.28	0.192		−0.147		0.069	
Annual temperature	0.760	0.24	−0.525		−0.243		−0.147	
Annual precipitation	0.695	0.22	0.114		−0.476		0.361	
Soil texture	0.018		0.035		0.131		0.974	1.00
Soil depth	0.846	0.26	−0.019		0.082		−0.017	

load of each land indicator in each factor: slope, annual precipitation, and annual temperature are grouped into factor 1; pH, number of base cations, CEC, and C-organic content are grouped into factor 2; base saturation is classified as factor 3; and soil texture is classified as factor 4. With PCA analysis results as basis, the newly formed factor groups and the degree of importance of all soil attributes are presented in Figure 3 and Table 4.

3.3 Membership Value of Land Attribute and JMF of Factors

Individual membership values range from 0 to 1. If a land attribute has a membership value of 1, then it is optimal for the growth of a plant and vice versa. Table 5 shows that some land attributes are below the tolerance threshold values listed in Table 2. For example, the individual membership of land attributes in the form of pH, CEC, and annual average rainfall and temperature is <0.4 for cocoa plant growth in Bukit Ayun land unit. This finding indicates that in Bukit Ayun land unit, the land properties do not meet the requirements for growing cocoa plants. In general, soil attributes for coffee plant growth have a higher membership value than those for other plants. In some land units, the individual membership value (for coffee plant growth) is equal to 1, indicating optimal suitability. For example, in Pendreh and Danau Lindu land units, land attributes such as temperature, rainfall, and slope have optimal suitability for coffee growth with individual membership values of >0.9. In general, the problems in the research area are temperature, CEC, and base saturation; many land units have individual membership values below the threshold value for clove plant growth. Land properties for pepper plant growth with individual membership values <0.4 are only found in Bukit Balang, Bukit Ayun, Maput, and Watampone land units. Although only a few land properties have individual membership values below the threshold, the research location generally fails to reach optimal suitability for clove growth with values of <0.85 and >0.4.

JMF values for evaluating the suitability of crops are listed in Table 6. These values indicate the quality of the land for the potential development of plantation crops. Similar to individual membership values, JMF also consists of a number range from 0 to 1. A high JMF indicates that the land has optimal potential for plantation development. The JMF value for coffee plant growth ranges from 0.38 to 1. A JMF of 0.38 is found for Sungai Aur land unit at factor 3. This finding indicates that factor 3 is a limiting factor for coffee plant growth.

