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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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Wed,

Dr Risma - Neswati:

Dr. Komariah Komariah has added a comment to the submission, "ANALYSIS OF AGRICULTURAL LAND SUITABILITY USING A COMBINATION OF PCA AND FUZZY METHODS" in SAINS TANAH - Journal of Soil Science and Agroclimatology:

Please revise the references according to the directions on the manuscript.

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[STJSSA] Editor Decision (REVISIONS REQUIRED)

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Editorial Team of Sains Tanah <jurnal@mail.uns.ac.id>
to me, Nurfadila, Sumbangan, Didi

Fri

Dear Dr Risma Neswati:

We have reached a decision regarding your submission to SAINS TANAH - Journal of Soil Science and Agroclimatology, "ANALYSIS OF AGRICULTURAL LAND SUITABILITY USING A COMBINATION OF PCA AND FUZZY METHODS".

Our decision is: Revisions Required (due date is: October 07, 2022)

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ANALYSIS OF AGRICULTURAL LAND SUITABILITY USING A COMBINATION OF PCA AND FUZZY METHODS

II. First author:

1. Name : Nurfadila JS
2. Afiliation : Faculty of Post-Graduate, Hasanuddin University, Indonesia
3. E-mail : dilajs01@gmail.com
4. Orcid ID : https://orcid.org/0000-0002-6977-6005
5. Phone/HP/WA : 085230304645

III. Second author:

1. Name : Sumbangan Baja
2. Afiliation : Department of Soil Science, Hasanuddin University, Indonesia
3. E-mail : sbja02@yahoo.com.au
4. Orcid ID : https://orcid.org/0000-0002-5157-9767

IV. Third author:

1. Name : Risma Neswati
2. Afiliation : Department of Soil Science, Hasanuddin University, Indonesia
3. E-mail : neswati76@gmail.com
4. Orcid ID : https://orcid.org/0000-0003-0358-389X

V. Fourth author:

1. Name : Didi Rukmana
2. Afiliation : Department of Agriculture Socio-Economics, Hasanuddin University, Indonesia
3. E-mail : drukmana@gmail.com
4. Orcid ID : https://orcid.org/0000-0001-5855-7301

VI. The main findings and why they are important and useful.

The approach to land suitability assessment uses multiple criteria where the importance between criteria is assessed objectively based on the characteristics of the area itself.

VII. Why the readers of the journal would be interested in the work.

This research demonstrates a method of evaluating land suitability with multi objective decision making using the fuzzy method and the principle of component analysis. The importance of land evaluation criteria is not determined in advance by researchers or decision makers but is the result of an analysis of soil properties in the research area itself.

VIII. Suggested Reviewers : *(2 reviewers from different country with authors, and Scopus H-index minimum 2)*

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ANALYSIS OF AGRICULTURAL LAND SUITABILITY USING A COMBINATION OF PCA AND FUZZY METHODS

ABSTRACT

Land suitability assessment in this study uses a combination of fuzzy methods and PCA. Variables used included: soil texture, pH, sum of basic cations, base saturation, cations Exchange capacity (CEC), C-organic, soil depth, slope, annual temperature and precipitation data. One of the challenges in the land suitability evaluation method is that the assessment of the weight importance of variables is still subjective and relies on weights that have been used by other researchers in other areas. In fact, the characteristics and correlation between land attributes are not the same from one region to another, so it is necessary to carry out an assessment that is in accordance with the characteristics of the region itself. Using PCA, 4 new factors are formed. This is achieved by creating new uncorrelated variables that successively maximize variance. As a by-product, a better interpretation of the data is obtained. The loading corresponding and variance values obtained from the rotated component matrix are used as a consideration for the weights of the land indicators and new four factor groups. The results showed that LSI of cloves ranged from 0.4 to 0.81, coffee 0.52 to 0.99, cocoa 0.52 to 0.86, pepper 0.5 to 0.87. based on linearity test, it was found that there was a correlation between LSI and production with a value of f = 0.00 so it could be concluded that the model applied in the study was good 26 and could be used to predict production.

Keywords: land suitability index; Fuzzy method; Principle component analysis; Multi objective decision making.

INTRODUCTION

Sustainable agriculture is defined as a comprehensive system of plant production practices with a site-specific application that would over the long term: fulfill human food and fiber needs; improve environmental quality, and strengthen the natural resource base on which the agricultural economy is based; ensure effective and efficient use of non-renewable resources and on-farm resources; maintain agriculture processes' economic viability; improve the quality of life for farmers and society as a whole (Rigby and Caceres, 1997). Sustainable agriculture is ensuring the most efficient use of agricultural resources (Pan et al., 2022). One of the main goals of sustainable agriculture is to ensure that agriculture does not deviate from the natural system itself. Therefore, evaluating the suitability of agricultural land becomes very important. Land suitability evaluation is the key and first step in designing sustainable land use. Good farming practices can lead to better (Prakash, 2003; Vasu et al., 2018). Appropriate land suitability for certain agricultural activities will encourage better production. Agricultural production is closely related to the income of the farming community, if the farming community feels that they get high income from their farming, they will maintain their agricultural activities so that they can support agricultural sustainability (Duffy, 2009) and subsequently have a positive impact on other sectors such as increasing the number of workers (Ngeleza et al., 2011).

In practice, land suitability assessments must consider multiple criteria (MC). Decision making with MC is a tool that deals with decision problems related to conflicting criteria. MC is classified into two categories, namely multi-attribute (MADM) and multi-objective decision making (MODM) (Leake

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& Malczewski, 2000; Zimmermann & Gutsche, 1991). MA is suitable for decision making using discrete criteria where the importance between attributes has been determined by the decision maker. The criteria in the MADM method are usually filtered, prioritized and finally ranked by the decision maker (Gebre et al., 2021). Some examples of multiple criteria decision making using the MADM method are pairwise comparisons such as process hierarchy analysis (AHP), value or utility functions such as MAVT, MAUT and SAW (Liu et al., 2013; Zhang et al., 2016; Ananda & Herath, 2009). In contrast to MADM, MODM is a decision-making method using criteria whose degree of importance between criteria is not predetermined. The importance between criteria in the MODM method 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 used (Gebre et al., 2021).

The problem that is often encountered when using the MADM method to determine the degree of importance between soil criteria in the evaluation of land suitability is that there are differences of opinion among several experts, causing bias and confusion for researchers. In addition, the effect of a soil trait on other soil properties in an area is not always the same as in other areas. This difference is caused by many factors including the way farmers cultivate, and the characteristics of the soil in the area itself. Equating the assessment of the degree of importance of soil properties in land evaluation based on research that has been carried out in different areas can lead to bias. This study aims to analyze the suitability of agricultural land with MODM and fuzzy methods. The importance of land evaluation criteria is not determined in advance by researchers or decision makers but is the result of an analysis of soil properties in the research area itself.

MATERIAL AND METHODS

The study area was conducted in Enrekang, one of the districts in South Sulawesi, Indonesia. Four cultivated plants were analyzed and compared at the study site (coffee, cocoa, pepper and cloves). Guidelines for Land Suitability Assessment Using Technical Guidelines for Land Evaluation of Agricultural Commodities by Ritung et al. (2011) also guidelines by Sys (1993) on Land Evaluation Part III on Plant Requirements. The three main variables used in the assessment include; climate variables, topographic variables and soil variables, with a total of ten indicators. The variables used in the study are summarized in the Table 1.

Field Sampling and Laboratory Analysis

There are land attributes that can be estimated or measured directly in the field, and some must be assessed in the laboratory (FAO, 1976). Field observations included soil depth and slope measurements, while other soil variables were analyzed in the laboratory. A land unit map of research area (Figure 1) was used as references for soil sampling. The land unit map is combined information of the ecological principles relating to rock types, hydro-climate, landforms, soil, and organisms (Blasi et al., 2008). According to Zonneveld (1989), the survey results including the unit map, could be used as a basis for land evaluation.

Thirty soil samples were taken. Samples were taken from top (depth 0-25 cm) and subsoil (depth> 25 cm) from 15 land units. Those used for texture and CEC analysis were obtained from subsoil, while those for pH, basic cations (including Ca, Mg, K, and Na), and base saturation analysis were taken from the topsoil. Texture, CEC, pH, sum of basic cations, base saturation, and C-organic were analyzed in the laboratory. The various approaches used by the factors were as follows: pipette method for texture analysis, 1: 2.5 soil water suspense for pH procedure, the Walkley-Black method with 105^{o}C

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dry soil samples for C-organic analysis, while the sum of basic cations, CEC, and base saturation used the cations exchange rate (NH4-Acetat 1N, pH 7) in dry soil sample of 105ºC.

Terms and Stages of Land Suitability Assessment

Land suitability assessment in this study implements a fuzzy model by Zadeh (1965). The fuzzy set function can analyze soil characteristics continuously without categorizing them into different classes. In fuzzy analysis, land attribute values are converted to sustainable values ranging from zero to one. 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 semantic import model (SIM) that is widely used as in the study conducted by Baja (2002), and is described in the modeling of Figure 2.

In the modeling of Figure 2, some important values such as; b which is the value of a land attribute at the ideal point, lower crossover (LCP) and upper crossover (UCP) are the lower and upper thresholds/margins of a land attribute 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. The optimal point in the fuzzy function model 1 is used to assess soil attributes which have one ideal point but have 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. Fuzzy model 3 can be interpreted that 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. Land characteristics in the fuzzy function model 4 are interpreted that the smaller a land characteristic, the better, as is the case with the slope level. The research control points in Table 2 are arranged based on; agricultural land evaluation criteria made by Ritung (2011) and Sys (1993), Fuzzy modeling in Figure 2, and land characteristics at the research site. The following steps were used to calculate the land suitability index:

1. Determine the variables that are considered important in research.
2. Forming new factors/variables from land attributes that have been considered for inclusion in land suitability assessment. Factor analysis was carried out on soil attributes using the principle component analysis (PCA) to group land attributes that were considered to have the same characteristics into one new factor/variable (Pearson,1901; Hotelling ,1933). In some studies, PCA is indeed used as a data reduction technique. However, because this study used the total data set principle, there is no reduction in land attributes. This study used PCA to analyze the correlation between land attributes and then classifies them into new factors without reducing them. This is achieved by creating new uncorrelated variables that successively maximize variance. As a by-product, a better interpretation of the data is obtained. PCA components that are retained are those that have one or more eigenvalues (see Figure 3). The number of indicators for each component or factor will be the same as the number of land indicators analyzed, but each component/factor will only maintain one or more indicators with a maximum loading corresponding. The variance of each component/factor will explain how much the component contributes in explaining the data as a whole, while the loading corresponding explains how much the correlation between the indicator and the component is (Armenise et al., 2013; Mukherjee & Lal, 2014). Based on the results of PCA analysis, four new factors included in calculating land suitability index (LSI) (Figure 3 and Table 4)

3. Standardize the land indicators on each new factor with a value of 0-1, carried out by the equation 1.

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

$MF(x_i) = 1$, if $(b_1+d_1) \le xi \le (b_2 - d_2)$ (fuzzy model 2)

$MF(x_i) = 1$, if $xi > b$ (fuzzy model 3)

$MF(x_i) = 1$, if $xi < b$ (fuzzy model 4)

4. Calculate the weight of the importance of land attributes on each factor used in land suitability assessment by equation 2. The weighting (W_i) given will consider the loading factor value of each indicator (y_i) and total loading factor value ($\sum y$) in each factor.

$$W_i = \frac{|y_i|}{\sum |y|} \quad (2)$$

5. Calculates the join membership value (JMF) of all factors included in the land suitability assessment using equation 3.

$$JMF(X_{i.....z}) = \sum_{i=1}^{n} Wi\ (MFi) \quad (3)$$

6. Calculate the importance weight of all factors used in land suitability assessment by equation 4. The weight given to each factor considers the value of the variance component of a factor i (m_i) and the total value of the variance component formed ($\sum m$).

$$H_{Fi} = \frac{|m_i|}{\sum |mi|}\ x\ 100 \quad (4)$$

7. Calculate the land suitability index. The MF of each factor is then integrated with the weight of the factor (H_{fi}) to determine the LSI using the equation 5:

$$LSI = \sum_{i=1}^{n} \mathrm{Hf}i\ (JMFxi) \quad (5)$$

RESULTS

Land Properties in the Study Area

A summary of some of the land characteristics at the research location can be seen in Table 3. Soil pH in the entire study areas are acidic with minimum range of 4.56 and maximum of 6.04. The basic cations used are calcium (Ca), magnesium (Mg), Potassium (K) and Sodium (Na). Sum of basic cations found in both top and sub soil in all land system had quite high for plantation plant growth with ranged of 4.1 cmol/kg to 8.88 cmol/kg. 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 was classified as moderate with a range of 12.14 cmol/kg to 19.22 cmol/kg. In the Bukit Ayun, Bukit Pandan and Watampone land units, the C-organic content was found to be very low, less than 1%. The highest value of c-organic of 2.46% was found in the Kalung land unit. Slope data obtained from digital elevation model (DEM) 30 m SRTM image extraction. The slopes recorded ranged from 2% to more than 50%. The annual precipitation in the research region is quite high, with annual average rainfall ranging from 1676 to more than 2634 mm/year. average annual temperature ranges from 21° C to 28° C. Based on the results of the field survey, it is known that the effective soil depth of the research location ranges from 90 to 150 cm.

New Factor Groups and Important Weight

In principle, PCA will produce as many components (factors) as the indicators included in the analysis.

However, only component factor having eigenvalues > 1 were retained for inclusion in the next analysis. According to this rule, four factors are maintained, each labeled factor 1, factor 2, factor 3 and factor 4. The 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 component, each following component is obtained by partially out of the previous component. Based on the maximum loading corresponding of each land indicator in each factor: slope, annual precipitation, annual temperature are grouped into factor 1; pH, number of base cations, CEC, C-organic become factor 2; base saturation to factor 3; Soil texture is a factor 4.

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Each land attributes has a greatest loading corresponding to each of the 4 factors. For example, slope is correlated 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. 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, and so on. Slope has a greater correlation to factor 1 than other factors, and then the slope is classified as factor 1. This also applies to other land attributes. As previously explained, the weight of the land indicator (W_i) is the result of the corresponding loading divided by total loading corresponding of the land attributes classified in that factor. Among several soil attributes included in factor 1, slope has the largest correspondent load. Therefore the importance weight on the slope is greater (0.28) than the other land attributes which are included in factor 1. The total weight (W_i) of each faktor is 1. This rule also applies to other land attributes. The results of the PCA analysis, the newly formed factor groups and the degree of importance of all soil attributes are presented in Figure 3 and Table 4.

Membership Value of Land Attribute and JMF of Factors

Individual membership values consist of numbers ranging from 0 to 1. If a land attribute has a membership value of 1, it indicates that the land attribute is optimal for the growth of a plant and vice versa. Based on Table 5, it is known that some land attributes are below the tolerance threshold value set as in Table 2. For example, individual membership of land attributes in the form of pH, CEC, average rainfall and annual temperature of less than 0.4 for cocoa plant growth in the Bukit Ayun land unit. This indicates that in the 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 other plants. In some land units, the individual membership value (for coffee plant growth) is equal to 1 which indicates optimal suitability. For example, in Pendreh and Danau Lindu land units, land attributes such as temperature, rainfall and slope have an optimal suitability for coffee growth with individual membership values of more than 0.9. In general, the problems faced by the research area are temperature, CEC and base saturation where 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 less than 0.4 were 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, in general the growth of clove plants in the research location did not reach optimal suitability with values less than 0.85 and more than 0.4.

Joint membership values (JMF) for evaluating the suitability of crops can be seen in Table 6. These figures indicate the quality of the land for the potential development of plantation crops. Just like individual membership values, JMF also consists of a number range from 0 to 1. The higher the JMF value indicates that a land has optimal potential for plantation development. The JMF value for coffee plant growth ranged from 0.38 to 1. A JMF of 0.38 was found in the Sungai Aur land unit at Factor 3. This indicates that factor 3 is a limiting factor for coffee plant growth. Cocoa JMF values ranged from 0.45 to 1. The lowest cocoa JMF was found in the 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 cocoa growth. Cloves and pepper have a low JMF value at a factor of 3, which is 0.3 at the Sungai Aur land unit. As previously explained there is only one land property in factor 3, namely basic saturation. Thus, the low value of factor 3 indicates the quality of the base saturation that is less supportive of plant growth.

Land Suitability Index

The multiplication function in equation 5 is used to generate a spatial land suitability index data layer with continuous values, ranging from 0 to 1. 1 indicates optimal suitability for plant development. Based on the analysis, it was found that the LSI of cloves ranged from 0.4 to 0.81, coffee 0.52 to 0.99, cocoa 0.52 to 0.86, pepper 0.5 to 0.87. The results are visualized in Figure 4. To evaluate land area, raster data is converted into vector data and then categorized based on its pixel value into several land suitability classes. Areas with a pixel value of > 0.8 are included in the optimal suitable category, while areas with a pixel value of $0.8 \leq LSI > 0.6$ are included in the moderate suitability category, and areas with a pixel value of $0.6 > LSI > 0.4$ are included in the marginal suitability category. Of the total area analyzed for coffee plants, 76.28% of the area is in the moderate suitability, 23.26% in the optimal suitable, and 0.45% in the marginal suitability category. For cocoa, 90% of the research area is included in the moderate suitability category, 0.29% and 9.6% are included in the marginal suitability and optimal suitable. A total of 86.89% of the research area is included in the moderate suitability category for pepper plants, while 6.68% areas are included in the optimal suitable and 6.41% areas are in the marginal suitability category. For clove commodity, 78.74% of the total area is included in the moderate suitability category, while for areas with marginal and very suitable suitability categories are 19.26% and 1.98%, respectively.

DISCUSSION

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Your objective is: "This study aims to analyze the suitability of agricultural land with MODM and fuzzy methods"
So, start the Discussion with the suitability as your main finding.
Then, explain your main finding with the data in this manuscript, COMPREHENSIVELY.

For instance:
"coffee is not suitable in the study site because the soil pH is too low (Table/ Figure…).. etc.

Then support your findings with the relevant references.

All soil and climate indicators with low variance values implied insignificant spatial variability throughout the area researched. Soil pH in the entire study areas is acidic with a range of 4.56 to 6.04 due to farmers' widespread use of inorganic fertilizers. Overall, the pH for both clove and pepper plant still meets requirements as tolerance limits for plant growth with a pH above 4 (Ritung et al., 2011). However, for coffee and cocoa, some land units are still below the minimum threshold of 5.2. It is normal for areas with high precipitation to have an acidic soil pH. Areas that have high precipitation cause basic cations to be leached from the adsorption complex and lost through water drainage. From the observations of several farmers it is known that the addition of calcium hydroxide can increase the pH value (Gentili et al., 2018). Organic matter varied between 0.68 % to 2.46 %. According to Grossman (1996), the organic matter of less than 2% was considered poor. The low soil organic matter is caused by land management do not pay attention to soil fertility. The land is planted continuously but not accompanied by efforts to improve soil fertility. According to West & Post (2002), this loss was reduced by restoring to native vegetation or cultivating permanent plant. CEC ranged from 12.14 to 21.25 cmol/kg. According to Saikh, Varadachari, & Ghosh (1998) the main issue of decreased CEC is deforestation and cultivation. Different CEC values are strongly influenced by organic matter content and soil pH (Barady, 1976). The Kalung land unit has higher CEC values compared to other land units. This land unit also has higher organic matter values compared to other land units, as well as its pH values. Base saturation was defined as ratio of the sum of basic cations to the amount of CEC obtained by colloidal soils, ranged from 28.54 to 46.30 %. Base saturation was defined as ratio of the sum of basic cations to the amount of CEC obtained by colloidal soils, ranged from 28.54 to 46.30 %. The low value of base saturation at the study site reflects the low content of basic cations also indicates that the soil is undergoing a lot of leaching. The most influential factor on the suitability of crop land is climate. Variability and climate change have a significant impact on the uncertainty of production from year to year (Edwinraj et al., 2017; Toshichika and Navin 2015.