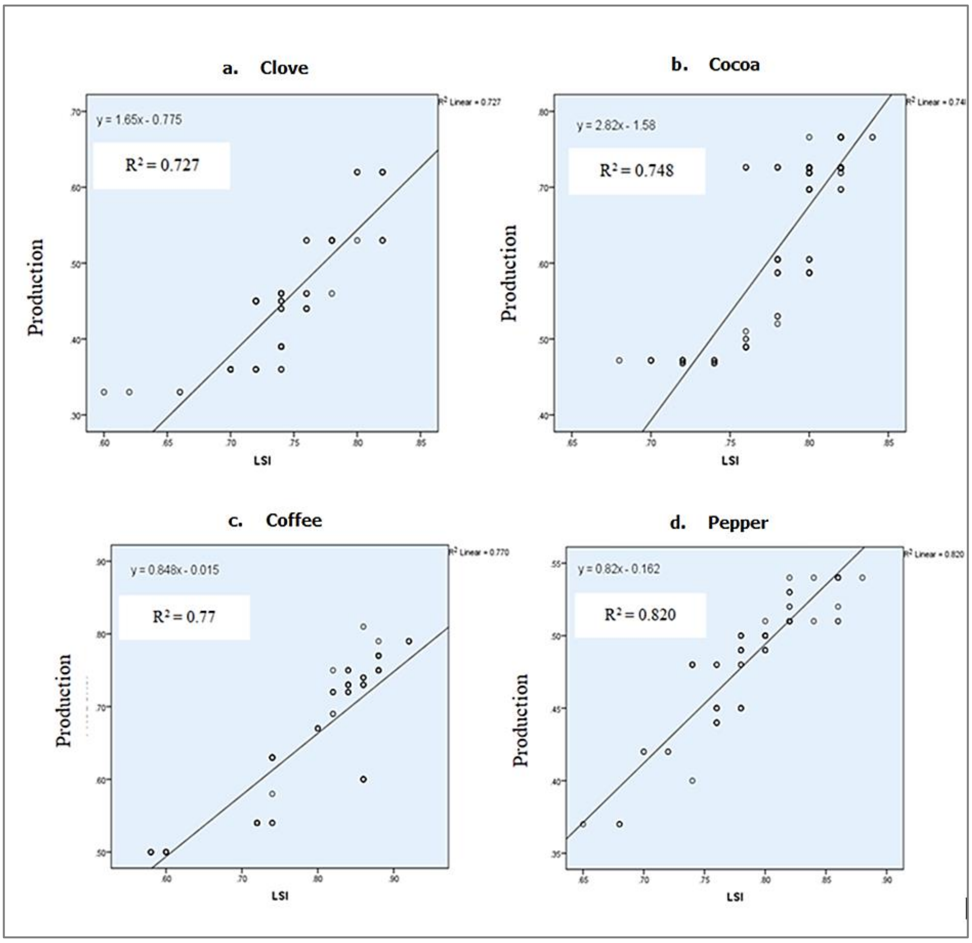

Figure 5. Linear regression between LSI and land production (ton ha^{-1}).

Cocoa JMF values range from 0.45 to 1. The lowest cocoa JMF is found in Bukit Ayun land unit on factors 1 and 2. The low JMF value in factor 1 indicates that climatic factors and soil physical factors are limiting factors for cocoa growth. Cloves and pepper have a low JMF of 0.3 in Sungai Aur land unit at a factor of 3. As previously explained, factor 3 has only one land property, namely, basic saturation. Thus, the low JMF of factor 3 indicates that the quality of base saturation is less supportive of plant growth.

3.4 LSI

The multiplication function in equation 5 was used to generate a spatial LSI data layer with continuous values ranging from 0 to 1, where 1 indicates optimal suitability for plant development. Analysis revealed that the LSI ranges 0.4–0.81 for cloves, 0.52–0.99 for coffee, 0.52–0.86 for cocoa, and 0.5–0.87 for pepper. The results are visualized in Figure 4. For land area evaluation, raster data were converted into vector data and then categorized based on the pixel value into several land suitability classes. Areas with a pixel value of > 0.8 were included in the optimal suitability category, areas with a pixel value of 0.8 ≤ LSI > 0.6 were included in the moderate suitability category, and areas with a pixel value of 0.6 > LSI > 0.4 were included in the marginal suitability category. Of the total area analyzed for coffee plants, 76.28% is moderately suitable, 23.26% is optimally suitable, and 0.45% is marginally suitability. For cocoa, 90% of the research area is moderately suitable, 0.29% is marginally suitable, and 9.6% is optimally suitable. For pepper, 86.89% of the research area is moderately suitable, 6.68% is optimally suitable, and 6.41% is marginally suitable. For cloves, 78.74% of the total area is moderately suitable, 19.26% is marginally suitable, and 1.98% is optimally suitable.

4. DISCUSSION

Approximately 76.28% of the study area has moderate suitability for coffee growth with an index range of 0.6 to 0.8. The same suitability class also dominates cocoa growth at 90% with an index range of 0.6–0.8. Meanwhile, 86.89% and 78.74% of the area is dominated by moderate suitability for pepper and clove growth, respectively. Land suitability for the four crops was successfully assessed in this study using fuzzy–AHP as evidenced by the accuracy test on the proposed model (Figure 5). Seyedmohammadi et al. (2019) conducted a validation test by comparing the pixel values of the LSI as a map to be assessed and production data as ground truth data to obtain a match. This strategy was also applied in the current research. Commodity production data were extracted spatially into polygon maps, which were then matched with LSI data. Validation points were randomly assigned and then processed to assess linear or nonlinearity between the LSI and production data (Figure 5). The rule of decision-making using regression test is as follows: if f < 0.05, then linearity occurs between LSI and production. On the basis of the test results of all analyzed plants, linearity was found between LSI and production with f = 0.00. Therefore, the model used in the current study is good and can be employed in other evaluations related to suitability assessment.