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PCA used to analyze the correlation between land attributes and then classifies them into new factors without reducing them. This is achieved by creating new uncorrelated variables that successively maximize variance. According to Jolliffe and Cadima (2016), PCA is an adaptive technique that is able to determine several new variables. Four main components (PC1, PC2, PC3 and PC4) with eigenvalues greater than 1 were extracted. This technique succeeded in reducing ten variables into four main components (new group of variables) and described 86.24% of the original variance. Sahoo et al. (2021) also used the PCA technique only to construct new variables from land attributes for land suitability assessment. In our research, the results of PCA analysis are further used to determine the degree of importance of each component and the degree of importance of variables in a component. It does so by utilizing the variance value of each component and the loading factor value of each land attribute. Factor 1 have a strong loading on slope, mean annual temperature and precipitation, and soil depth while factor 2 have a strong loading on pH, sum basic cations, organic matter and CEC. Base saturation and soil texture in groups 3 and 4, respectively. Based on the variance, factor 1 is the most important variable and is given the highest weight compared to other factors which describes 48% total data. Ayehu and Atnafu (2015); Huynh and Van (2008) give greatest importance to physical factors such as precipitation and temperature. Among several variables that have a high correlation with factor 1, the slope is considered the most important and has the greatest influence on other land attributes in the factor 1 group so that it is given the highest weight. This is rational, according to research by Fan et al. (2020), slope is very influential on soil microclimate and soil quality. Factor 2 is considered unimportant from factor 1 based on the value of the variance which only affects 25% of the total data. As a consideration, factor 2 consists of soil fertility properties whose deficiencies can be corrected by certain treatments so that their weight can be considered given a lower value to the land suitability assessment. For example, in soils with low pH, fertility can be improved by adding calcium hydroxide (Gentili et al., 2018).

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Individual membership value is the standardization of each land quality to plant growing requirements. Membership values for pH, sum of basic cations, base saturation, and soil texture in all land units are the integration of the membership values in the top and bottom soil layers. The same treatment for soil sampling was also carried out by Nurmiaty and Baja (2014). The membership value is greatly influenced by the control points and fuzzy models used (Table 2). The control points in question are the optimal value (b), the upper and lower limits (UCP and LCP) and the width of the transition zone (d). Membership values of pH, annual temperature and annual precipitation apply symmetric functions (Model 2), while slopes and soil texture apply right asymmetric functions (Model 4), and other variables use left asymmetric functions (Model 3). Some properties and fuzzy models for the same land properties are also used by Baja (2002) The membership value defines the quality of individual attributes on the land suitability. The greater the membership value, the more appropriate the individual attributes with the plant's recruitment.

Joint membership is the sum of the multiples of the membership value of the soil attribute with the respective weights for each of the formed factors. There are 4 factors that will be included in the land suitability assessment, each of which will be calculated for the join membership value. Slope, annual precipitation, annual temperature and soil depth were used to calculate the join membership value of factor 1 while pH, sum of basic cations, CEC and C-organic for the join membership value of factor 2. Base saturation and soil texture to calculate the membership value of factors 3 and 4. Membership value is a number range from 0 to 1. The greater JMF, the more appropriate these factors are to the requirements of plant growth.

Agricultural land evaluation is an assessment using multiple criteria of land attributes to the requirements for plant growth. According to Steiner et al. (2000) and Stoms et al. (2002), land suitability evaluation is a multi-criteria analysis for a particular land use purpose, the results of which also depend on the opinion of experts in determining the most desirable factors for the stated purpose. The principle to determine the LSI is the same as the mathematical operations of multiplication and sum between the join membership value (JMF) of a factor and the weight of the factor (H_{fi}). From the analysis carried out, the main limiting factors for coffee plant growth are pH and base saturation. However, this does not have much effect on the final results of the suitability assessment of coffee plants because pH and base saturation are in the groups that have the second and third degrees of importance. The main limiting factors for cocoa growth are pH, CEC and temperature. In this land suitability assessment, temperature is a very important factor and is in the group with the first degree of importance. This is in line with the opinion of Geo and Saediman (2019) which states that climatic factors greatly affect cocoa growth. They state that the dry months are ideal for cocoa growth. The main limiting factor for clove growth in the study area was temperature. According to Ritung et al. (2011), the optimal daily average temperature for clove growth ranges from 26^{o} C to 28^{o} C. Most of the research areas have an average daily temperature of $<26^{o}$ C. This resulted in many sites in the assessment reaching lower threshold values for temperature.

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Validation test is carried out to test the accuracy of the model applied in the research (Figure 5). Seyedmohammadi et al. (2019) conducted a validation test by comparing the pixel values of the land suitability index as a map to be assessed and production data as ground truth data to obtain a match. Commodity production data is extracted spatially into polygon maps which are then matched with land suitability index data. Validation points are taken at random, then processed to assess linear or nonlinearity between the land suitability index and production data (Figure 5). The rule of decision making using regression test is if the value of f <0.05 then indicates that there is linearity between LSI and production. From the results of tests carried out on all analyzed plants, it was concluded that there was a linearity between LSI and production with a value of f = 0.00. Based on this, it can be concluded that the model used in the study is good and can be applied in other applications related to suitability assessment.

CONCLUSION

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Land suitability assessment is a decision-making method using several criteria. One of the challenges in the land suitability evaluation method to date is that the assessment of the importance of variables (biophysics) is still subjective and relies on weights that have been used by other researchers in other areas. In fact, the characteristics and correlation between biophysical parameters are not the same from one region to another, so it is necessary to carry out an assessment that is in accordance with the characteristics of the region itself.

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A total of ten land attributes used for LSI analysis include: data on soil texture, pH, cations exchange capacity (CEC), sum of basic cations, base saturation, organic matter, effective soil depth, slope, annual temperature and annual rainfall data. Soil sampling for several land attributes refers to the land unit map of the research location. Fuzzy logic is used to standardize all land attributes. The standardization value (MF) of land attributes ranges from 0 to 1 which depends on the quality of the land attribute itself. MF value close to 1 indicates optimal fit. The novelty of this research is an objective assessment of the importance of land attributes. Therefore, before assessing the weight of importance between parameters, a factor analysis was carried out first on the land attributes using the principle component analysis (PCA) method. The purpose of factor analysis is to identify the correlation between land attributes and to find the main factors that most influence the land attributes. the attributes that are considered to have the greatest influence on other land attributes are given a higher weight. From the factor analysis performed, four new variables/factors were formed, each labeled “factor 1”, “factor 2”, “factor 3” and “factor 4”. Based on the maximum loading corresponding of each land indicator in each factor: slope, annual precipitation, annual temperature are grouped into factor 1; pH, number of base cations, CEC, C-organic become factor 2; base saturation to factor 3; Soil texture is a factor 4. Each factor is given a weight. The factor with the largest variance value is given a greater weight than the other factors. Sum of multiplications between JMF and the weights (H*fi*) of these four factors results in land suitability index. The results showed that LSI of cloves ranged from 0.4 to 0.81, coffee 0.52 to 0.99, cocoa 0.52 to 0.86, pepper 0.5 to 0.87.

Figure and Table

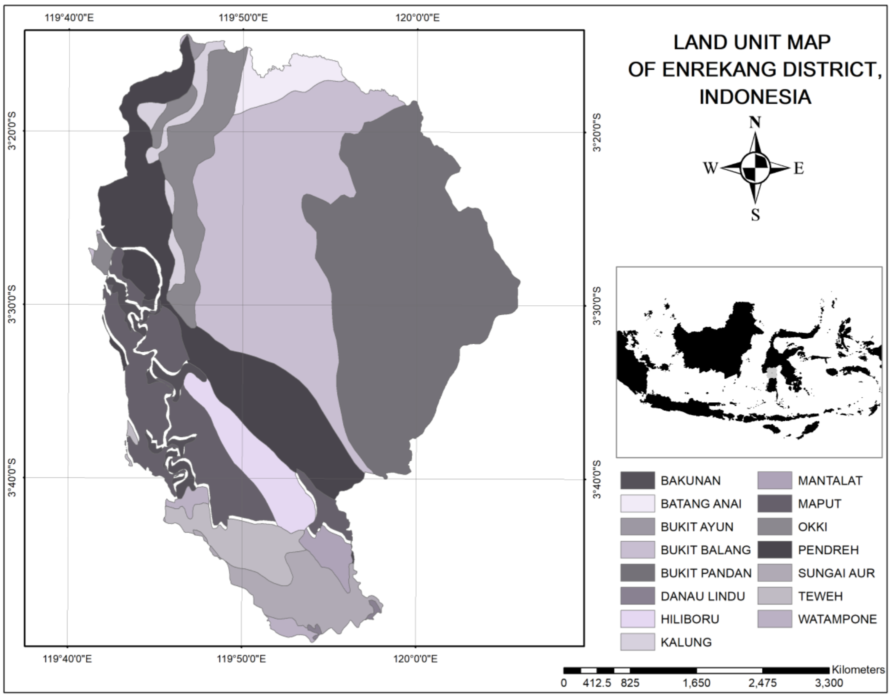

Figure 1. Land unit map of research area

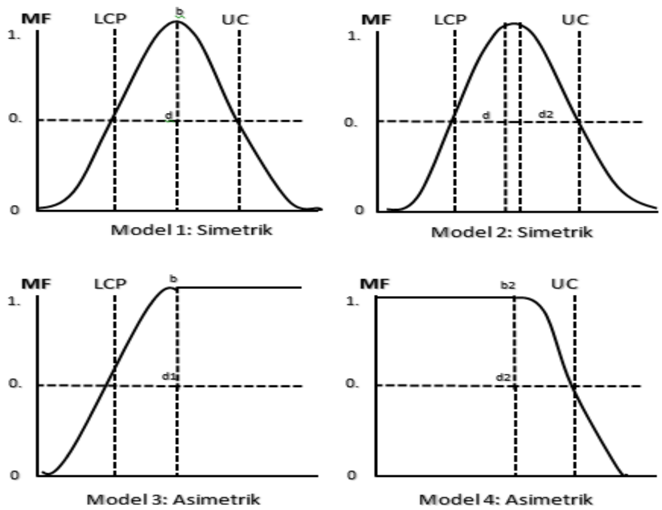

Figure 1. Fuzzy set model for land suitability assessment

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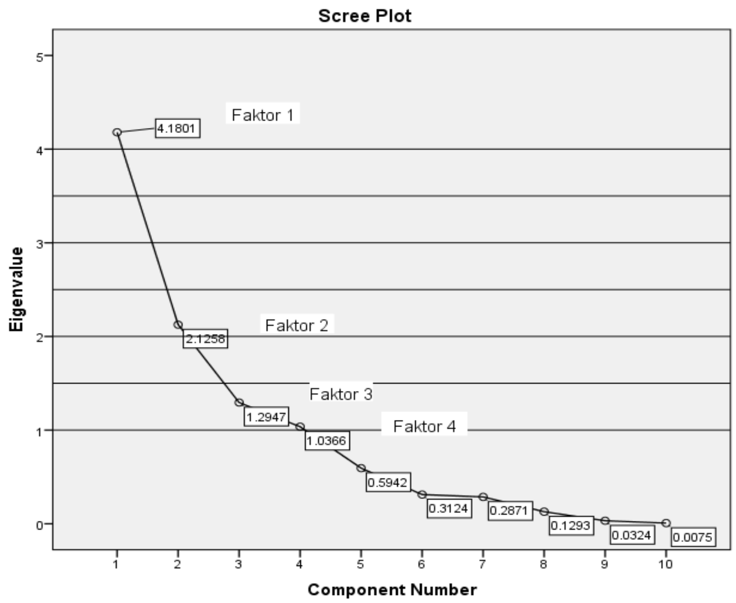

Figure 2. Scree Plot which plots the eigenvalue by the component number.

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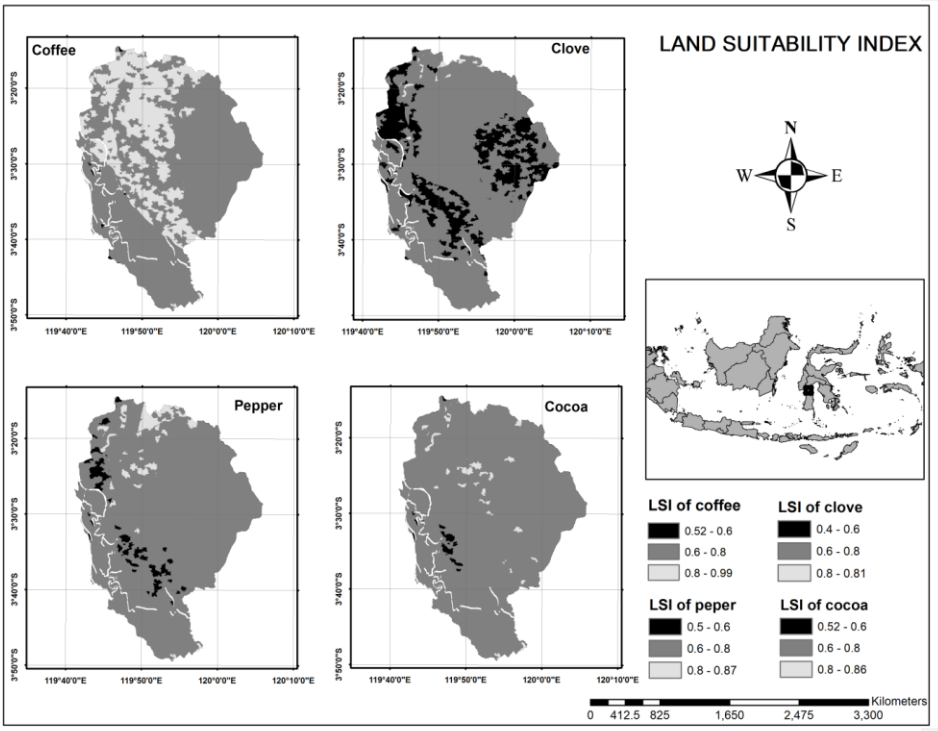

Figure 3. Land suitability index for plantation crops in research area

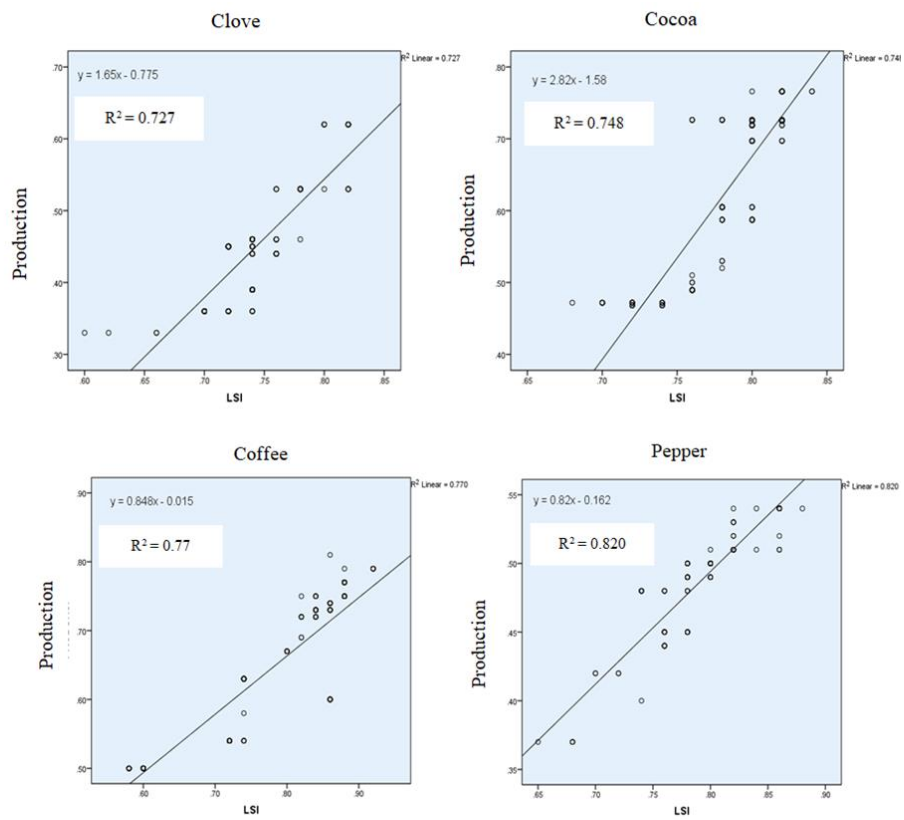

Figure 4. Linear regression between LSI and land production (tones/ha)

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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 one to fourteen	The results of laboratory analysis
Sum of basic cations (V2)	cmol/kg	The number of basic cations that can be absorbed by the soil include elements of calcium (Ca), magnesium (Mg), potassium (K), 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.	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 (cm)	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 temperatur (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

Table 2. Research control points for land suitability assessment

Commodity	Land indicators	LCP	b	d1	UCP	d2	Fuzzy Model
Coffee	pH H2O	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 H2O	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 H2O	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 H2O	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

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

Variabel	Minimum	Maximum	Mean	S. E	Std. Deviation	Variance
pH H2O	4.56	6.04	5.22	.12	0.46	0.21
Sum of basic cations	4.15	8.27	5.14	.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	.54	2.08	4.33
C-organic	0.64	2.46	1.42	.14	0.54	0.29
Slope	2.00	58.00	13.27	1.96	7.58	57.50
Annual temperatur	21.00	28.00	26.07	.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	.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	
Fctor Weight (H_{fi})	**0.48**		**0.25**		**0.15**		**0.12**	
Faktor loading:		**(W*i*)**		**(W*i*)**		**(W*i*)**		**(W*i*)**
pH H2O	-.071		.655	0.22	.594		.157	
Sum of basic cations	.231		.671	0.22	.622		.095	
Base saturation	.089		.115		.945	1.00	.106	
CEC	.262		.871	0.29	-.194		-.071	
C-organic	-.027		.830	0.27	.303		.060	
Slope	.898	0.28	.192		-.147		.069	
Annual temperature	.760	0.24	-.525		-.243		-.147	
Annual precipitation	.695	0.22	.114		-.476		.361	
Soil texture	.018		.035		.131		.974	1.00
Soil depth	.846	0.26	-.019		.082		-.017	

Table 1. Individual membership of land attributes

Land attribut	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. Join 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

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Analysis of agricultural land suitability using a combination of PCA and fuzzy methods

ABSTRACT

Land suitability of plantation crops in this study was analyzed based on; soil texture, pH, sum of basic cations, base saturation, cations Exchange capacity (CEC), C-organic, soil depth, slope, annual temperature and precipitation data using a combination of fuzzy and PCA methods. The fuzzy method is used to describe the factual conditions of land suitability for plant growth with a value range of 0 to 1, while PCA is used to form new uncorrelated variable and to appraise the degree of importance of variables based on the characteristics of the area itself. Using PCA, 4 new factors are formed. Slope, annual precipitation, annual temperature and soil depth as factor 1; pH, sum of basic cations, CEC and C-organic as factor 2; Base saturation as factor 3 and soil texture as factor 4. The loading corresponding and variance values obtained from the rotated component matrix are used as a consideration for the weights of the land indicators and new four factor groups. The results showed that LSI of cloves ranged from 0.4 to 0.81, coffee 0.52 to 0.99, cocoa 0.52 to 0.86, pepper 0.5 to 0.87. based on linearity test, it was found that there was a correlation between LSI and production with a value of f = 0.00 so it could be concluded that the model applied in the study was good.

Keywords: land suitability index; Fuzzy method; Principle component analysis; Multi objective decision making.

INTRODUCTION

Sustainable agriculture is defined as a comprehensive system of plant production practices with a site-specific application that would over the long term: fulfill human food and fiber needs; improve environmental quality, and strengthen the natural resource base on which the agricultural economy is based; ensure effective and efficient use of non-renewable resources and on-farm resources; maintain agriculture processes' economic viability; improve the quality of life for farmers and society as a whole (Rigby and Caceres, 1997). Sustainable agriculture is ensuring the most efficient use of agricultural resources (Pan et al., 2022). One of the main goals of sustainable agriculture is to ensure that agriculture does not deviate from the natural system itself. ~~Therefore, evaluating the suitability of agricultural land becomes very important~~.

Land suitability evaluation is- the key and first step in designing sustainable land use. ~~Good farming practices can give better result (Vasu et al., 2018).~~ Appropriate land suitability for certain agricultural activities will encourage better production. Agricultural production is closely related to the income of the farming community, if the farming community feels that they get high income from their farming, they will maintain their agricultural activities so that they can support agricultural sustainability (Piñeiro et al., 2020) and subsequently have a positive impact on other sectors such as increasing the number of workers (Ngeleza et al., 2011).

Fuzzy method is a development of the Boolean method which is considered too rigid and standard which has only two values, true and false (0 or 1). Fuzzy methods allows membership values to be transformed to zero up to one, where in the land suitability assessment the index increases close to

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Commented [A17]: Too long for reader one indicates a more optimal land suitability. According to Qiu, Chastain, & Zhou (2014), land suitability maps generated using this method is more informative and better at accuracy. Many studies have used fuzzy methods for land use optimization (Morteza et al., 2019; Vavatsikos et al., 2020; Arabsheibani., 2016). For instance, Nabati et al. (2020) used a fuzzy inference system to identify land capabilities based on agro-ecological zoning. Meanwhile, Feizizadeh and Blaschke (2013) standardized the criteria for land suitability analysis in Iran using the fuzzy set method. They standardized land evaluation criteria using a scale of 0 to 1.

There are three main stages of analysis using the fuzzy method: fuzzification, fuzzy inference (fuzzy logic operations) and defuzzification. Fuzzification transforms crisp values into fuzzy sets with the function membership 0 to 1, 0 to 10 or 0 to 100 (Feizizadeh and Blaschke, 2013; Gougam et all., 2019). There are two commonly used fuzzy inferences: rule-based fuzzy inference (Reshmidevi,2019) and multi-criteria decision making method (MCDM) (Tercan and Dereli, 2020; Elaalem, 2013; Maddahi et al., 2017). A fuzzy rule-base employs rules in the "IF proposisi fuzzy> THEN proposisi fuzzy>" format developed based on the opinions of experts or farmers, and then the minimum-maximum (Min-Max) fuzzy inference method is used to aggregate the rules, while inferences with MCDM method using several land factor as criteria then determine the weight of the criteria (ordered weighted average and linear weighted combination is commonly used) to obtain membership values for various classes at each evaluation unit (Liu et al., 2013).

Currently, fuzzy inference with the multi-criteria decision making method has been developed by many experts. Based on the fuzzy process described previously, it is known that membership values and weight of indicators play a very important role in fuzzy modeling using the MCDM method (Giordano and Liersch, 2012; Liu et al., 2013). Most researchers use analytical hierarchy process (AHP) in determining the weight of research indicators (Mosadeghi et al., 2015; Keshavarzi et al., 2020; Nasery et al., 2021; Zalhaf et al., 2021). This is due to the application of the AHP method is simpler and easier to implement. However, by using this method, the weight of the indicator is usually determined subjectively by the researcher or by the expert opinions. The problem that is often encountered is that there are differences of opinion among several experts, causing bias and confusion for researchers. Other than that, Most studies directly provide value ranges based on relevant studies. In addition, the effect of a land trait on other land properties in an area is not always the same as in other areas. This difference is caused by many factors, including the way farmers cultivate, and the characteristics of the soil in the area itself. Equating the assessment of the degree of importance of soil properties in land evaluation based on research that has been carried out in different areas can lead to bias. While Maddahi et al. (2014) and Luan et al. (2017) point out that the weight between land assessment indicators must be considered objectively based on the data or characteristics of the area itself for accurate evaluation. In the evaluation of land suitability, the assignment of land characteristics should be based on data.

Because soil properties vary widely, intercorrelation can cause multicollinearity issues. Bernardi et al. (2016) point out that Multivariate statistical approaches could be used to solve these problems and to assist in better land management, resulting in better land ecosystem services (Montanaro et al., 2017). Principle component analysis (PCA) is another well-known multivariate statistical technique that aims to display the relative positions of data points in fewer dimensions while retaining as much information as possible, as well as to investigate relationships between dependent variables. Ranjbar et al. (2015) compared various multivariate methods on 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 interpreted better. PCA can effectively determine the weighted value to achieve a desired result (Bas, Das & Pal, 2020). According to Pennsylvania State University (2018) PCA has traditionally been used not only to identify which variables have the most influence on a process, but also to simplify the data into multiple PCs which account for most of the variability in the data. Ghaemi et al. (2014); Nguyen et al. (2020); Said et al. (2020) use PCA to reduce dimensional data into few factors. However, research by Ranjbar et al. (2016) point out that not reducing data is the most accurate method for evaluating land quality and providing consistent results. Because of this, PCA method in this study was only used to determine the importance of soil attributes without reducing it to a few data.

Recently, fuzzy-AHP combinations are widely used by researchers for land evaluation (Kelic et al., 2022; Paul and Ghosh, 2022; Sengupta et al., 2022). As previously explained, the use of a combination of these methods is very subjective in determining the importance of land attributes, which can lead to bias. Therefore, this study aims to analyze land suitability used Fuzzy-PCA as a new approach which can deal with this problem. By using the fuzzy PCA method, the importance of land attributes can be determined more objectively based on the characteristics of the research area itself.

MATERIAL AND METHODS

The study area was conducted in Enrekang, one of the districts in South Sulawesi, Indonesia. Four cultivated plants were analyzed and compared at the study site (coffee, cocoa, pepper and cloves). Guidelines for Land Suitability Assessment Using Technical Guidelines for Land Evaluation of Agricultural Commodities by Ritung et al. (2011) also guidelines by Sys (1993) on Land Evaluation Part III on Plant Requirements. The three main variables used in the assessment include; climate variables, topographic variables and soil variables, with a total of ten indicators. The variables used in the study are summarized in the Table 1.

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Field Sampling and Laboratory Analysis

There are land attributes that can be estimated or measured directly in the field, and some must be assessed in the laboratory (FAO, 1976). Field observations included soil depth and slope measurements, while other soil variables were analyzed in the laboratory. A land unit map of research area (Figure 1) was used as references for soil sampling. The land unit map is combined information of the ecological principles relating to rock types, hydro-climate, landforms, soil, and organisms (Blasi et al., 2008). According to Zonneveld (1989), the survey results including the unit map, could be used as a basis for land evaluation.

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Thirty soil samples were taken. Samples were taken from top (depth 0-25 cm) and subsoil (depth> 25 cm) from 15 land units. Those used for texture and CEC analysis were obtained from subsoil, while those for pH, basic cations (including Ca, Mg, K, and Na), and base saturation analysis were taken from the topsoil. Texture, CEC, pH, sum of basic cations, base saturation, and C-organic were analyzed in the laboratory. The various approaches used by the factors were as follows: pipette method for texture analysis, 1: 2.5 soil water suspense for pH procedure, the Walkley-Black method with 105ºC dry soil samples for C-organic analysis, while the sum of basic cations, CEC, and base saturation used the cations exchange rate (NH4-Acetat 1N, pH 7) in dry soil sample of 105°C.

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Terms and Stages of Land Suitability Assessment

Land suitability assessment in this study implements a fuzzy model by Zadeh (1965). The fuzzy set function can analyze soil characteristics continuously without categorizing them into different classes. In fuzzy analysis, land attribute values are converted to sustainable values ranging from zero to one. 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 semantic import model (SIM) that is widely used, and is described in the modeling of Figure 2.

In the modeling of Figure 2, some important values such as; b which is the value of a land attribute at the ideal point, lower crossover (LCP) and upper crossover (UCP) are the lower and upper thresholds/margins of a land attribute 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. The optimal point in the fuzzy function model 1 is used to assess soil attributes which have one ideal point but have 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. Fuzzy model 3 can be interpreted that 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. Land characteristics in the fuzzy function model 4 are interpreted that the smaller a land characteristic, the better, as is the case with the slope level. The research control points in Table 2 are arranged based on; agricultural land evaluation criteria made by Ritung (2011) and Sys (1993), Fuzzy modeling in Figure 2, and land characteristics at the research site. The following steps were used to calculate the land suitability index:

1. Determine the variables that are considered important in research.
2. Forming new factors/variables from land attributes that have been considered for inclusion in land suitability assessment. Factor analysis was carried out on soil attributes using the principle component analysis (PCA) to group land attributes that were considered to have the same characteristics into one new factor/variable (Pearson,1901; Hotelling ,1933). In some studies, PCA is indeed used as a data reduction technique. However, because this study used the total data set principle, there is no reduction in land attributes. This study used PCA to analyze the correlation between land attributes and then classifies them into new factors without reducing them. This is achieved by creating new uncorrelated variables that successively maximize variance. As a by-product, a better interpretation of the data is obtained. PCA components that are retained are those that have one or more eigenvalues (see Figure 3). The number of indicators for each component or factor will be the same as the number of land indicators analyzed, but each component/factor will only maintain one or more indicators with a maximum loading corresponding. The variance of each component/factor will explain how much the component contributes in explaining the data as a whole, while the loading corresponding explains how much the correlation between the indicator and the component is (Armenise et al., 2013; Mukherjee & Lal, 2014). In principle, PCA will produce as many components (factors) as the indicators included in the analysis. However, only component factor having eigenvalues > 1 were retained for inclusion in the next analysis. According to this rule, four factors are maintained, each labeled factor 1, factor 2, factor 3 and factor 4. The

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 component, each following component is obtained by partially out of the previous component. Based on the results of PCA analysis, four new factors included in calculating land suitability index (LSI) (Figure 3 and Table 4)

3. Standardize the land indicators on each new factor with a value of 0-1, carried out by the equation 1.

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

$$MF (x_i) = 1, \text{ if } (b_1+d_1) \leq xi \leq (b_2 - d_2) \quad \text{(fuzzy model 2)}$$

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

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

4. Calculate the weight of the importance of land attributes on each factor used in land suitability assessment by equation 2. The weighting (W_i) given will consider the loading factor value of each indicator (y_i) and total loading factor value ($\sum y$) in each factor.

$$W_i = \frac{|\, yi \,|}{\sum |\, y \,|} \quad (2)$$

5. Calculates the join membership value (JMF) of all factors included in the land suitability assessment using equation 3.

$$JMF (X_{i.....z}) = \sum_{i=1}^{n} Wi\ (MFi) \quad (3)$$

6. Calculate the importance weight of all factors used in land suitability assessment by equation 4. The weight given to each factor considers the value of the variance component of a factor i (m_i) and the total value of the variance component formed ($\sum m$).

$$H_{Fi} = \frac{|\, m_i \,|}{\sum |\, mi \,|}\ x\ 100 \quad (4)$$

7. Calculate the land suitability index. The MF of each factor is then integrated with the weight of the factor (H_{fi}) to determine the LSI using the equation 5:

$$LSI = \sum_{i=1}^{n} \mathrm{H}fi\ (JMFxi) \quad (5)$$

RESULTS

Land Properties in the Study Area

A summary of some of the land characteristics at the research location can be seen in Table 3. Soil pH in the entire study areas are acidic with minimum range of 4.56 and maximum of 6.04. The basic cations used are calcium (Ca), magnesium (Mg), Potassium (K) and Sodium (Na). Sum of basic cations found in both top and sub soil in all land system had quite high for plantation plant growth with ranged of 4.1 cmol/kg to 8.88 cmol/kg. 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 was classified as moderate with a range of 12.14 cmol/kg to 19.22 cmol/kg. In the Bukit Ayun, Bukit Pandan and Watampone land units, the C-organic content was found to be very low, less than 1%. The highest value of c-organic of 2.46% was found in the Kalung land unit. Slope data obtained from digital elevation model (DEM) 30 m SRTM image extraction. The slopes recorded ranged from 2% to more than 50%. The annual precipitation in the research region is quite high, with annual average rainfall ranging from 1676 to more than 2634 mm/year. average annual temperature ranges from 21^{o} C to 28^{o} C. Based on the results of the field survey, it is known that the effective soil depth of the research location ranges from 90 to 150 cm.

New Factor Groups and Important Weight

Each land attributes has a greatest loading corresponding to each of the 4 factors. For example, slope is correlated 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. 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, and so on. Slope has a greater correlation to factor 1 than other factors, and then the slope is classified as factor 1. This also applies to other land attributes. As previously explained, the weight of the land indicator (W_i) is the result of the corresponding loading divided by total loading corresponding of the land attributes classified in that factor. Among several soil attributes included in factor 1, slope has the largest correspondent load. Therefore the importance weight on the slope is greater (0.28) than the other land attributes which are included in factor 1. The total weight (W_i) of each faktor is 1. This rule also applies to other land attributes. Based on the maximum loading corresponding of each land indicator in each factor: slope, annual precipitation, annual temperature are grouped into factor 1; pH, number of base cations, CEC, C-organic become factor 2; base saturation to factor 3; Soil texture is a factor 4. The results of the PCA analysis, the newly formed factor groups and the degree of importance of all soil attributes are presented in Figure 3 and Table 4.

Membership Value of Land Attribute and JMF of Factors

Individual membership values consist of numbers ranging from 0 to 1. If a land attribute has a membership value of 1, it indicates that the land attribute is optimal for the growth of a plant and vice versa. Based on Table 5, it is known that some land attributes are below the tolerance threshold value set as in Table 2. For example, individual membership of land attributes in the form of pH, CEC, average rainfall and annual temperature of less than 0.4 for cocoa plant growth in the Bukit Ayun land unit. This indicates that in the 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 other plants. In some land units, the individual membership value (for coffee plant growth) is equal to 1 which indicates optimal suitability. For example, in Pendreh and Danau Lindu land units, land attributes such as temperature, rainfall and slope have an optimal suitability for coffee growth with individual membership values of more than 0.9. In general, the problems faced by the research area are temperature, CEC and base saturation where 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 less than 0.4 were 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, in general the growth of clove plants in the research location did not reach optimal suitability with values less than 0.85 and more than 0.4.

Joint membership values (JMF) for evaluating the suitability of crops can be seen in Table 6. These figures indicate the quality of the land for the potential development of plantation crops. Just like individual membership values, JMF also consists of a number range from 0 to 1. The higher the JMF value indicates that a land has optimal potential for plantation development. The JMF value for coffee plant growth ranged from 0.38 to 1. A JMF of 0.38 was found in the Sungai Aur land unit at Factor 3. This indicates that factor 3 is a limiting factor for coffee plant growth. Cocoa JMF values ranged from 0.45 to 1. The lowest cocoa JMF was found in the 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 cocoa growth. Cloves and pepper have a low JMF value at a factor of 3, which is 0.3 at the Sungai Aur land unit. As previously explained there is only one land property in factor 3, namely basic saturation. Thus, the low value of factor 3 indicates the quality of the base saturation that is less supportive of plant growth.

Land Suitability Index

The multiplication function in equation 5 is used to generate a spatial land suitability index data layer with continuous values, ranging from 0 to 1. 1 indicates optimal suitability for plant development. Based on the analysis, it was found that the LSI of cloves ranged from 0.4 to 0.81, coffee 0.52 to 0.99, cocoa 0.52 to 0.86, pepper 0.5 to 0.87. The results are visualized in Figure 4. To evaluate land area, raster data is converted into vector data and then categorized based on its pixel value into several land suitability classes. Areas with a pixel value of > 0.8 are included in the optimal suitable category, while areas with a pixel value of 0.8≤LSI>0.6 are included in the moderate suitability category, and areas with a pixel value of 0.6>LSI>0.4 are included in the marginal suitability category. Of the total area analyzed for coffee plants, 76.28% of the area is in the moderate suitability, 23.26% in the optimal suitable, and 0.45% in the marginal suitability category. For cocoa, 90% of the research area is included in the moderate suitability category, 0.29% and 9.6% are included in the marginal suitability and optimal suitable. A total of 86.89% of the research area is included in the moderate suitability category for pepper plants, while 6.68% areas are included in the optimal suitable and 6.41% areas are in the marginal suitability category. For clove commodity, 78.74% of the total area is included in the moderate suitability category, while for areas with marginal and very suitable suitability categories are 19.26% and 1.98%, respectively.

DISCUSSION

76.28% of the study areas were identified having moderate suitability with an index range of 0.6 to 0.8. The same suitability class also dominates cocoa with 90% of regions having an index of 0.6 to 0.8. Meanwhile, 86.89% of the area is dominated by medium suitability of pepper and 78.74% of the area is dominated by medium suitability of cloves. Land suitability for the four crops was successfully assessed in this study using fuzzy-AHP. This is evidenced by the accuracy test carried out on the model applied in the study (Figure 5). Seyedmohammadi et al. (2019) conducted a validation test by comparing the pixel values of the land suitability index as a map to be assessed and production data as ground truth data to obtain a match. This is also applied in this research. Commodity production data is extracted spatially into polygon maps which are then matched with land suitability index data. Validation points are taken at random, then processed to assess linear or nonlinearity between the land suitability index and production data (Figure 5). The rule of decision making using regression test is if the value of f <0.05 then indicates that there is linearity between LSI and production. From the results of tests carried out on all analyzed plants, it was concluded that there was a linearity between LSI and production with a value of f = 0.00. Based on this, it can be concluded that the model used in the study is good and can be applied in other applications related to suitability assessment.

This method is easy and simple to apply in environmental management, especially in evaluating land suitability more objectively without involving expert opinion in determining the importance of the assessment parameters. Fuzzy linear functions are used to standardize (individual membership) soil attributes, and the same thing was done by Nurmiaty and Baja (2014). In addition, PCA used to analyze the correlation between land attributes and then classifies them into new factors without reducing them. This is achieved by creating new uncorrelated variables that successively maximize variance. Four main components (PC1, PC2, PC3 and PC4) with eigenvalues greater than 1 were extracted. This technique succeeded in grouping ten variables into four main components (new group of variables) and described 86.24% of the original variance. Sahoo et al. (2021) also used the PCA technique only to construct new variables from land attributes for land suitability assessment. In line with that, Jolliffe and Cadima (2016) point out that PCA is an adaptive technique that is able to determine several new variables. In our research, the results of PCA analysis are further used to determine the degree of importance of each component and the degree of importance of variables or land indicators in a component. It does so by utilizing the variance value of each component and the loading factor value of each land attribute. Factor 1 have a strong loading on slope, mean annual temperature and precipitation, and soil depth while factor 2 have a strong loading on pH, sum basic cations, organic matter and CEC. Base saturation and soil texture in groups 3 and 4, respectively. Based on the variance, factor 1 is the most important variable and is given the highest weight compared to other factors which describes 48% total data. In several studies that also used PCA, such as Ghaemi et al. (2014) and Said et al. (2020) gave greater importance to PC 1. Ayehu and Atnafu (2015) also give 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 and has the greatest influence on other land attributes in the factor 1 group so that it is given the highest weight.