Table 5. Individual membership of land attributes

Land attribute	VI	V2	V3	V4	V5	V6	V7	V8	V9	V10	VI	V2	V3	V4	V5	V6	V7	V8	V9	V10
Land unit	**Cacao**										**Coffee**									
Bukit Balang	0.68	0.98	0.87	0.55	0.73	0.71	1.00	0.76	0.28	0.37	0.90	0.98	0.63	0.55	0.73	0.86	1.00	0.59	0.90	0.50
Bukit Ayun	0.11	0.77	0.74	0.46	0.47	0.71	1.00	0.39	0.34	0.44	0.18	0.77	0.41	0.46	0.47	0.86	1.00	0.94	0.97	0.50
Pendreh	0.60	0.92	0.78	0.57	0.70	0.76	0.50	0.69	0.34	0.88	0.89	0.92	0.48	0.57	0.70	0.93	0.50	0.98	0.97	1.00
Batang Anai	0.62	0.96	0.98	0.46	0.70	0.66	1.00	0.59	0.50	0.80	0.94	0.96	0.92	0.46	0.70	0.78	1.00	1.00	0.97	1.00
Bukit Pandan	0.29	0.87	0.72	0.64	0.48	0.86	1.00	0.78	0.50	0.44	0.51	0.87	0.40	0.64	0.48	1.00	1.00	0.93	0.97	0.86
Okki	0.46	0.77	0.69	0.54	0.81	0.86	1.00	0.71	0.28	0.35	0.68	0.77	0.36	0.54	0.81	1.00	1.00	0.97	0.90	0.34
Kalung	0.99	1.00	0.98	0.78	1.00	0.86	0.50	0.47	0.41	0.25	1.00	1.00	0.91	0.78	1.00	1.00	0.50	0.99	1.00	0.20
Maput	0.20	0.80	0.69	0.55	0.78	0.76	1.00	0.97	0.41	0.60	0.28	0.80	0.36	0.55	0.78	0.93	1.00	0.80	1.00	0.80
Bakunan	0.22	0.36	0.79	0.37	0.71	0.61	0.50	1.00	0.61	0.68	0.42	0.36	0.49	0.37	0.71	0.69	0.50	0.73	0.90	0.92
Hiliboru	0.32	0.80	0.75	0.51	0.67	0.76	0.50	0.90	0.50	0.39	0.54	0.80	0.43	0.51	0.67	0.93	0.50	0.63	0.97	0.41
Teweh	0.14	0.71	0.74	0.41	0.71	0.66	0.80	0.85	0.74	0.88	0.24	0.71	0.41	0.41	0.71	0.78	0.80	0.89	0.80	1.00
Watampone	0.22	0.84	0.86	0.41	0.48	0.71	0.80	0.97	0.74	0.80	0.38	0.84	0.61	0.41	0.48	0.86	0.80	0.80	0.80	1.00
Sungai Aur	0.57	0.83	0.67	0.60	0.65	0.56	0.80	1.00	0.61	0.91	0.89	0.83	0.34	0.60	0.65	0.61	0.80	0.69	0.90	0.92
Danau Lindu	0.97	0.49	0.81	0.60	1.00	0.61	1.00	1.00	0.50	0.98	1.00	0.49	0.52	0.60	1.00	0.69	1.00	0.69	0.97	1.00