Based on our data processing experience, it can be seen that when the fuzzy method is used, the threshold set by the researcher (LCP and UCP) in Table 2 becomes sensitive thing that affects the results of individual membership values of land attributes in Table 5. In addition, this is also influenced by the quality of the land itself. This is also emphasized by Qiu et al. (2014) that thresholds cannot be determined arbitrarily and must be based on expert knowledge of the situation. Based on Table 5, it can be concluded that some land attributes such us texture in Batang Anai and Bukit Pandan are optimal for plantation plant growth with individual membership values = 1, but some other land attributes such us pH in Maput and Bakunan do not meet the plant growth requirements with individual membership values < 0.4. Soil pH in all study areas was acidic in the range of 4.56-6.04, while 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, Mantalat, because is unable to meet the specified threshold and resulting in low membership values. As for the growth of clove and pepper plants, the individual membership value of pH was quite high with a value > 0.5 in all land units. This is due to the pH values meet the minimum threshold set for clove and pepper growth based on the criteria compiled by Ritung et al. (2011). In addition, another major limiting factor for cocoa growth in the study area is temperature. In this land suitability assessment, temperature is a very important factor and is in the group with the first degree of importance. This is in line with the opinion of Geo and Saediman (2019) which states that climatic factors greatly affect cocoa growth. They state that the 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 while most of the research areas have an average daily temperature of <26° C. This resulted in many sites in the assessment reaching lower threshold values for temperature. Another land indicator that needs to be an important issue in the research location is CEC. Many land units do not meet the minimum CEC standards for plant growth, both for coffee, cocoa, pepper, and cloves. CEC ranged from 12.14 to 21.25 cmol/kg while the minimum CEC standard for plant growth is 15 cmol/kg. The main problems in the research area are temperature, pH and CEC. Temperature is considered to be the main limiting factor for the development of cocoa, clove and pepper crops as it has the highest importance among the three main limiting factors. However, temperature is an attribute that is difficult to modify by any treatment. In contrast to pH and CEC. To overcome the problem of low pH at the research site, the opinion of Gentili et al. (2018) that the pH can be increased by the addition of calcium hydroxide can be applied to the research area. While the research of Martinsen et al. (2015) which revealed that the addition of biochars to acid soil can increase pH and CEC can be used to overcome soil fertility problems in the study area.

CONCLUSION

Land suitability for coffee using a combination of fuzzy and AHP methods consists of optimal suitability with an index range of 0.6 to 0.8 covering 23.26% of the area, 76.28% having moderate suitability with an index range of 0.8 to 0.99 and 0 .45% of the area that has a marginal suitability with an index of 0.52 to 0.6. Meanwhile, Cocoa consists of optimal suitability with an index of 0.8 to 0.88 which covers 9.6% of the area and marginal suitability with an index of 0.6 to 0.8 which covers 90% of the area. In addition, clove has a marginal suitability which covers 19.26% of the area with an index of 0.4 to 0.6, 78.74% has a moderate suitability and only 1.98% has an optimal suitability with index of 0.8 to 0.81. Pepper consists of optimal suitability with index 0.8 to 0.87 covering 6.68% area, marginal suitability covering 86.89% area and 6.41% area having marginal suitability index 0.5 to 0.6. Based on the validation tests carried out, it can be concluded that the combination of fuzzy-AHP models applied in the study succeeded in revealing the suitability of plantation land well more objectively, so that this model is feasible to be applied in other fields of land management.

Figure and Table

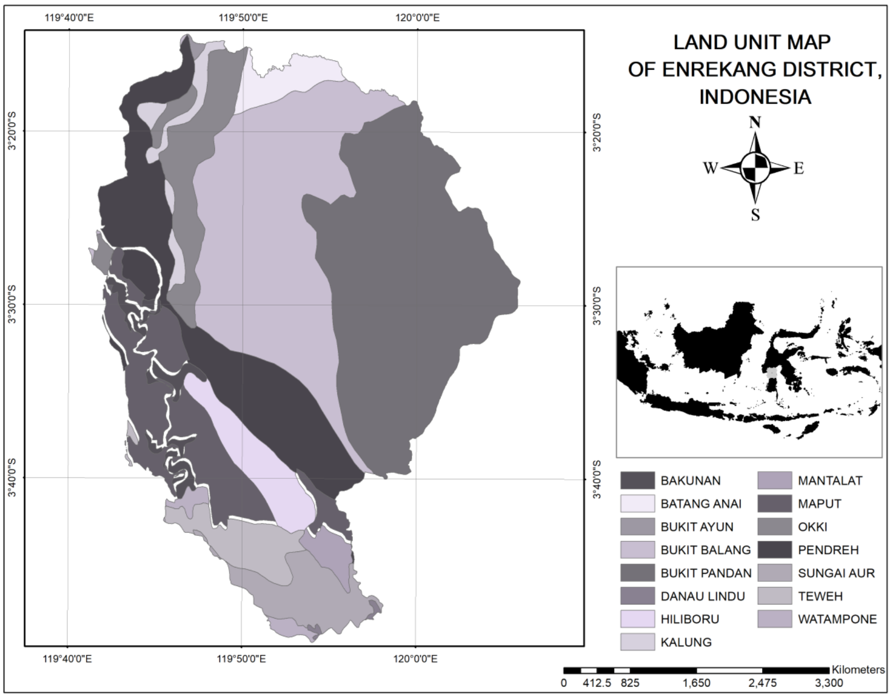

Figure 1. Land unit map of research area

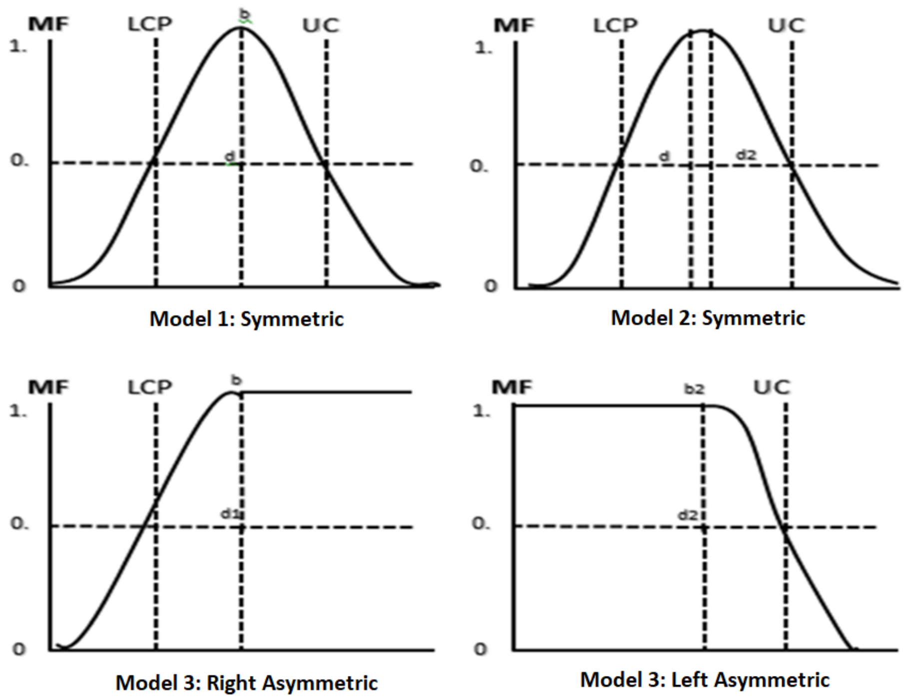

Figure 12. Fuzzy set model for land suitability assessment

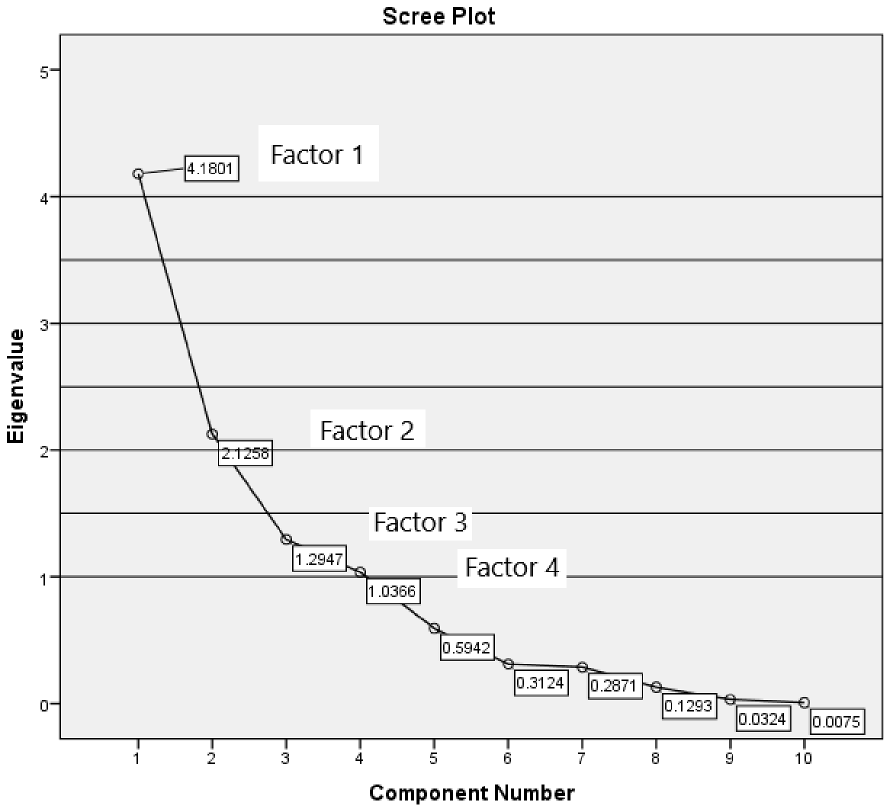

Figure 23. Scree Plot which plots the eigenvalue by the component number.

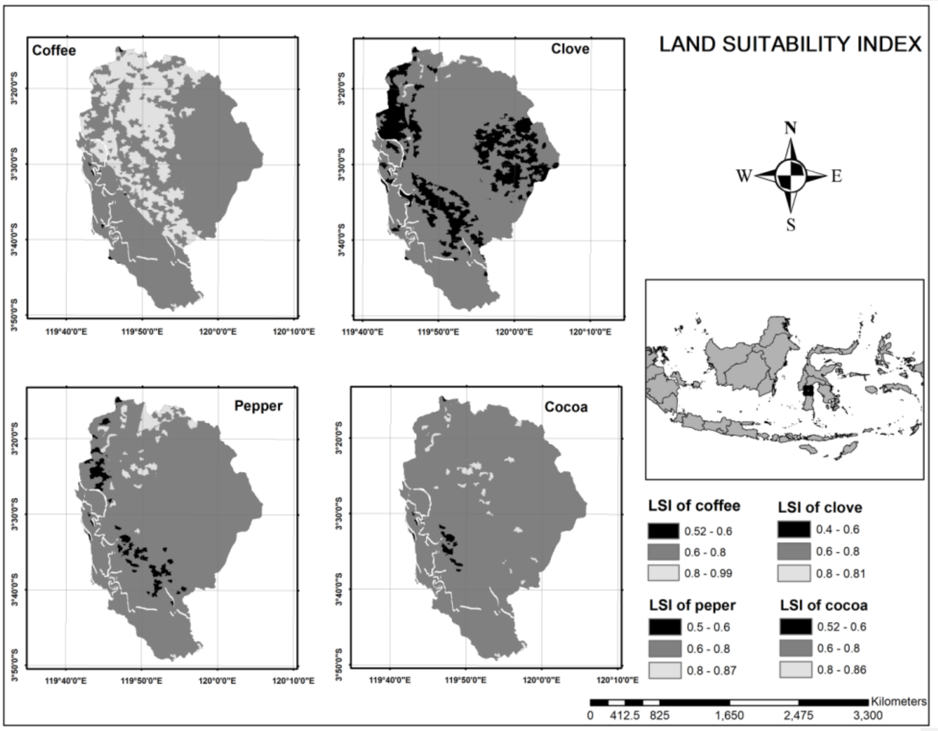

Figure 34. Land suitability index for plantation crops in research area

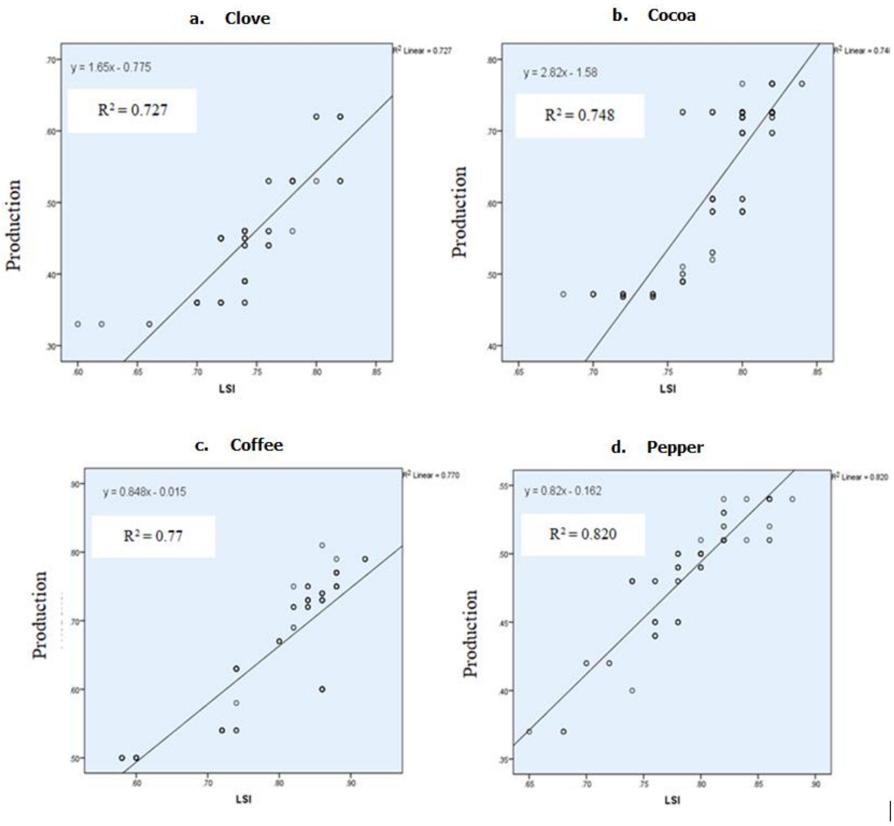

Figure 45. Linear regression between LSI and land production (tones/ha)

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 one to fourteen	The results of laboratory analysis
Sum of basic cations (V2)	cmol/kg	The number of basic cations that can be absorbed by the soil include elements of calcium (Ca), magnesium (Mg), potassium (K), 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.	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 (cm)	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 temperatur (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

Table 2. Research control points for land suitability assessment

Commodity	Land indicators	LCP	b	d1	UCP	d2	Fuzzy Model
Coffee	pH H2O	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 H2O	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 H2O	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 H2O	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

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

Variabel	Minimum	Maximum	Mean	S. E	Std. Deviation	Variance
pH H2O	4.56	6.04	5.22	.12	0.46	0.21
Sum of basic cations	4.15	8.27	5.14	.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	.54	2.08	4.33
C-organic	0.64	2.46	1.42	.14	0.54	0.29
Slope	2.00	58.00	13.27	1.96	7.58	57.50
Annual temperatur	21.00	28.00	26.07	.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	.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	
Fctor Weight (H_{fi})	**0.48**		**0.25**		**0.15**		**0.12**	
Faktor loading:		**(W*i*)**		**(W*i*)**		**(W*i*)**		**(W*i*)**
pH H2O	-.071		.655	0.22	.594		.157	
Sum of basic cations	.231		.671	0.22	.622		.095	
Base saturation	.089		.115		.945	1.00	.106	
CEC	.262		.871	0.29	-.194		-.071	
C-organic	-.027		.830	0.27	.303		.060	
Slope	.898	0.28	.192		-.147		.069	
Annual temperature	.760	0.24	-.525		-.243		-.147	
Annual precipitation	.695	0.22	.114		-.476		.361	
Soil texture	.018		.035		.131		.974	1.00
Soil depth	.846	0.26	-.019		.082		-.017	

Table 15. Individual membership of land attributes

Land attribut	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. Join 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

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REVIEWER A

Page number	Line number	Reviewer's Comment	Author's Revision
15	1 & 2	More refining of the title appropriately is recommended. For instance: adding regional information/ location etc	Based on the reviewer's suggestion our title was changed to "Land suitability assessment for agricultural crops in Enrekang, Indonesia: a combination of principal component analysis and fuzzy methods"
15	7, 2, 18, 20	Many abbreviations such as LSI were mentioned but not initially defined as what the acronym stands for..	We have added the definition of all abbreviations contained in the abstract at the first time, such as potensi of hydrogen (pH), cations exchange capacity (CEC), organic carbon (OC), principal component analysis (PCA).
15	13 to 15 and	The abstract can be improved by adding one statement on how different indicators may contribute to different crops? The conclusion in the abstract can be trengthened	We have added a statement about how the indicator control points for each crop differ and the factors that affect the final land suitability assessment. Here is the statement "Final land suitability index is strongly influenced by the threshold used by the researcher and by the quality of the land indicator itself. Plant threshold values are different due to the different plant recruitment. " In addition, at the end of the conclusion, we also explain the views and advantages of the method we use. Here is the statement "Principal component analysis (PCA) is an effective method to determine the weights of multiple factors in a systematic and more objective manner."
16	3 to 33	The literature did not thoroughly review the existing research in terms of	The second paragraph of the introduction discusses specifically about the current research in terms of objectives, methods and indicators of land suitability

		objectives, methodology, and datasets. Without a comprehensive explanation about the common methods, authors started to talk about Fuzzy and PCA. Create a separate paragraph to name some models and algorithms and their applications/advantages/disadvantages and explain why you chose this particular method over other common methods.	assessment. In addition, this paragraph provides a brief overview of why we use the fuzzy-AHP method. Here is the statement "Recent technological advances in Geographic Information System (GIS), Remote Sensing (RS), Decision Support System (DSS), and web-based applications have enabled more powerful, highly accurate, and long-term intervention in agriculture in terms of where to farm and which plant is best fit. Land suitability assessment is commonly referred to as multi-criteria evaluation (MC) due to the large number of factors considered during the process. Information on climate, hydrology, topography, vegetation, and soil properties should be considered in land suitability analysis (Mosleh et al., 2017; Cartwright et al., 2020; Yang et al., 2021). Land suitability assessment with MC is a tool that deals with decision problems related to conflicting criteria. Land suitability assessment with MC is classified into two categories, namely multi-attribute (MADM) and multi-objective decision making (MODM) (Leake & Malczewski, 2000; Zimmermann & Gutsche, 1991). Land suitability assessment with MADM is suitable for decision making using discrete criteria where the importance between attributes has been determined by the decision maker. The criteria in the MADM method are usually filtered, prioritized and finally ranked by the decision maker (Gebre et al., 2021). Some examples of land suitability assessment using the MADM method are pairwise comparisons such as process hierarchy analysis (AHP), value or utility functions such as MAVT, MAUT and SAW (Liu et al., 2013; Zhang et al., 2016; Ananda & Herath, 2009). For instance, Barati et al. (2019) integrated analytic hierarchy process (AHP) and Matrix Cross-reference Multiplication methods for determining Key

			Agricultural Strategic Factors. Also, Devi and Yadav (2013) combined fuzzy elimination and elimination and choice translating reality method to optimize plant location. In another paper, Rajabi and Mousavizadeh (2015) used the technique for others reference by similarity to Ideal Solution (TOPSIS) method to rank candidate locations for agricultural industries in Iran. The problem that is often faced in assessing land suitability using the MADM method is the strong subjectivity of researchers in determining the importance of land attributes. As a solution, the researcher uses PCA in the land suitability analysis method in terms of assessing 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 between criteria is not predetermined. The importance between criteria in the MODM method 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 used (Gebre et al., 2021). Nasrollahi et al. (2019) suggest in future research to use multi-objective mathematical programming model for the location optimization and capacity planning problem."
30 32	1 1	Provide more details on indicators used. Can include a table	Descriptions of research indicators, data sources and statistical descriptions of indicators used are shown in Tables 1 (page 30 line number 1) and 3 (page 32 line number 1).
19 20	18 to 41 1 to 24	Description on section "Steps were used to calculate land use suitability" can be improved. Instead of explaining step by step,	We have rearranged parts of the steps used to calculate land use suitability becomes more professional. This can be seen in the Materials and Methods section, especially in the Subsection of the Terms and Stages of Land Suitability Assessment in the third to seventh paragraphs of this section.

		authors can re-arrange the section to be more professional. Remember, this is not a lab manual	
24	31 to 38	Conclusion. –Some solutions, recommendations, and statements on your future work would enrich the research.	Some solutions, recommendations, and statements on our future work. Here is the statement ''Mean annual temperature < 26 ^{o}C, acidic soil pH, and low CEC were the main limiting factor for the growth of plantation crops in the study site. As a solution, the addition of biochars and calcium hydroxide to acid soils can increase soil pH and CEC" "For a more accurate land suitability assessment, further research needs to compare various methods to calculate the final land suitability index.''

Remarks: in the revised copy, it must include highlighted changes and modifications recommended in the revision to ensure that all editor/reviewer(s)' comments were considered.

REVIEWER B

Page number	Line number	Reviewer's Comment	Author's Revision
15	1 & 2	Title- I strongly recommend for full words	In the title we have changed the abbreviation from "PCA" to "Principal Component Analysis" Based on the reviewer's suggestion our title was changed to "Land suitability assessment for agricultural crops in Enrekang, Indonesia: a combination of principal component analysis and fuzzy methods"
15	6	Dear Author Thank you for your great research work. Please add a short introduction at the beginning of your paper abstract	We have added a short introduction at the beginning of our paper abstract. Here is the statement "Land suitability assessment is essential for efficient use of diminishing fertile agricultural land"

15	2,8, 18, 20	Abstract: When you use abbreviation of an concept it must be define at the first time.	We have added the definition of all abbreviations contained in the abstract at the first time, such as potensi of hydrogen (pH), cations exchange capacity (CEC), organic carbon (OC), principal component analysis (PCA).
15	8	Abstract: Cation Exchange Capacity (CEC)	We have removed the letter "s" after the word "cations" to "cation exchange capacity"
15	8	Abcstract: Organic Carbon (OC)	The abbreviation for organic carbon is (OC)
15	8 to 9	Abstract: Total or mean or max or min,they should be clear define	We used mean annual precipitation and temperature data
15	6 to 22	Too long material and methods in abstract. The abstract should give more results of your research, this type of M&M make your writing a few weak	In general, we have improved the structure of abstract writing. We only present the research material after a brief introduction in the abstract. A description of the advantages of the method we used is included as part of the results in the abstract. Here is our latest abstract "Land suitability assessment is essential for efficient use of diminishing fertile agricultural land. Assessment parameters including soil texture, potential of hydrogen (pH), sum of basic cations, base saturation, cation exchange capacity (CEC), organic carbon (OC), soil depth, slope, mean annual temperature and precipitation data. The results showed: 76.28% of the total area was optimally suitable for coffee growth and 23.26% was Moderat, 9.6% area was optimally suitable for cocoa growth and 90% was moderat, 1.98% area was optimally suitable for clove growth, 78.74% was moderat and 19.26% was marginal, 6.68% total area was optimally suitable for pepper, 86.89% was moderat and 6.41% was marginal. Final land suitability index is strongly influenced by the threshold values used by the researcher and by the quality of the land indicator

			itself. Plant threshold values are different due to the different plant recruitment. The most limiting factors included mean annual temperature < 26 oC, acidic soil pH, and low CEC. This study shows that that the fuzzy method is a greet operation for converting numerical data of various magnitudes into membership function values, and representing land suitability. Principal component analysis (PCA) is an effective method to determine the weights of multiple factors in a systematic and more objective manner. Based on linearity test, it was found that there was a correlation between LSI and production with a value of f = 0.00 which indicated that the model applied has an ideal effect for predicting agricultural production and can be applied to other agricultural land management."
15	9 to 13	Abstract: What it means for readers you should your final findings the digits are not the final findings you must show it is suitable or not which one is more suitable etc	We have converted the unit of land suitability index to a more informative and understandable final result. Hire is our latest statement "The results showed 76.28% of the total area was optimally suitable for coffee growth and 23.26% was Moderat. 9.6% area was optimally suitable for cocoa growth and 90% was moderat. 1.98% area was optimally suitable for clove growth, 78.74% was moderat and 19.26% was marginal. 6.68% total area was optimally suitable for pepper, 86.89% was moderat and 6.41% was marginal.
15	19	Abstract: (Based) on the first word of sentences is capital	We have fixed the writing error. All the first words of the sentence are capitals
1 5	9 to 22	The results in abstract must be around 50 % of it	In general, we have improved the structure of abstract writing. Around 50% of it is the result. Here is the statement "The results showed 76.28% of the total area was optimally suitable for coffee growth and 23.26% was Moderat. 9.6% area was optimally suitable for cocoa

			growth and 90% was moderat. 1.98% area was optimally suitable for clove growth, 78.74% was moderat and 19.26% was marginal. 6.68% total area was optimally suitable for pepper, 86.89% was moderat and 6.41% was marginal. Final land suitability index is strongly influenced by the threshold values used by the researcher and by the quality of the land indicator itself. Plant threshold values are different due to the different plant recruitment. The most limiting factors included mean annual temperature < 26 oC, acidic soil pH, and low CEC. This study shows that that the fuzzy method is a greet operation for converting numerical data of various magnitudes into membership function values, and representing land suitability. Principal component analysis (PCA) is an effective method to determine the weights of multiple factors in a systematic and more objective manner. Based on linearity test, it was found that there was a correlation between LSI and production with a value of f = 0.00 which indicated that the model applied has an ideal effect for predicting agricultural production and can be applied to other agricultural land management."
15	19 to 22	Abstract: (Good) English writing is poor and need improve by a near native or native.	We've changed the word "good" to "ideal". This sentence has been altered in general This is our latest statement "Based on linearity test, it was found that there was a correlation between LSI and production with a value of f = 0.00 which indicated that the model applied has an ideal effect for predicting agricultural production and can be applied to other agricultural land management."
15	19 to 22	Abstract: It was good ?????????? just this ?? I strongly recommend you to show your real conclusion	At the end of the abstract, we add conclusions that the reader can consider and refer to. This is our latest statement

		that you work for it, some of the reviewer make decision with your abstract.	"Based on linearity test, it was found that there was a correlation between LSI and production with a value of f = 0.00 which indicated that the model applied has an ideal effect for predicting agricultural production and can be applied to other agricultural land management."
15	24 to 25	The keywords must rearrange alphabetically and avoid to use the words of title	The keywords have been rearranged alphabetically and as much as possible avoiding the words in the title. Here is our latest keyword **"Keywords:** Agricultural land management; Crop diversification; Fuzzy logic; Multi objective decision making; Principle component analysis."
15	28 to 29	Introduction: Long sentences in scientific paper is not accepted, only their reffs are different please rewrite this	We have corrected and rewritten the sentence. Here is the latest sentence. "Sustainable agriculture is defined as a comprehensive system of crop production practices with site-specific applications that will persist over the long term (Rigby and Caceres, 1997).According to Pan et al. (2022), sustainable agriculture is ensuring the most efficient use of agricultural resources. One of the main goals of sustainable agriculture is to ensure that agriculture does not deviate from the natural system itself"
15 16	32 to 41 1 to 2	Please consider that at introduction you must - Explain the land suit ability and its benefit	The following is an explanation of land suitability and its benefits. "Land suitability evaluation is one of the key in designing sustainable land use. Land suitability is the fitness of a specific type of land to be used for a specific purpose (FAO, 1976). Land suitability is determined by evaluating the climate, soil, and topographical components, as well as 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 et al. (2020), Evaluation of

			agricultural land suitability is critical for increasing production and planning a sustainable agricultural system. Evaluation of agricultural land suitability is useful in aligning agricultural land use, assisting agricultural land use planning decisions in overcoming competition between various possible land uses so that more land can be used efficiently. Furthermore, appropriate land suitability for certain agricultural activities will encourage better production. Agricultural production is closely related to farmers' income and influences farmer decisions to support sustainable agriculture (Piñeiro et al., 2020)."
16	3 to33	Please consider that at introduction you must - Explain method of land suitability measurements	The second paragraph of the introduction discusses specifically about the current research in terms of objectives, methods and indicators of land suitability assessment. In addition, this paragraph provides a brief overview of why we use the fuzzy-AHP method. Here is the statement "Recent technological advances in Geographic Information System (GIS), Remote Sensing (RS), Decision Support System (DSS), and web-based applications have enabled more powerful, highly accurate, and long-term intervention in agriculture in terms of where to farm and which plant is best fit. Land suitability assessment is commonly referred to as multi-criteria evaluation (MC) due to the large number of factors considered during the process. Information on climate, hydrology, topography, vegetation, and soil properties should be considered in land suitability analysis (Mosleh et al., 2017; Cartwright et al., 2020; Yang et al., 2021). Land suitability assessment with MC is a tool that deals with decision problems related to conflicting criteria. Land suitability assessment with MC is classified into two categories, namely multi-attribute (MADM) and multi-objective decision making (MODM) (Leake & Malczewski, 2000; Zimmermann & Gutsche, 1991). Land suitability assessment with MADM is

			suitable for decision making using discrete criteria where the importance between attributes has been determined by the decision maker. The criteria in the MADM method are usually filtered, prioritized and finally ranked by the decision maker (Gebre et al., 2021). Some examples of land suitability assessment using the MADM method are pairwise comparisons such as process hierarchy analysis (AHP), value or utility functions such as MAVT, MAUT and SAW (Liu et al., 2013; Zhang et al., 2016; Ananda & Herath, 2009). For instance, Barati et al. (2019) integrated analytic hierarchy process (AHP) and Matrix Cross-reference Multiplication methods for determining Key Agricultural Strategic Factors. Also, Devi and Yadav (2013) combined fuzzy elimination and elimination and choice translating reality method to optimize plant location. In another paper, Rajabi and Mousavizadeh (2015) used the technique for others reference by similarity to Ideal Solution (TOPSIS) method to rank candidate locations for agricultural industries in Iran. The problem that is often faced in assessing land suitability using the MADM method is the strong subjectivity of researchers in determining the importance of land attributes. As a solution, the researcher uses PCA in the land suitability analysis method in terms of assessing 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 between criteria is not predetermined. The importance between criteria in the MODM method 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 used (Gebre et al., 2021). Nasrollahi et al. (2019) suggest in future research to use multi-

			objective mathematical programming model for the location optimization and capacity planning problem.”
16 17	34 to 43 1 to 23	Please consider that at introduction you must - Fuzzy and PCA singly - Why you decided to put together Fuzzy and PCA ,what are they separate weakness and why incombination became more stronger through review	The following is a paragraph about why PCA and fuzzy put together, fuzzy and PCA singly, the weakness of other methods and the strength of these combination method. “Land suitability analysis with multiple criteria must pay attention to two main things in terms of how to equalize the unit of assessment and how the conflicting interests between these multiple attributes are assessed. Membership values and weight of indicators play a very important role in the final result of land suitability assessment using MCDM (Giordano and Liersch, 2012; Liu et al., 2013). The researcher employs a combination of fuzzy and PCA to answer these two main issues.” “Fuzzy is used to standardize attributes while PCA is used to assess conflicting interests between attributes. Currently, fuzzy inference has been developed by many experts. Fuzzy method is a development of the Boolean method which is considered too rigid and standard which has only two values, true and false (0 or 1). Fuzzy methods allows membership values to be transformed to zero up to one, where in the land suitability assessment the index increases close to one indicates a more optimal land suitability. According to Qiu, Chastain, & Zhou (2014), land suitability maps generated using this method is more informative and better at accuracy. Many studies have used fuzzy methods for land use optimization (Morteza et al., 2019; Vavatsikos et al., 2020; Arabsheibani., 2016). For instance, Nabati et al. (2020) used a fuzzy inference system to identify land capabilities based on agro-ecological zoning. Meanwhile, Feizizadeh and Blaschke (2013) standardized the criteria for land suitability

			analysis in Iran using the fuzzy set method. They standardized land evaluation criteria using a scale of 0 to 1. Because soil properties vary widely, intercorrelation can cause multicollinearity issues. Bernardi et al. (2016) point out that Multivariate statistical approaches could be used to solve these problems and to assist in better land management, resulting in better land ecosystem services (Montanaro et al., 2017). Principle component analysis (PCA) is another well-known multivariate statistical technique that aims to display the relative positions of data points in fewer dimensions while retaining as much information as possible, as well as to investigate relationships between dependent variables. Ranjbar et al. (2015) compared various multivariate methods on 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 interpreted better. PCA can effectively determine the weighted value to achieve a desired result (Bas, Das & Pal, 2020). According to Pennsylvania State University (2018) PCA has traditionally been used not only to identify which variables have the most influence on a process, but also to simplify the data into multiple PCs which account for most of the variability in the data. Ghaemi et al. (2014); Nguyen et al. (2020); Said et al. (2020) use PCA to reduce dimensional data into few factors. However, research by Ranjbar et al. (2016) point out that not reducing data is the most accurate method for evaluating land quality and providing consistent results. Because of this, PCA method in this study was only used to determine the importance of soil attributes without reducing it to a few data.”

17	29 to 43	The gap of you works sometime is more important than the other parts -	“However, by using fuzzy-MADM method, the weight of the indicator is usually determined subjectively by the researcher or by the expert opinions. The problem that is often encountered is that there are differences of opinion among several experts, causing bias and confusion for researchers. Other than that, most studies directly provide value ranges based on relevant studies. In addition, the effect of a land trait on other land properties in an area is not always the same as in other areas. This difference is caused by many factors, including the way farmers cultivate, and the characteristics of the soil in the area itself. Equating the assessment of the degree of importance of soil properties in land evaluation based on research that has been carried out in different areas can lead to bias. While Maddahi et al. (2014) and Luan et al. (2017) point out that the weight between land assessment indicators must be considered objectively based on the data or characteristics of the area itself for accurate evaluation. In the evaluation of land suitability, the assignment of land characteristics should be based on data. Therefore, this study aims to analyze land suitability used Fuzzy-PCA as a new approach which can deal with this problem. By using the fuzzy PCA method, the importance of land attributes can be determined more objectively based on the characteristics of the research area itself.”
18	2 to 7	Exactly where, its geographical place and information	Administratively, it consists of 12 sub-districts with an area of 1,786.01 Km². This district has a varied topography consisting of hills, mountains, valleys, and rivers at elevations ranging from 47 to 3293 meters above sea level. The land use is dominated by forest areas and plantation areas (25.3% of total area). Astronomically, Enrekang is located between 3o14'36”

			and 3o50'0” South Latitude, and between 19o40’53” and 120o06’33” East Longitude.
18	18 to 26	How you select the sampling points?	A land unit map of research area (Figure 1) was used as references for soil sampling which consisted of fifteen land units. The land unit map is combined information of the ecological principles relating to rock types, hydro-climate, landforms, soil, and organisms (Blasi et al., 2008). According to Zonneveld (1989), the survey results including the unit map, could be used as a basis for land evaluation. Soil samples are taken at random in each land unit. The soil sample taken is undisturbed soil, with the aim of providing an overview of the physical properties of the soil on a plot of land with a relatively homogeneous area. Some of the requirements are not burial ground, not in residential areas, not plantation areas and not areas managed by the community.
		Minimum 70 samples is necessity for statistical analysis in Fuzzy and Fuzzy AHP why 30?	We based on a minimum number of n samples for general statistical analysis. In addition, the scale of the land system map for determining the land unit that we use is 1:250.000 so that it is more general so that there are fewer sampling points.

Remarks: in the revised copy, it must include highlighted changes and modifications recommended in the revision to ensure that all editor/reviewer(s)’ comments were considered.

Land Suitability Assessment for Agricultural Crops in Enrekang, Indonesia: a Combination of Principal Component Analysis and Fuzzy Methods

ABSTRACT

Land suitability assessment is essential for efficient use of diminishing fertile agricultural land. Assessment parameters including soil texture, potential of hydrogen (pH), sum of basic cations, base saturation, cation exchange capacity (CEC), organic carbon (OC), soil depth, slope, mean annual temperature and precipitation data. The results showed 76.28% of the total area was optimally suitable for coffee growth and 23.26% was Moderat. 9.6% area was optimally suitable for cocoa growth and 90% was moderat. 1.98% area was optimally suitable for clove growth, 78.74% was moderat and 19.26% was marginal. 6.68% total area was optimally suitable for pepper, 86.89% was moderat and 6.41% was marginal. Final land suitability index is strongly influenced by the threshold values used by the researcher and by the quality of the land indicator itself. Plant threshold values are different due to the different plant recruitment. The most limiting factors included mean annual temperature < 26 ºC, acidic soil pH, and low CEC. This study shows that that the fuzzy method is a greet operation for converting numerical data of various magnitudes into membership function values, and representing land suitability. Principal component analysis (PCA) is an effective method to determine the weights of multiple factors in a systematic and more objective manner. Based on linearity test, it was found that there was a correlation between Land suitability index (LSI) and production with a value of f = 0.00 which indicated that the model applied has an ideal effect for predicting agricultural production and can be applied to other agricultural land management.

Keywords: Agricultural land management; Crop diversification; Fuzzy logic; Multi objective decision making; Principle component analysis.

INTRODUCTION

Sustainable agriculture is defined as a comprehensive system of crop production practices with site-specific applications that will persist over the long term (Rigby and Caceres, 1997). According to Pan et al. (2022), sustainable agriculture is ensuring the most efficient use of agricultural resources. One of the main goals of sustainable agriculture is to ensure that agriculture does not deviate from the natural system itself. Land suitability evaluation is one of the key in designing sustainable land use. Land suitability is the fitness of a specific type of land to be used for a specific purpose (FAO, 1976). Land suitability is determined by evaluating the climate, soil, and topographical components, as well as 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 et al. (2020), Evaluation of agricultural land suitability is critical for increasing production and planning a sustainable agricultural system. Evaluation of agricultural land suitability is useful in aligning agricultural land use, assisting agricultural land use planning decisions in overcoming competition between various possible land uses so that more land can be used efficiently. Furthermore, appropriate land suitability for certain agricultural activities will encourage better production.

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Based on the reviewer's suggestion our title was changed

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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 (GIS), Remote Sensing (RS), Decision Support System (DSS), and web-based applications have enabled more powerful, highly accurate, and long-term intervention in agriculture in terms of where to farm and which plant is best fit. Land suitability assessment is commonly referred to as multi-criteria evaluation (MC) due to the large number of factors considered during the process. Information on climate, hydrology, topography, vegetation, and soil properties should be considered in land suitability analysis (Mosleh et al., 2017; Cartwright et al., 2020; Yang et al., 2021). Land suitability assessment with MC is a tool that deals with decision problems related to conflicting criteria. Land suitability assessment with MC is classified into two categories, namely multi-attribute (MADM) and multi-objective decision making (MODM) (Leake & Malczewski, 2000; Zimmermann & Gutsche, 1991). Land suitability assessment with MADM is suitable for decision making using discrete criteria where the importance between attributes has been determined by the decision maker. The criteria in the MADM method are usually filtered, prioritized and finally ranked by the decision maker (Gebre et al., 2021). Some examples of land suitability assessment using the MADM method are pairwise comparisons such as process hierarchy analysis (AHP), value or utility functions such as MAVT, MAUT and SAW (Liu et al., 2013; Zhang et al., 2016; Ananda & Herath, 2009). For instance, Barati et al. (2019) integrated analytic hierarchy process (AHP) and Matrix Cross-reference Multiplication methods for determining Key Agricultural Strategic Factors. Also, Devi and Yadav (2013) combined fuzzy elimination and elimination and choice translating reality method to optimize plant location. In another paper, Rajabi and Mousavizadeh (2015) used the technique for others reference by similarity to Ideal Solution (TOPSIS) method to rank candidate locations for agricultural industries in Iran. The problem that is often faced in assessing land suitability using the MADM method is the strong subjectivity of researchers in determining the importance of land attributes. As a solution, the researcher uses PCA in the land suitability analysis method in terms of assessing 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 between criteria is not predetermined. The importance between criteria in the MODM method 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 used (Gebre et al., 2021). Nasrollahi et al. (2019) suggest in future research to use multi-objective mathematical programming model for the location optimization and capacity planning problem.