Mantalat	0.11	0.90	0.66	0.74	0.62	0.56	0.80	1.00	0.50	0.60	0.19	0.90	0.33	0.74	0.62	0.61	0.80	0.69	0.97	0.80
Land unit	**Clove**										**Pepper**									
Bukit Balang	0.97	0.98	0.63	0.55	0.73	0.71	1.00	0.98	0.20	0.37	0.97	0.98	0.63	0.55	0.73	0.92	1.00	0.98	0.34	0.37
Bukit Ayun	0.66	0.77	0.41	0.46	0.47	0.71	1.00	0.50	0.25	0.44	0.66	0.77	0.41	0.46	0.47	0.92	1.00	0.30	0.41	0.44
Pendreh	0.96	0.92	0.48	0.57	0.70	0.76	0.50	1.00	0.25	0.88	0.96	0.92	0.48	0.57	0.70	0.96	0.50	0.89	0.41	0.88
Batang Anai	0.96	0.95	0.92	0.46	0.70	0.66	1.00	0.98	0.39	0.80	0.96	0.95	0.92	0.46	0.70	0.86	1.00	0.70	0.61	0.80
Bukit Pandan	0.87	0.87	0.40	0.64	0.48	0.86	1.00	0.97	0.39	0.44	0.87	0.87	0.40	0.64	0.48	1.00	1.00	1.00	0.61	0.44
Okki	0.91	0.77	0.36	0.54	0.81	0.86	1.00	0.99	0.20	0.35	0.91	0.77	0.36	0.54	0.81	1.00	1.00	0.92	0.34	0.35
Kalung	1.00	1.00	0.91	0.78	1.00	0.86	0.50	0.73	0.31	0.25	1.00	0.81	0.91	0.78	1.00	1.00	0.50	0.45	0.50	0.25
Maput	0.79	0.80	0.36	0.55	0.78	0.76	1.00	0.83	0.31	0.60	0.79	0.80	0.36	0.55	0.78	0.96	1.00	0.91	0.50	0.60
Bakunan	0.82	0.72	0.49	0.37	0.71	0.61	0.50	0.77	0.50	0.68	0.82	0.72	0.49	0.37	0.71	0.80	0.50	0.84	0.74	0.68
Hiliboru	0.88	0.80	0.43	0.51	0.67	0.76	0.50	0.65	0.39	0.39	0.88	0.80	0.43	0.51	0.67	0.96	0.50	0.69	0.61	0.39
Teweh	0.72	0.71	0.41	0.41	0.71	0.66	0.80	0.93	0.64	0.88	0.72	0.71	0.41	0.41	0.71	0.86	0.80	0.99	0.86	0.88
Watampone	0.81	0.84	0.61	0.41	0.48	0.71	0.80	0.83	0.64	0.80	0.81	0.84	0.61	0.41	0.48	0.92	0.80	0.91	0.86	0.80
Sungai Aur	0.96	0.83	0.34	0.60	0.65	0.56	0.80	0.72	0.50	0.91	0.96	0.83	0.34	0.60	0.65	0.74	0.80	0.78	0.74	0.91
Danau Lindu	1.00	0.97	0.52	0.60	1.00	0.61	1.00	0.72	0.39	0.98	1.00	0.97	0.52	0.60	1.00	0.80	1.00	0.78	0.61	0.98
Mantalat	0.67	0.90	0.33	0.74	0.62	0.56	0.80	0.72	0.39	0.60	0.67	0.90	0.33	0.74	0.62	0.74	0.80	0.78	0.61	0.60