Land suitability analysis with multiple criteria must pay attention to two main things in terms of how to equalize the unit of assessment and how the conflicting interests between these multiple attributes are assessed. Membership values and weight of indicators play a very important role in the final result of land suitability assessment using MCDM (Giordano and Liersch, 2012; Liu et al., 2013). The researcher employs a combination of fuzzy and PCA as a solution to these two main issues. Fuzzy is used to standardize attributes while PCA is used to assess conflicting interests between attributes. Currently, fuzzy inference has been developed by many experts. Fuzzy method is a development of the Boolean method which is considered too rigid and standard which has only two values, true and false (0 or 1). Fuzzy methods allows membership values to be transformed to zero up to one, where in the land suitability assessment the index increases close to one indicates a more optimal land suitability. According to Qiu, Chastain, & Zhou (2014), land suitability maps generated using this method is more

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informative and better at accuracy. Many studies have used fuzzy methods for land use optimization (Morteza et al., 2019; Vavatsikos et al., 2020; Arabsheibani., 2016). For instance, Nabati et al. (2020) used a fuzzy inference system to identify land capabilities based on agro-ecological zoning. Meanwhile, Feizizadeh and Blaschke (2013) standardized the criteria for land suitability analysis in Iran using the fuzzy set method. They standardized land evaluation criteria using a scale of 0 to 1. Because soil properties vary widely, intercorrelation can cause multicollinearity issues. Bernardi et al. (2016) point out that Multivariate statistical approaches could be used to solve these problems and to assist in better land management, resulting in better land ecosystem services (Montanaro et al., 2017). Principle component analysis (PCA) is another well-known multivariate statistical technique that aims to display the relative positions of data points in fewer dimensions while retaining as much information as possible, as well as to investigate relationships between dependent variables. Ranjbar et al. (2015) compared various multivariate methods on 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 interpreted better. PCA can effectively determine the weighted value to achieve a desired result (Bas, Das & Pal, 2020). According to Pennsylvania State University (2018) PCA has traditionally been used not only to identify which variables have the most influence on a process, but also to simplify the data into multiple PCs which account for most of the variability in the data. Ghaemi et al. (2014); Nguyen et al. (2020); Said et al. (2020) use PCA to reduce dimensional data into few factors. However, research by Ranjbar et al. (2016) point out that not reducing data is the most accurate method for evaluating land quality and providing consistent results. Because of this, PCA method in this study was only used to determine the importance of soil attributes without reducing it to a few data.

Currently, fuzzy combined with MODM in land suitability assessment has not been widely developed by researchers. Most researchers combine fuzzy and MADM such as the AHP method (Mosadeghi et al., 2015; Keshavarzi et al., 2020; Nasery et al., 2021; Zalhaf et al., 2021 Kelic et al., 2022; Paul and Ghosh, 2022; Sengupta et al., 2022). This is due to the application of the methods simpler and easier to implement. However, by using fuzzy-MADM method, the weight of the indicator is usually determined subjectively by the researcher or by the expert opinions. The problem that is often encountered is that there are differences of opinion among several experts, causing bias and confusion for researchers. Other than that, most studies directly provide value ranges based on relevant studies. In addition, the effect of a land trait on other land properties in an area is not always the same as in other areas. This difference is caused by many factors, including the way farmers cultivate, and the characteristics of the soil in the area itself. Equating the assessment of the degree of importance of soil properties in land evaluation based on research that has been carried out in different areas can lead to bias. While Maddahi et al. (2014) and Luan et al. (2017) point out that the weight between land assessment indicators must be considered objectively based on the data or characteristics of the area itself for accurate evaluation. In the evaluation of land suitability, the assignment of land characteristics should be based on data. Therefore, this study aims to analyze land suitability used Fuzzy-PCA as a new approach which can deal with this problem. By using the fuzzy PCA method, the importance of land attributes can be determined more objectively based on the characteristics of the research area itself.

MATERIAL AND METHODS

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The study area was conducted in Enrekang, one of the districts in South Sulawesi, Indonesia. Administratively, it consists of 12 sub-districts with an area of 1,786.01 Km^2. This district has a varied topography consisting of hills, mountains, valleys, and rivers at elevations ranging from 47 to 3293 meters above sea level. The land use is dominated by forest areas 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 were analyzed and compared at the study site (coffee, cocoa, pepper and cloves). Guidelines for Land Suitability Assessment Using Technical Guidelines for Land Evaluation of Agricultural Commodities by Ritung et al. (2011) also guidelines by Sys (1993) on Land Evaluation Part III on Plant Requirements. The three main variables used in the assessment include; climate variables, topographic variables and soil variables, with a total of ten indicators. The variables used in the study are summarized in the Table 1.

Field Sampling and Laboratory Analysis

There are land attributes that can be estimated or measured directly in the field, and some must be assessed in the laboratory (FAO, 1976). Field observations included soil depth and slope measurements, while other soil variables were analyzed in the laboratory. A land unit map of research area (Figure 1) was used as references for soil sampling which consisted of fifteen land systems. The land unit map is combined information of the ecological principles relating to rock types, hydro-climate, landforms, soil, and organisms (Blasi et al., 2008). According to Zonneveld (1989), the survey results including the unit map, could be used as a basis for land evaluation. Soil samples are taken at random in each land unit. The soil sample taken is undisturbed soil, with the aim of providing an overview of the physical properties of the soil on a plot of land with a relatively homogeneous area. Some of the requirements are not burial ground, not in residential areas, not plantation areas and not areas managed by the community.

Thirty soil samples were taken. Samples were taken from top (depth 0-25 cm) and subsoil (depth> 25 cm) from 15 land units. Those used for texture and CEC analysis were obtained from subsoil, while those for pH, basic cations (including Ca, Mg, K, and Na), and base saturation analysis were taken from the topsoil. Texture, CEC, pH, sum of basic cations, base saturation, and C-organic were analyzed in the laboratory. The various approaches used by the factors were as follows: pipette method for texture analysis, 1: 2.5 soil water suspense for pH procedure, the Walkley-Black method with 105°C dry soil samples for C-organic analysis, while the sum of basic cations, CEC, and base saturation used the cations exchange rate (NH_4-Acetat 1N, pH 7) in dry soil sample of 105°C.

Terms and Stages of Land Suitability Assessment

Land suitability assessment in this study implements a fuzzy model by Zadeh (1965). The fuzzy set function can analyze soil characteristics continuously without categorizing them into different classes. In fuzzy analysis, land attribute values are converted to sustainable values ranging from zero to one. 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 semantic import model (SIM) that is widely used, and is described in the modeling of Figure 2.

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In the modeling of Figure 2, some important values such as; b which is the value of a land attribute at the ideal point, lower crossover (LCP) and upper crossover (UCP) are the lower and upper thresholds/margins of a land attribute 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. The optimal point in the fuzzy function model 1 is used to assess soil attributes which have one ideal point but have 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. Fuzzy model 3 can be interpreted that 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. Land characteristics in the fuzzy function model 4 are interpreted that the smaller a land characteristic, the better, as is the case with the slope level. The research control points in Table 2 are arranged based on; agricultural land evaluation criteria made by Ritung (2011) and Sys (1993), Fuzzy modeling in Figure 2, and land characteristics at 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 the land suitability assessment. For this reason, factor analysis was carried out using PCA to group land attributes that were considered to have the same characteristics into one new factor/variable (Pearson,1901; Hotelling ,1933). In many studies, PCA is indeed used as a data reduction technique. However, because this study used the total data set principle, there is no reduction in land attributes. This study used PCA to analyze the correlation between land attributes and then classifies them into new factors without reducing them. This is achieved by creating new uncorrelated variables that successively maximize variance. As a by-product, a better interpretation of the data is obtained. PCA components that are retained are those that have one or more eigenvalues (see Figure 3). The number of indicators for each component or factor will be the same as the number of land indicators analyzed, but each component/factor will only maintain one or more indicators with a maximum loading corresponding. The variance of each component/factor will explain how much the component contributes in explaining the data as a whole, while the loading corresponding explains how much the correlation between the indicator and the component is (Armenise et al., 2013; Mukherjee & Lal, 2014). In principle, PCA will produce as many components (factors) as the indicators included in the analysis. However, only component factor having eigenvalues > 1 were retained for inclusion in the next analysis. According to this rule, four factors are maintained, each labeled factor 1, factor 2, factor 3 and factor 4. The 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 component, each following component is obtained by partially out of the previous component. Based on the results of the PCA analysis, four new factors were added to the calculation of the land suitability index (LSI) (See details in Figure 3 and Table 4).

After the soil attributes are determined and new variables are created, the next step is to standardize the land attributes. Standardization is carried out to equalize the unit of assessment for several soil attributes with a value range of 0 to 1 by the equation 1.

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

$$MF(x_i) = 1, \text{ if } (b_1+d_1) \leq xi \leq (b_2 - d_2) \quad \text{(fuzzy model 2)}$$

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

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

Another important step in this research is the objective weight assessment. The weight is calculated using a simple mathematical modeling (equation 2). The weight assigned ranges from 0 to 1. The weighting of a factor (W_f) and individual land indicator (W_i) given will consider the loading factor value of each indicator (y_i), total loading factor value ($\sum y$) and values of varians component each factor (m) and total values of varians component formed ($\sum m$).

$$W_i = \frac{|yi|}{\sum |y|} \quad (2)$$

$$W_f = \frac{|m_i|}{\sum |mi|} x\ 100$$

Join membership function (JMF) calculation is also one of the most important stages of this research. Based on the results of the factor analysis carried out, there are 4 new factors that will be included in the land suitability assessment. Each new factor will be calculated the JMF value. The JMF value reflects the quality of the land; the higher the JMF value, the better the land quality. JMF is calculated using the equation 3.

$$JMF\ (X_{i.....z}) = \sum_{i=1}^{n} Wi\ (MFi) \quad (3)$$

The land suitability index is calculated after all of the parameters of the land suitability calculation have been determined. To determine the LSI, JMF of each factor is then integrated with the weight of the factor (Wf) using the equation 5:

$$LSI = \sum_{i=1}^{n} \mathrm{H}fi\ (JMFxi) \quad (5)$$

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RESULTS

Land Properties in the Study Area

A summary of some of the land characteristics at the research location can be seen in Table 3. Soil pH in the entire study areas are acidic with minimum range of 4.56 and maximum of 6.04. The basic cations used are calcium (Ca), magnesium (Mg), Potassium (K) and Sodium (Na). Sum of basic cations found in both top and sub soil in all land system had quite high for plantation plant growth with ranged of 4.1 cmol/kg to 8.88 cmol/kg. 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 was classified as moderate with a range of 12.14 cmol/kg to 19.22 cmol/kg. In the Bukit Ayun, Bukit Pandan and Watampone land units, the C-organic content was found to be very low, less than 1%. The highest value of c-organic of 2.46% was found in the Kalung land unit. Slope data obtained from digital elevation model (DEM) 30 m SRTM image extraction. The slopes recorded ranged from 2% to more than 50%. The annual precipitation in the research region is quite high, with annual average rainfall ranging from 1676 to more than 2634 mm/year. average annual temperature ranges from 21° C to 28° C. Based on the results of the field survey, it is known that the effective soil depth of the research location ranges from 90 to 150 cm.

New Factor Groups and Important Weight

Each land attributes has a greatest loading corresponding to each of the 4 factors. For example, slope is correlated 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. 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, and so on. Slope has a greater correlation to factor 1 than other factors, and then the slope is classified as factor 1. This also applies to other land attributes. As previously explained, the weight of the land indicator (W_i) is the result of the corresponding loading divided by total loading corresponding of the land attributes classified in that factor. Among several soil attributes included in factor 1, slope has the largest correspondent load. Therefore the importance weight on the slope is greater (0.28) than the other land attributes which are included in factor 1. The total weight (W_i) of each faktor is 1. This rule also applies to other land attributes. Based on the maximum loading corresponding of each land indicator in each factor: slope, annual precipitation, annual temperature are grouped into factor 1; pH, number of base cations, CEC, C-organic become factor 2; base saturation to factor 3; Soil texture is a factor 4. The results of the PCA analysis, the newly formed factor groups and the degree of importance of all soil attributes are presented in Figure 3 and Table 4.

Membership Value of Land Attribute and JMF of Factors

Individual membership values consist of numbers ranging from 0 to 1. If a land attribute has a membership value of 1, it indicates that the land attribute is optimal for the growth of a plant and vice versa. Based on Table 5, it is known that some land attributes are below the tolerance threshold value set as in Table 2. For example, individual membership of land attributes in the form of pH, CEC, average rainfall and annual temperature of less than 0.4 for cocoa plant growth in the Bukit Ayun land unit. This indicates that in the 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 other plants. In some land units, the individual membership value (for coffee plant growth) is equal to 1 which indicates optimal suitability. For example, in Pendreh and Danau Lindu land units, land attributes such as temperature, rainfall and slope have an optimal suitability for coffee growth with individual membership values of more than 0.9. In general, the problems faced by the research area are temperature, CEC and base saturation where 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 less than 0.4 were 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, in general the growth of clove plants in the research location did not reach optimal suitability with values less than 0.85 and more than 0.4.

Joint membership values (JMF) for evaluating the suitability of crops can be seen in Table 6. These figures indicate the quality of the land for the potential development of plantation crops. Just like individual membership values, JMF also consists of a number range from 0 to 1. The higher the JMF value indicates that a land has optimal potential for plantation development. The JMF value for coffee plant growth ranged from 0.38 to 1. A JMF of 0.38 was found in the Sungai Aur land unit at Factor 3. This indicates that factor 3 is a limiting factor for coffee plant growth. Cocoa JMF values ranged from 0.45 to 1. The lowest cocoa JMF was found in the 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 cocoa growth. Cloves and pepper have a low JMF value at a factor of 3, which is 0.3 at the Sungai Aur land unit. As previously explained there is only one land property in factor 3, namely basic saturation. Thus, the low value of factor 3 indicates the quality of the base saturation that is less supportive of plant growth.

Land Suitability Index

The multiplication function in equation 5 is used to generate a spatial land suitability index data layer with continuous values, ranging from 0 to 1. 1 indicates optimal suitability for plant development. Based on the analysis, it was found that the LSI of cloves ranged from 0.4 to 0.81, coffee 0.52 to 0.99, cocoa 0.52 to 0.86, pepper 0.5 to 0.87. The results are visualized in Figure 4. To evaluate land area, raster data is converted into vector data and then categorized based on its pixel value into several land suitability classes. Areas with a pixel value of > 0.8 are included in the optimal suitable category, while areas with a pixel value of 0.8≤LSI>0.6 are included in the moderate suitability category, and areas with a pixel value of 0.6>LSI>0.4 are included in the marginal suitability category. Of the total area analyzed for coffee plants, 76.28% of the area is in the moderate suitability, 23.26% in the optimal suitable, and 0.45% in the marginal suitability category. For cocoa, 90% of the research area is included in the moderate suitability category, 0.29% and 9.6% are included in the marginal suitability and optimal suitable. A total of 86.89% of the research area is included in the moderate suitability category for pepper plants, while 6.68% areas are included in the optimal suitable and 6.41% areas are in the marginal suitability category. For clove commodity, 78.74% of the total area is included in the moderate suitability category, while for areas with marginal and very suitable suitability categories are 19.26% and 1.98%, respectively.

DISCUSSION

76.28% of the study areas were identified having moderate suitability with an index range of 0.6 to 0.8. The same suitability class also dominates cocoa with 90% of regions having an index of 0.6 to 0.8. Meanwhile, 86.89% of the area is dominated by medium suitability of pepper and 78.74% of the area is dominated by medium suitability of cloves. Land suitability for the four crops was successfully assessed in this study using fuzzy-AHP. This is evidenced by the accuracy test carried out on the model applied in the study (Figure 5). Seyedmohammadi et al. (2019) conducted a validation test by comparing the pixel values of the land suitability index as a map to be assessed and production data as ground truth data to obtain a match. This is also applied in this research. Commodity production data is extracted spatially into polygon maps which are then matched with land suitability index data. Validation points are taken at random, then processed to assess linear or nonlinearity between the land suitability index and production data (Figure 5). The rule of decision making using regression test is if the value of f <0.05 then indicates that there is linearity between LSI and production. From the results of tests carried out on all analyzed plants, it was concluded that there was a linearity between LSI and production with a value of f = 0.00. Based on this, it can be concluded that the model used in the study is good and can be applied in other applications related to suitability assessment.

This method is easy and simple to apply in environmental management, especially in evaluating land suitability more objectively without involving expert opinion in determining the importance of the assessment parameters. Fuzzy linear functions are used to standardize (individual membership) soil attributes, and the same thing was done by Nurmiaty and Baja (2014). In addition, PCA used to analyze the correlation between land attributes and then classifies them into new factors without reducing them. This is achieved by creating new uncorrelated variables that successively maximize variance. Four main components (PC1, PC2, PC3 and PC4) with eigenvalues greater than 1 were extracted. This technique succeeded in grouping ten variables into four main components (new group of variables) and described 86.24% of the original variance. Sahoo et al. (2021) also used the PCA technique only to construct new variables from land attributes for land suitability assessment. In line with that, Jolliffe and Cadima (2016) point out that PCA is an adaptive technique that is able to determine several new variables. In our research, the results of PCA analysis are further used to determine the degree of importance of each component and the degree of importance of variables or land indicators in a component. It does so by utilizing the variance value of each component and the loading factor value of each land attribute. Factor 1 have a strong loading on slope, mean annual temperature and precipitation, and soil depth while factor 2 have a strong loading on pH, sum basic cations, organic matter and CEC. Base saturation and soil texture in groups 3 and 4, respectively. Based on the variance, factor 1 is the most important variable and is given the highest weight compared to other factors which describes 48% total data. In several studies that also used PCA, such as Ghaemi et al. (2014) and Said et al. (2020) gave greater importance to PC 1. Ayehu and Atnafu (2015) also give 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 and has the greatest influence on other land attributes in the factor 1 group so that it is given the highest weight.

Based on our data processing experience, it can be seen that when the fuzzy method is used, the threshold set by the researcher (LCP and UCP) in Table 2 becomes sensitive thing that affects the results of individual membership values of land attributes in Table 5. In addition, this is also influenced by the quality of the land itself. This is also emphasized by Qiu et al. (2014) that thresholds cannot be determined arbitrarily and must be based on expert knowledge of the situation. Based on Table 5, it can be concluded that some land attributes such us texture in Batang Anai and Bukit Pandan are optimal for plantation plant growth with individual membership values = 1, but some other land attributes such us pH in Maput and Bakunan do not meet the plant growth requirements with individual membership values < 0.4. Soil pH in all study areas was acidic in the range of 4.56-6.04, while 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, Mantalat, because is unable to meet the specified threshold and resulting in low membership values. As for the growth of clove and pepper plants, the individual membership value of pH was quite high with a value > 0.5 in all land units. This is due to the pH values meet the minimum threshold set for clove and pepper growth based on the criteria compiled by Ritung et al. (2011). In addition, another major limiting factor for cocoa growth in the study area is temperature. In this land suitability assessment, temperature is a very important factor and is in the group with the first degree of importance. This is in line with the opinion of Geo and Saediman (2019) which states that climatic factors greatly affect cocoa growth. They state that the 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^{o} C to 28^{o} C while most of the research areas have an average daily temperature of <26^{o} C. This resulted in many sites in the assessment reaching lower threshold values for temperature. Another land indicator that needs to be an important issue in the research location is CEC. Many land units do not meet the minimum CEC standards for plant growth, both for coffee, cocoa, pepper, and cloves. CEC ranged from 12.14 to 21.25 cmol/kg while the minimum CEC standard for plant growth is 15 cmol/kg. The main problems in the research area are temperature, pH and CEC. Temperature is considered to be the main limiting factor for the development of cocoa, clove and pepper crops as it has the highest importance among the three main limiting factors. However, temperature is an attribute that is difficult to modify by any treatment. To overcome the problem of low pH at the research site, the opinion of Gentili et al. (2018) that the pH can be increased by the addition of calcium hydroxide can be applied. While the research of Martinsen et al. (2015) which revealed that the addition of biochars to acid soil can increase pH and CEC can be used to overcome soil fertility problems in the study area.

CONCLUSION

Land suitability for coffee consists of optimal suitability with an index range of 0.6 to 0.8 covering 23.26% of the area, moderate suitability with an index range of 0.8 to 0.99 covering 76.28% and marginal suitability covering 0.45% of the area with an index of 0.52 to 0.6. Meanwhile, Cocoa consists of optimal suitability with an index of 0.8 to 0.88 covering 9.6% of the area and marginal suitability with an index of 0.6 to 0.8 covering 90% of the area. In addition, clove has a marginal suitability covering 19.26% area with an index of 0.4 to 0.6, moderate suitability covering 78.74% area and optimal suitability covering only 1.98% area with index of 0.8 to 0.81. Pepper consists of optimal suitability covering 6.68% area with index 0.8 to 0.87, moderat suitability covering 86.89% area marginal suitability covering 6.41% with index 0.5 to 0.6. Mean annual temperature < 26 ^{o}C, acidic soil pH, and low CEC were the main limiting factor for the growth of plantation crops in the study site. As a solution, the addition of biochars and calcium hydroxide to acid soils can 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 very simple and easy to implement. Based on the validation tests carried out, it can be concluded that the combination of fuzzy-PCA models succeeded in revealing the suitability of plantation land well more objectively, so that this model is feasible to be applied in other fields of land management. For a more accurate land suitability assessment, further research needs to compare various methods to calculate the final land suitability index.

Commented [A21]: Some solutions, recommendations

Figure and Table

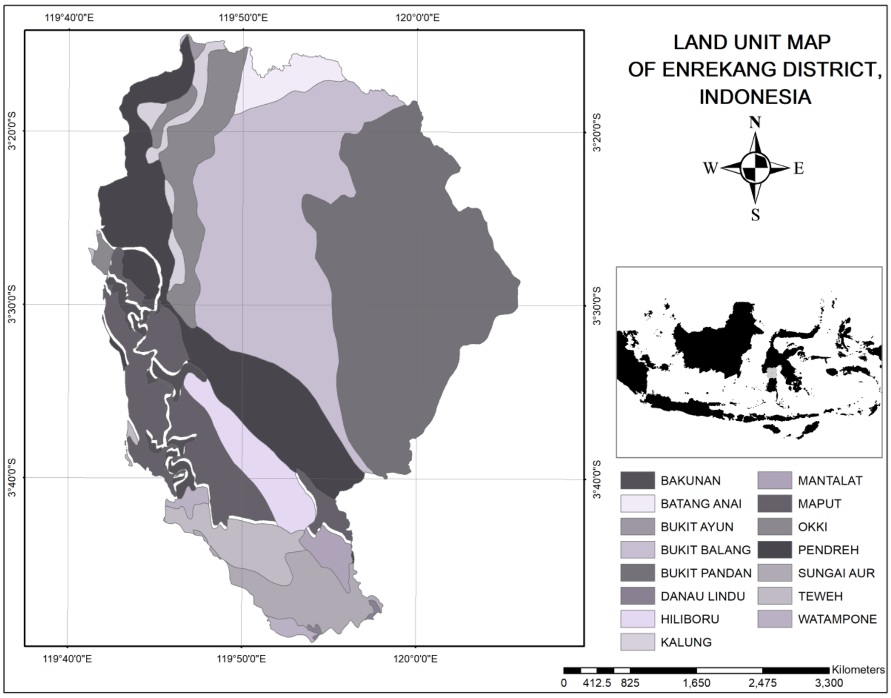

Figure 1. Land unit map of research area

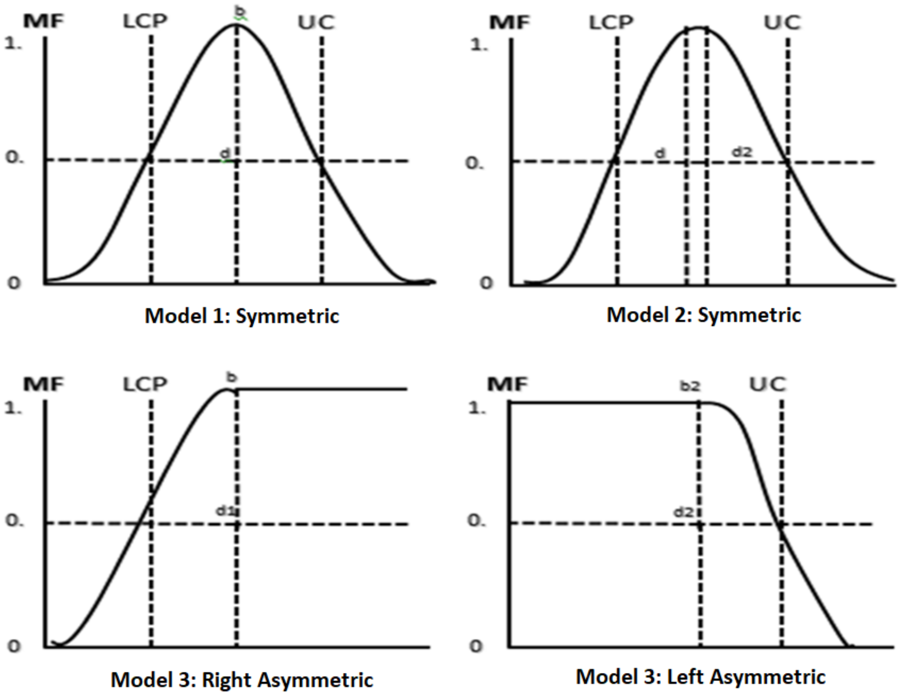

Figure 1. Fuzzy set model for land suitability assessment

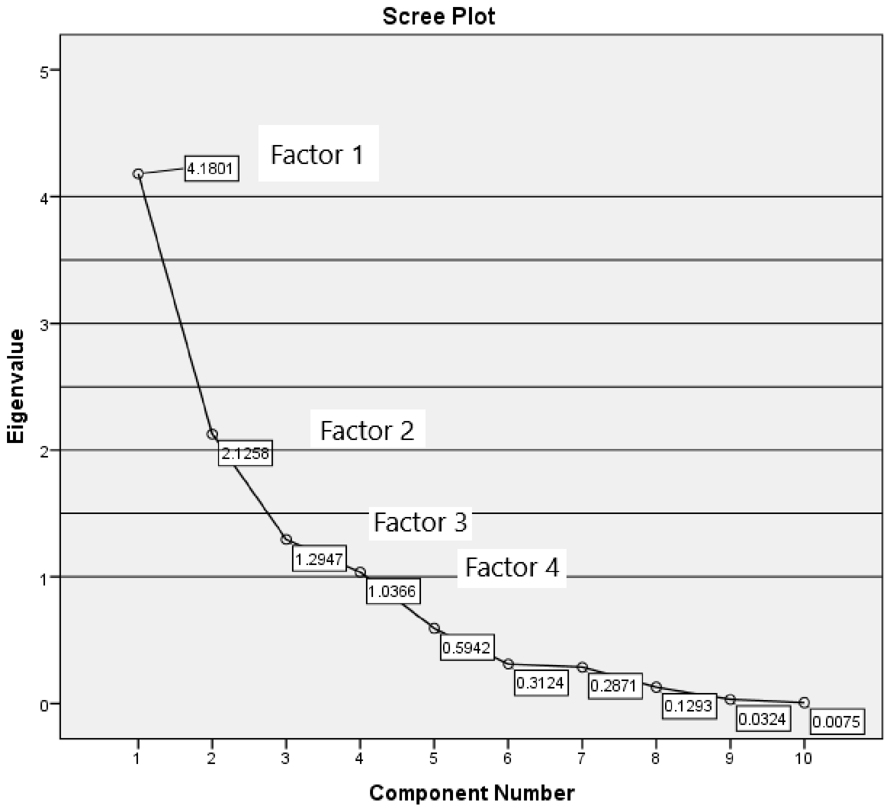

Figure 2. Scree Plot which plots the eigenvalue by the component number.

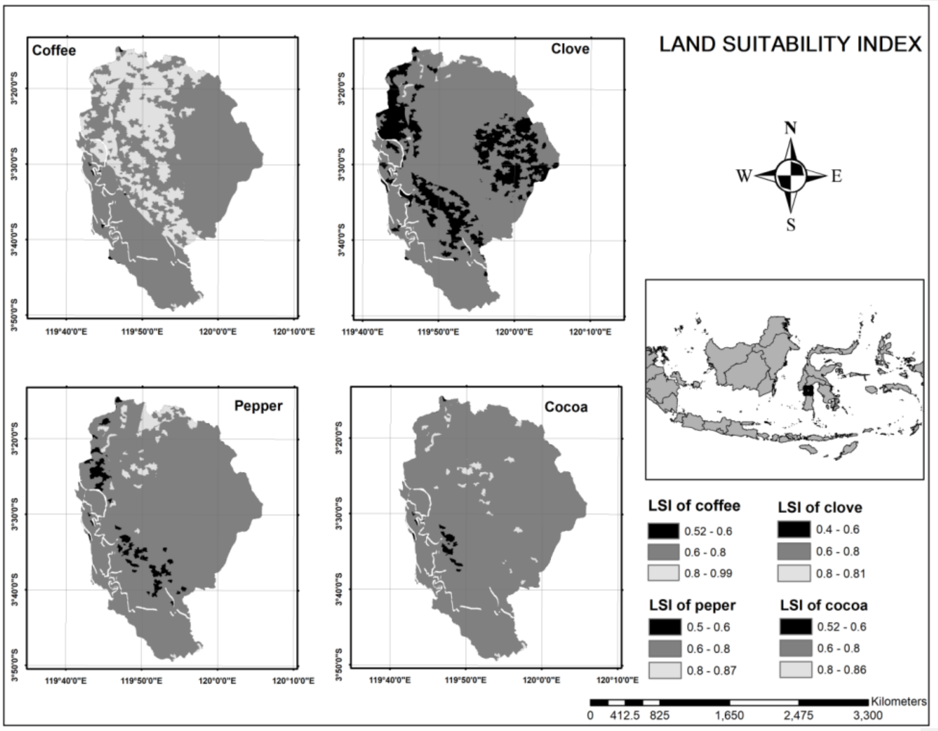

Figure 3. Land suitability index for plantation crops in research area

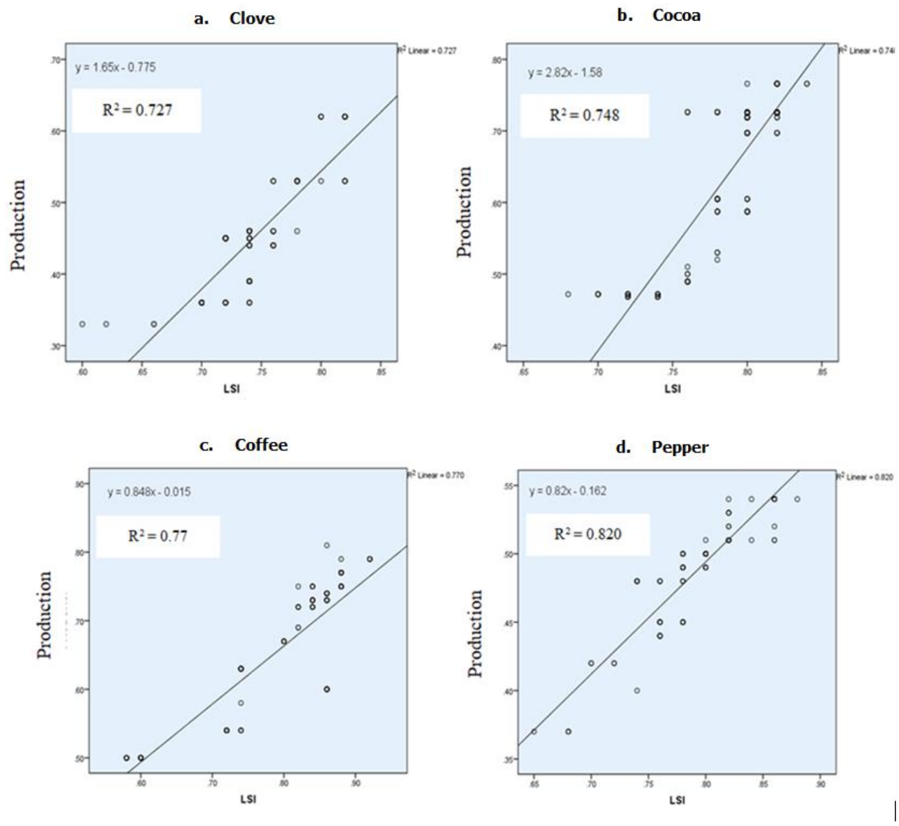

Figure 4. Linear regression between LSI and land production (tones/ha)

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 one to fourteen	The results of laboratory analysis
Sum of basic cations (V2)	cmol/kg	The number of basic cations that can be absorbed by the soil include elements of calcium (Ca), magnesium (Mg), potassium (K), 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.	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 (cm)	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 temperatur (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

Table 2. Research control points for land suitability assessment

Commodity	Land indicators	LCP	b	d1	UCP	d2	Fuzzy Model
Coffee	pH H2O	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 H2O	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 H2O	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 H2O	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

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

Variabel	Minimum	Maximum	Mean	S. E	Std. Deviation	Variance
pH H2O	4.56	6.04	5.22	.12	0.46	0.21
Sum of basic cations	4.15	8.27	5.14	.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	.54	2.08	4.33
C-organic	0.64	2.46	1.42	.14	0.54	0.29
Slope	2.00	58.00	13.27	1.96	7.58	57.50
Annual temperatur	21.00	28.00	26.07	.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	.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	
Fctor Weight (H_{fi})	**0.48**		**0.25**		**0.15**		**0.12**	
Faktor loading:		**(W*i*)**		**(W*i*)**		**(W*i*)**		**(W*i*)**
pH H2O	-.071		.655	0.22	.594		.157	
Sum of basic cations	.231		.671	0.22	.622		.095	
Base saturation	.089		.115		.945	1.00	.106	
CEC	.262		.871	0.29	-.194		-.071	
C-organic	-.027		.830	0.27	.303		.060	
Slope	.898	0.28	.192		-.147		.069	
Annual temperature	.760	0.24	-.525		-.243		-.147	
Annual precipitation	.695	0.22	.114		-.476		.361	
Soil texture	.018		.035		.131		.974	1.00
Soil depth	.846	0.26	-.019		.082		-.017	

Table 1. Individual membership of land attributes

Land attribut	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. Join 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

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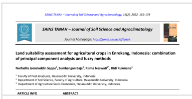

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Land Suitability Assessment for Agricultural Crops in Enrekang, Indonesia: ~~a~~ Combination of Principal Component Analysis and Fuzzy Methods

ABSTRACT

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

Keywords: ~~Agricultural~~agricultural land management~~; Crop~~, crop diversification~~; Fuzzy~~, fuzzy logic~~;~~ ~~Multi-~~, multi-objective decision~~-~~-making~~; Principle~~, principle component analysis~~.~~

INTRODUCTION

Sustainable agriculture is defined as a comprehensive system of crop production practices with site-specific applications that will persist ~~over~~in the long term (Rigby and Caceres, 1997). According to Pan et al. (2022), sustainable agriculture ~~is ensuring~~ensures the most efficient use of agricultural resources. One of ~~the~~its main goals ~~of sustainable agriculture~~ is to ensure that agriculture does not deviate from the natural system itself. Land suitability evaluation is one of the ~~key~~keys in designing sustainable land use. Land suitability is the ~~fitness~~eligibility of a specific type of land ~~to be used~~ for a specific purpose (FAO, 1976~~). Land suitability~~) and is determined by evaluating the climate, soil, and topographical components~~, as well as~~ 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 et al. (2020), ~~Evaluation~~the evaluation of agricultural land suitability is critical ~~for increasing~~to increase production and ~~planning~~plan a

Commented [Editor1]: Remark: Note that usually, an abbreviation needs to be spelled out once in the abstract, again in the main text, in the figure/table legends, and used consistently thereafter. Also, abbreviations should not be used for terms present only once in the text. However, if the abbreviations are standard in your field, they need not be defined. Please check throughout for all such instances and revise accordingly.

sustainable agricultural system. ~~Evaluation of agricultural land suitability is~~This assessment is also useful in aligning agricultural land use~~,~~, and assisting agricultural land use planning decisions ~~in overcoming~~to overcome the competition between various possible land uses so that~~ more~~ land can be used efficiently. Furthermore, appropriate land suitability for certain agricultural activities will encourage ~~better~~ production. Agricultural production is closely related to ~~farmers'~~farmers' income and influences farmer decisions to support sustainable agriculture (Piñeiro et al., 2020).

Recent technological advances in Geographic Information System~~ (GIS),~~, Remote Sensing~~ (RS),~~, Decision Support System~~ (DSS),~~, and web-based applications have enabled ~~more~~ powerful, highly accurate, and long ~~-~~term ~~intervention~~interventions in agriculture in terms of where to farm and which plant is the best fit. Land suitability assessment is commonly referred to as ~~multi-criteria~~ multicriteria (MC) evaluation ~~(MC)~~ due to the large number of factors considered ~~during~~in the process. Information on climate, hydrology, topography, vegetation, and soil properties should be considered in ~~land suitability~~this analysis (Mosleh et al., 2017; Cartwright et al., 2020; Yang et al., 2021). Land suitability assessment with MC evaluation is a tool that deals with decision problems related to conflicting criteria~~. Land suitability assessment with MC~~ and is classified into two categories, namely, multi-attribute decision-making (MADM) and multi-objective decision~~-~~-making (MODM) (Leake & Malczewski, 2000; Zimmermann & Gutsche, 1991). Land suitability assessment with MADM is suitable for decision~~-~~-making using discrete criteria where the importance between attributes ~~has been~~is determined by the decision maker. The criteria in ~~the~~ MADM ~~method~~ are usually filtered, prioritized, and finally ranked by the decision maker (Gebre et al., 2021). Some examples of land suitability assessment using ~~the~~ MADM ~~method~~ are pairwise comparisons such as ~~process~~ analytic hierarchy ~~analysis~~ process (AHP~~),~~) and value or utility functions such as MAVT, MAUT, and SAW (Liu et al., 2013; Zhang et al., 2016; Ananda & Herath, 2009). For instance, Barati et al. (2019) integrated ~~analytic hierarchy process (~~AHP~~)~~ and ~~Matrix Cross~~matrix cross-reference ~~Multiplication~~multiplication methods ~~for determining Key Agricultural Strategic Factors. Also,~~to determine key agricultural strategic factors. Devi and Yadav (2013) combined fuzzy elimination ~~and~~with elimination and choice translating reality method to optimize plant location. ~~In another paper,~~ Rajabi and Mousavizadeh (2015) used the technique for ~~others~~other reference by similarity to ~~Ideal Solution (TOPSIS)~~ideal solution method to rank candidate locations for agricultural industries in Iran. The problem ~~that is~~ often faced in ~~assessing~~ land suitability assessment using ~~the~~ MADM ~~method~~ is the strong subjectivity of researchers in determining the importance of land attributes. ~~As a solution, the researcher uses~~ To solve this problem, researchers used principle component analysis (PCA) in ~~the~~ land suitability ~~analysis method in terms of assessing~~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 ~~between criteria~~ is not predetermined. The importance between criteria in ~~the~~ MODM~~ method~~ 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 ~~used~~ (Gebre et al., 2021). Nasrollahi et al. (2019) ~~suggest in future research to~~suggested the use of multi-objective mathematical programming model for ~~the~~ location optimization and capacity planning ~~problem~~in future research.