Table 6. Joint membership value of each factor

Land Unit	FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4
	Coffee				**Pepper**			
Bukit balang	0.70	0.79	0.65	1.00	0.64	0.78	0.63	1.00
Bukit ayun	0.79	0.46	0.45	1.00	0.53	0.57	0.41	1.00
Pendreh	0.96	0.78	0.51	0.50	0.79	0.77	0.48	0.50
Batang anai	0.93	0.73	0.92	1.00	0.75	0.74	0.92	1.00
Bukit pandan	0.93	0.67	0.43	1.00	0.75	0.69	0.40	1.00
Okki	0.77	0.71	0.39	1.00	0.64	0.74	0.36	1.00
Kalung	0.76	1.00	0.90	0.50	0.55	0.94	0.91	0.50
Maput	0.87	0.62	0.40	1.00	0.74	0.72	0.36	1.00
Bakunan	0.81	0.44	0.52	0.50	0.76	0.64	0.49	0.50
Hiliboru	0.72	0.63	0.47	0.50	0.66	0.70	0.43	0.50
Teweh	0.86	0.50	0.45	0.80	0.89	0.63	0.41	0.80
Watampone	0.86	0.49	0.63	0.80	0.87	0.61	0.61	0.80
Sungai aur	0.78	0.77	0.38	0.80	0.79	0.74	0.34	0.80
Danau lindu	0.84	0.81	0.55	1.00	0.80	0.88	0.52	1.00
Mantalat	0.76	0.70	0.36	0.80	0.68	0.73	0.33	0.80
	Clove				**Cocoa**			
Bukit balang	0.55	0.79	0.63	1.00	0.52	0.72	1.00	1.00
Bukit ayun	0.48	0.57	0.41	1.00	0.47	0.45	0.97	1.00
Pendreh	0.72	0.76	0.48	0.50	0.68	0.69	0.99	0.50
Batang anai	0.70	0.73	0.92	1.00	0.65	0.67	1.00	1.00
Bukit pandan	0.65	0.69	0.40	1.00	0.64	0.57	0.93	1.00
Okki	0.59	0.74	0.36	1.00	0.54	0.64	0.90	1.00
Kalung	0.53	0.94	0.91	0.50	0.50	0.92	1.00	0.50
Maput	0.62	0.71	0.36	1.00	0.68	0.59	0.89	1.00
Bakunan	0.64	0.64	0.49	0.50	0.71	0.51	1.00	0.50
Hiliboru	0.54	0.70	0.43	0.50	0.63	0.58	0.98	0.50
Teweh	0.78	0.63	0.41	0.80	0.78	0.50	0.96	0.80
Watampone	0.75	0.60	0.61	0.80	0.80	0.48	0.96	0.80
Sungai aur	0.68	0.73	0.34	0.80	0.77	0.66	0.87	0.80
Danau lindu	0.69	0.88	0.52	1.00	0.77	0.87	1.00	1.00
Mantalat	0.57	0.72	0.33	0.80	0.65	0.61	0.84	0.80

The proposed method is easy and simple to apply in environmental management, especially in objectively evaluating land suitability without involving expert opinion to determine the importance of the assessment parameters. Fuzzy linear functions were used to standardize (individual membership) soil attributes, similar to Nurmiaty and Baja (2014). PCA was employed to analyze the correlation between land attributes and then classify them into new factors without reducing them. This goal was achieved by creating new uncorrelated variables that successively maximize variance. Four main components (PC1, PC2, PC3, and PC4) with eigenvalues >1 were extracted. This technique succeeded in grouping 10 variables into four main components (new group of variables) and described 86.24% of the original variance. Sahoo et al. (2021) also used PCA only to construct new variables from land attributes for land suitability assessment. Jolliffe and Cadima (2016) pointed out that PCA is an adaptive technique that can determine several new variables. In our research, the results of PCA analysis were further used to determine the degree of importance of each component and of the variables or land indicators in a specific component by utilizing the variance of each component and the loading factor of each land attribute. Factor 1 has a strong loading on slope, mean annual temperature and precipitation, and soil depth, and factor 2 has a strong loading on pH, sum basic cations, organic matter, and CEC. Factors 3 and 4 have a strong loading on base saturation and soil texture, respectively. On the basis of variance values, factor 1 is the most important variable and is given the highest weight of describing 48% total data among the four factors. Several studies also used PCA. In particular, Ghaemi et al. (2014) and Said et al. (2020) gave great importance to PC 1. Ayehu and Besufekad (2015) gave the greatest importance to climatic factors such as precipitation and temperature. Among several variables that have a high correlation with factor 1, the slope is considered the most important, has the greatest influence on other land attributes in the factor 1 group, and thus is given the highest weight.

Our experience on data processing revealed that when the fuzzy method is used, the threshold set by the researcher (LCP and UCP) in Table 2 becomes a sensitive aspect that affects the results of individual membership values of land attributes in Table 5. The threshold is also influenced by the quality of the land itself. Qiu et al. (2014) emphasized that thresholds cannot be determined arbitrarily and must be based on expert knowledge of the situation. As shown in Table 5, some land attributes such us texture in Batang Anai and Bukit Pandan units are optimal for plantation plant growth with individual membership values = 1. Other land attributes such as pH in Maput and Bakunan units do not meet the plant growth requirements with individual membership values < 0.4. Soil pH in all study areas is acidic in the range of 4.56–6.04. For coffee and cocoa, the lower tolerable threshold is 5.2 (Sys et al., 1993). Therefore, pH is one of the main limiting factor for the growth of coffee and cocoa in several land units such as Bukit Balang, Bukit Pandan, Maput, Bakunan, Teweh, Watampone, and Mantalat because they fail to meet the specified threshold, resulting in their low membership values. For the growth of clove and pepper plants, the individual membership value of pH is quite high at > 0.5 in all land units. All the pH values meet the minimum threshold set for clove and pepper growth according to the criteria compiled by Ritung et al. (2011). Another major limiting factor for cocoa growth in the study area is temperature. In the present land suitability assessment, temperature is an important factor and is included in the group with the first degree of importance. This finding is in agreement with Geo and Saediman (2019), who stated that climatic factors greatly affect cocoa growth and dry months are ideal for cocoa growth. Temperature is also an important issue and a major limiting condition for the growth of pepper and clove plants. According to Ritung et al. (2011), the optimal daily average temperature for clove growth ranges from 26°C to 28°C. However, the majority of the research area has an average daily temperature of < 26°C; thus, many sites reach low threshold values for temperature. Another land indicator that must be considered in the research location is CEC. Many land units do not meet the minimum CEC standards for the growth of coffee, cocoa, pepper, and cloves. CEC in the study area ranges 12.14–21.25 cmol kg^{-1}, and the minimum CEC standard for plant growth is 15 cmol kg^{-1}. The main problems in the research area are temperature, pH, and CEC. Temperature is the main limiting factor for the development of cocoa, clove, and pepper crops because it has the highest importance among the three main limiting factors. However, temperature is an attribute that is difficult to modify using any treatment. To overcome the problem of low pH in the research site, Gentili et al. (2018) suggested that the pH can be increased by applying calcium hydroxide. Martinsen et al. (2015) revealed that the addition of biochars to acid soil can increase pH and CEC to overcome soil fertility problems in the study area.

5. CONCLUSION

For coffee growth, 23.26% of the study area is optimally suitable with an index of 0.6–0.8, 76.28% is moderately suitable with an index of 0.8–0.99, and 0.45% is marginally suitable with an index of 0.52–0.6. For cocoa growth, 9.6% of the study area is optimally suitable with an index of 0.8–0.88, and 90% is marginally suitable with an index of 0.6–0.8. For clove growth, 19.26% of the study area is marginally suitable with an index of 0.4–0.6, 78.74% is moderately suitable, and only 1.98% is optimally suitable with index of 0.8–0.81. For pepper growth, 6.68% of the study area is optimally suitable with an index of 0.8–0.87, 86.89% is moderately suitable, and 6.41% is marginally suitable with an index of 0.5–0.6. Mean annual temperature <26°C, acidic soil pH, and low CEC are the main limiting factors for the growth of plantation crops in the study site. As a solution, biochars and calcium hydroxide can be supplemented to acidic soils to increase soil pH and CEC. In addition to the quality of the land itself, the final land suitability is influenced by the threshold set by the researcher. The mathematical operations used to determine the weights are simple and easy to implement. Validation tests showed that the combination of fuzzy–PCA models succeeded in objectively revealing the suitability of plantation land. Therefore, this model can be applied in other fields of land management. For accurate land suitability assessment, further research must compare the ability of various methods in calculating the final LSI.

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Declaration of Competing Interest

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

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