Land suitability ~~analysis~~ assessment with multiple criteria must ~~pay attention to~~consider two main things~~ in terms of how to equalize~~: equalizing the unit of assessment and ~~how the~~evaluating conflicting interests between ~~these~~ multiple attributes~~ are assessed.~~. Membership values and weight of indicators play ~~a very~~an important role in the final result of land suitability assessment using MCDM (Giordano and Liersch, 2012; Liu et al., 2013). ~~The researcher employs~~Researchers employed a combination of fuzzy and PCA as a solution to these two main issues. Fuzzy is used to standardize attributes~~ while~~, and PCA is ~~used~~applied to assess conflicting interests between attributes. ~~Currently~~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 ~~which~~and has only two values, true and false (0 or 1). Fuzzy methods allows membership values to be transformed to ~~zero~~0 up to ~~one, where~~1; in ~~the~~ land suitability assessment, the closer an index ~~increases close~~ value is to ~~one indicates a more optimal~~1, the better the land suitability. According to Qiu, Chastain, ~~&~~and Zhou (2014), land suitability maps generated using this method ~~is more~~are informative and ~~better at accuracy.~~ accurate. Many studies~~ have~~ used fuzzy methods for land use optimization (Morteza et al., 2019; Vavatsikos et al., 2020; Arabsheibani., 2016). For instance, Nabati et al. (2020) used a fuzzy inference system to identify land capabilities ~~based on agro-ecological~~according to agroecological zoning. ~~Meanwhile,~~ Feizizadeh and Blaschke (2013) ~~standardized~~used the fuzzy set method to standardize the criteria for land suitability ~~analysis~~assessment in Iran ~~using the fuzzy set method. They standardized land evaluation criteria using~~by applying a scale of 0 to 1. ~~Because~~Owing to the wide variety of soil properties~~ vary widely~~, intercorrelation can cause multicollinearity issues. Bernardi et al. (2016) ~~point~~pointed out that ~~Multivariate~~multivariate statistical approaches could be used to solve these problems and ~~to~~ assist in ~~better~~ land management, resulting in ~~better~~improved land ecosystem services (Montanaro et al., 2017). PCA~~Principle component analysis (PCA)~~ is another well-known multivariate statistical technique that ~~aims to display~~displays the relative positions of data points in ~~fewer~~few dimensions while retaining as much information as possible~~, as well as to investigate~~ and investigates relationships between dependent variables. Ranjbar et al. (2015) compared the ability of various multivariate methods ~~on~~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~~ better~~. PCA can also effectively determine the weighted value to achieve a desired result (Bas, Das & Pal, 2020). According to Pennsylvania State University (2018~~)~~), PCA ~~has~~is traditionally ~~been~~ used~~ not only~~ to identify which variables have the most influence on a process~~, but also~~ and to simplify the data into multiple PCs ~~which~~that account for most of the variability in the data. Ghaemi et al. (2014~~);~~), Nguyen et al. (2020~~);~~), and Said et al. (2020) ~~use~~used PCA to reduce dimensional data into few factors. However, ~~research by~~ Ranjbar et al. (2016) ~~point~~pointed out that not reducing data is the most accurate method for evaluating land quality and providing consistent results. ~~Because of this, PCA method in this~~Hence, the current study ~~was~~ used PCA only~~ used~~ to determine the importance of soil attributes without reducing it to a few data.

~~Currently~~To date, fuzzy combined with MODM ~~in~~for land suitability assessment has not been widely ~~developed by researchers.~~adopted. Most researchers ~~combine~~combined fuzzy and MADM such as ~~the~~ AHP ~~method~~ (Mosadeghi et al., 2015; Keshavarzi et al., 2020; Nasery et al., 2021; Zalhaf et al., 2021 Kelic et al., 2022; Paul and Ghosh, 2022; Sengupta et al., 2022~~). This is~~) due to the simple application ~~of the methods simpler~~ and ~~easier to implement.~~easy implementation. However, ~~by using~~in fuzzy~~-~~–MADM~~ method~~, the weight of the indicator is usually determined subjectively by the researcher or ~~by the~~ in accordance with expert opinions. The ~~problem that is~~ most often encountered problem is ~~that there are~~the differences of opinion among several experts, causing bias and confusion for researchers. ~~Other than that, most~~ Most studies directly ~~provide~~provided value ranges based on relevant studies. In addition, the effect of a land trait on other land properties ~~in~~for an area is not always the same as ~~in~~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. ~~Equating~~Using the assessment of the degree of importance of soil properties in land evaluation ~~based on~~for a specific from previous research ~~that has been carried out in~~on different areas can lead to bias. ~~While~~ Maddahi et al. (2014) and Luan et al. (2017) ~~point~~pointed out that the weight between land assessment indicators must be considered objectively ~~based on~~according to the data or characteristics of the area itself for accurate evaluation. ~~In the evaluation of~~In land suitability assessment, the assignment of land characteristics should be based on data. Therefore, ~~this study~~the current work aims to analyze land suitability ~~used Fuzzy~~ using fuzzy–PCA as a new approach ~~which can deal with this~~to address the above problem. ~~By using~~With the ~~fuzzy PCA~~proposed method, the importance of land attributes can be determined ~~more~~ objectively ~~based~~ on the basis of the characteristics of the research area itself.

MATERIAL AND METHODS

~~The~~This study~~ area~~ was conducted in Enrekang, one of the districts in South Sulawesi, Indonesia. Administratively, ~~it~~ this district consists of 12 ~~sub-districts~~subdistricts with an area of 1,786.01 ~~Km². This district~~ km² and has a varied topography ~~consisting of~~comprising hills, mountains, valleys, and rivers at elevations ranging ~~from~~ 47~~ to~~ –3293 meters above sea level. ~~-~~The land use is dominated by forest~~ areas~~ and plantation areas (25.3% of total area). Astronomically, Enrekang is located between 3°~~°~~ ~~14'36~~14′36″ and 3°~~°~~ ~~50'0~~50′0″ South Latitude, and between 19°~~°~~40′53″ and 120°~~°~~06′33″ East Longitude. Four cultivated plants ~~were analyzed and compared at the study site~~ (coffee, cocoa, pepper, and cloves~~).~~) in the study site were analyzed and compared. Guidelines for ~~Land Suitability Assessment Using~~land suitability assessment were adopted from Technical Guidelines for Land Evaluation of Agricultural Commodities by Ritung et al. (2011) ~~also~~and guidelines by Sys (1993) on Land Evaluation Part III on Plant Requirements. The three main variables used in the assessment ~~include;~~were climate~~ variables, topographic variables~~, topography, and soil~~ variables~~, with a total of ~~ten~~10 indicators. The variables ~~used in the study~~ are ~~summarized~~listed in~~ the~~ Table 1.

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Field Sampling and Laboratory Analysis

~~There are~~Some land attributes~~ that~~ can be estimated or measured directly in the field, and some must be assessed in the laboratory (FAO, 1976). ~~Field~~Here, field observations included soil depth and slope measurements, ~~while~~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 ~~references~~reference for soil sampling~~ which consisted of fifteen land systems. The land unit~~. This map ~~is combined~~combines information of the ecological principles ~~relating~~related to rock types, ~~hydro-climate~~hydroclimate, landforms, soil, and organisms (Blasi et al., 2008). According to Zonneveld (1989), ~~the~~ survey results, including the unit map, could be used as a basis for land evaluation. Soil samples ~~are taken at random in~~ were randomly collected from each land unit. ~~The~~Undisturbed soil ~~sample taken is undisturbed soil, with the aim of providing~~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 ~~are~~were as follows: not burial ground, not in residential areas, not plantation areas, and not areas managed by the community.

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

Terms and Stages of Land Suitability Assessment

Land suitability assessment ~~in this study implements a~~was conducted using the fuzzy model by Zadeh (1965). The fuzzy set function can continuously analyze soil characteristics ~~continuously~~ without categorizing them into different classes. In fuzzy analysis, land attribute values are converted to sustainable values ranging from ~~zero~~0 to ~~one.~~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 ~~(SIM) that is widely used, and is described~~as illustrated in ~~the modeling of~~ Figure 2.

~~In~~The following important values are shown in the modeling of Figure 2~~, some important values such as~~~~;~~: 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. ~~The optimal point in~~In the fuzzy ~~function~~ model 1~~-~~, an optimal point is used to assess soil attributes ~~which have~~with one ideal point but ~~have~~ 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. ~~Fuzzy~~The fuzzy model 3 can be interpreted ~~that~~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. ~~Land characteristics in~~In the fuzzy function model 4~~-~~, land characteristics are interpreted ~~that the~~as follows: a smaller a land characteristic, the better~~, as~~. This trend is ~~the case with~~similar to the slope level. The research control points in Table 2 ~~are~~were arranged ~~based on;~~ according to the agricultural land evaluation criteria ~~made by~~of Ritung (2011) and Sys (1993), ~~Fuzzy~~fuzzy modeling in Figure 2, and land characteristics ~~at~~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 ~~the~~ 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 (Pearson, 1901; Hotelling~~–~~, 1933). ~~In many~~Many studies~~,~~ ~~PCA is indeed~~ used PCA as a data reduction technique. However, ~~because this study~~the current work used the total data set principle~~, there is no~~ and did not require any reduction in land attributes. ~~This study~~Thus, PCA was used ~~PCA~~only to analyze the correlation between land attributes and then ~~classifies~~classify them into new factors without reducing them. This ~~is~~goal was achieved by creating new uncorrelated variables that successively maximize variance. As a ~~by product, a better~~ result, good data interpretation ~~of the data is~~was obtained. PCA components ~~that are retained are those that have~~ with one or more eigenvalues ~~(see~~ were retained (Figure 3). The number of indicators for each component or factor ~~will be the~~ is same as that for the ~~number of land indicators~~ analyzed land, but each component/factor will only maintain one or more indicators with a maximum ~~loading corresponding~~ load. The variance of each component/factor ~~will explain how much~~ explains the contribution of the component ~~contributes~~ in ~~explaining the~~ interpreting data as a whole, ~~while~~and the ~~loading~~ corresponding load explains ~~how much~~ the extent of correlation between the indicator and ~~the~~ component ~~is~~ (Armenise et al., 2013; Mukherjee & Lal, 2014). In principle, PCA ~~will~~can produce as many components (factors) as the indicators included in the analysis. However, only ~~component factor having~~components with eigenvalues >1 were retained for ~~inclusion in~~ the next analysis. According to this rule, four factors ~~are~~were maintained~~, each~~ and labeled as factor 1, factor 2, factor 3, and factor 4. ~~The~~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~~, each following component is~~ was obtained ~~by~~ partially out of the previous component. ~~Based on~~On the ~~results~~basis of ~~the~~ PCA analysis, four new factors were added to the calculation of ~~the~~ land suitability index (LSI) (~~See details in~~ Figure 3 and Table 4).

After the soil attributes ~~are~~were determined and new variables ~~are~~were created, the next step ~~is~~was to standardize the land attributes~~. Standardization is carried out~~ to equalize the unit of assessment ~~for several soil attributes with a~~ using a value range of 0 to 1 ~~by the~~ from equation 1.

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

$$MF(x_i) = 1, \text{ if } (b_1 + d_1) \le xi \le (b_2 - d_2) \quad \text{(fuzzy model 2)},$$

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

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

Another important step in this research is the objective weight assessment. ~~The weight is~~Weight was calculated using ~~a~~ simple mathematical modeling (equation 2). The ~~weight~~ assigned ~~ranges~~weight ranged from 0 to 1. ~~The weighting~~ For the weight of a factor (W_f) and an individual land indicator (W_i~~) given will consider~~), the following must be considered: loading factor ~~value~~ of each indicator (y_i), total loading factor ~~value~~ ($\sum y$~~) and values of varians~~), variance component of each factor (m~~)~~), and total ~~values of varians~~variance component ~~formed~~ ($\sum m$).

$$W_i = \frac{|yi|}{\sum |y|} \quad (2)$$

$$W_f = \frac{|m_i|}{\sum |mi|} \times 100$$

Join membership function (JMF) calculation is also one of the most important stages of this research. ~~Based on the results of the~~According to factor analysis~~ carried out, there are 4~~, four new

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factors ~~that will be~~were included in the land suitability assessment. ~~Each new factor will be calculated the JMF value. The JMF value~~JMF, which reflects the quality of the land~~; the higher the JMF value, the better the~~, was calculated for each factor. A high JMF indicates a good land quality. JMF ~~is~~was calculated using ~~the~~ equation 3~~.~~:

$$JMF\ (X_{i,\dots,z}) = \sum_{i=1}^{n} Wi\ (MFi)\ . \qquad (3)$$

~~The land suitability index is~~LSI was calculated after all of the parameters of ~~the~~ land suitability ~~calculation have been~~assessment were determined. ~~To determine~~For LSI calculation, the ~~LSI,~~ JMF of each factor ~~is~~was then integrated with the weight of the factor (Wf) using ~~the~~ equation 5:

$$LSI = \sum_{i=1}^{n} Hfi\ (JMFxi)\ . \qquad (5)$$

RESULTS

Land Properties in the Study Area

~~A summary of some~~Some of the land characteristics ~~at~~ in the research location ~~can be seen~~are summarized in Table 3. Soil pH in the ~~entire~~ study ~~areas are~~ area is acidic with minimum ~~range~~ of 4.56 and maximum of 6.04. The basic cations used are calcium (Ca), magnesium (Mg), ~~Potassium~~potassium (K~~)~~), and ~~Sodium~~sodium (Na~~). Sum~~). The sum of basic cations found in ~~both~~ top and sub soil layers in all land ~~system had~~systems is quite high for plantation plant growth with ~~ranged~~a range of 4.1~~ cmol/kg to ~~–8.88 cmol/kg. 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 ~~was~~is classified as moderate with a range of 12.14~~ cmol/kg to ~~–19.22 cmol/kg. In ~~the~~ Bukit Ayun, Bukit Pandan, and Watampone land units, the C-organic content ~~was found to be very~~is extremely low~~, less than~~ at <1%. The highest ~~value of c~~C-organic content of 2.46% ~~was~~is found in ~~the~~ Kalung land unit. Slope ~~data~~values obtained from the digital elevation model ~~(DEM)~~after 30 m SRTM image extraction~~. The slopes recorded ranged~~ range from 2% to ~~more than~~ >50%. The annual precipitation in the research region is quite high, with annual average rainfall ranging from 1676 to ~~more than~~ >2634 mm/year~~. –~~ and annual average ~~annual~~ temperature ~~ranges~~ranging from ~~21° C to 28°~~ 21°C~~. Based on the results of~~ to 28°C. According to the field survey, ~~it is known that~~ the effective soil depth of the research location ranges ~~from~~ 90~~ to ~~–150 cm.

New Factor Groups and ~~Important~~Importance Weight

Each land ~~attributes~~attribute has ~~a~~ the greatest ~~loading~~load corresponding to each of the ~~4~~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~~loading's square represents the proportion of variance (R^2) explained by a specific factor. ~~Slope~~ 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~~, and so on. Slope~~. If the slope has a greater correlation to factor 1 than other factors, ~~and~~ 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 (W_i) is the result of ~~–~~the corresponding ~~loading~~load divided by the total ~~loading~~ corresponding load of the land attributes classified in that factor. Among ~~several~~the soil attributes included in factor 1, slope has the largest ~~correspondent~~corresponding load. Therefore, the importance weight ~~on~~of the slope is greater (0.28) than that of the other land attributes ~~which are~~

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Commented [Editor5]: Remark: The chemical and compound names in technical papers need not be defined at first mention. Generally, these are known by the target audience, so presenting their full meaning is unnecessary.

included in factor 1. The total weight (W_i) of each ~~faktor~~factor is 1. This rule is also ~~applies~~applicable to other land attributes. ~~Based~~The following classification is based on the maximum ~~loading~~ corresponding 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 ~~become~~content are grouped into factor 2; base saturation ~~to~~is classified as factor 3; ~~Soil~~and soil texture is ~~a~~classified as factor 4. ~~The results of the~~ 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.

Membership Value of Land Attribute and JMF of Factors

Individual membership values ~~consist of numbers ranging~~range from 0 to 1. If a land attribute has a membership value of 1, ~~it indicates that the land attribute~~then it is optimal for the growth of a plant and vice versa. ~~Based on~~ Table 5~~, it is known~~ shows that some land attributes are below the tolerance threshold ~~value set as~~values listed in Table 2. -For example, the individual membership of land attributes in the form of pH, CEC, and annual average rainfall and ~~annual~~ temperature ~~of less than~~ is <0.4 for cocoa plant growth in ~~the~~ Bukit Ayun land unit. This finding indicates that in ~~the~~ 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 ~~which indicates~~, indicating optimal suitability. For example, in Pendreh and Danau Lindu land units, land attributes such as temperature, rainfall, and slope have ~~an~~ optimal suitability for coffee growth with individual membership values of ~~more than~~ >0.9. In general, the problems ~~faced by~~in the research area are temperature, CEC, and base saturation ~~where~~; 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 ~~less than~~ <0.4 ~~were~~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, ~~in general the growth of clove plants in~~ the research location ~~did not~~generally fails to reach optimal suitability for clove growth with values ~~less than~~ of <0.85 and ~~more than~~ >0.4.

~~Joint membership~~JMF values ~~(JMF)~~ for evaluating the suitability of crops ~~can be seen~~are listed in Table 6. These ~~figures~~values indicate the quality of the land for the potential development of plantation crops. ~~Just like~~Similar to individual membership values, JMF also consists of a number range from 0 to 1. ~~The higher the~~A high JMF ~~value~~ indicates that ~~a~~the land has optimal potential for plantation development. The JMF value for coffee plant growth ~~ranged~~ranges from 0.38 to 1. A JMF of 0.38 ~~was~~ is found ~~in the~~ for Sungai Aur land unit at ~~Factor~~factor 3. This finding indicates that factor 3 is a limiting factor for coffee plant growth. Cocoa JMF values ~~ranged~~range from 0.45 to 1. The lowest cocoa JMF ~~was~~ is found in ~~the~~ 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 ~~value at a factor of 3, which is~~ of 0.3 ~~at the~~ in Sungai Aur land unit~~.~~ at a factor of 3. As previously explained~~ there is~~, factor 3 has only one land property ~~in factor 3~~, namely, basic saturation. Thus, the low ~~value~~JMF of factor 3 indicates that the quality of ~~the~~ base saturation ~~that~~ is less supportive of plant growth.

~~**Land Suitability Index**~~

LSI

The multiplication function in equation 5 ~~is~~ was used to generate a spatial ~~land suitability index~~LSI data layer with continuous values~~,~~ ranging from 0 to 1~~.~~, where 1 indicates optimal suitability for plant development. ~~Based on the analysis, it was found~~Analysis revealed that the LSI ~~of~~ ranges 0.4–0.81 for cloves~~ ranged from~~, 0.~~4 to~~ 52–0.~~81,~~99 for coffee, 0.52~~ to~~ –0.~~99,~~86 for cocoa, and 0.~~52 to~~ 5–0.~~86,~~87 for pepper~~ 0.5 to 0.87~~. The results are visualized in Figure 4. ~~To evaluate~~ For land area evaluation, raster data ~~is~~were converted into vector data and then categorized based on ~~its~~the pixel value into several land suitability classes. Areas with a pixel value of >~~-~~0.8 ~~are~~were included in the optimal ~~suitable~~ suitability category, ~~while~~ areas with a pixel value of 0.8≤LSI>0.6 ~~are~~were included in the moderate suitability category, and areas with a pixel value of 0.6>LSI>0.4 ~~are~~were included in the marginal suitability category. Of the total area analyzed for coffee plants, 76.28% ~~of the area is in the moderate suitability~~is moderately suitable, 23.26% ~~in the optimal~~is optimally suitable, and 0.45% ~~in the marginal~~is marginally suitability~~ category~~. For cocoa, 90% of the research area is ~~included in the moderate suitability category~~moderately suitable, 0.29% is marginally suitable, and 9.6% ~~are included in the marginal suitability and optimal~~is optimally suitable. ~~A total of~~For pepper, 86.89% of the research area is ~~included in the moderate suitability category for pepper plants, while~~moderately suitable, 6.68% ~~areas are included in the optimal~~is optimally suitable, and 6.41% ~~areas are in the marginal suitability category. For clove commodity~~is marginally suitable. For cloves, 78.74% of the total area is ~~included in the moderate suitability category, while for areas with marginal and very suitable suitability categories are~~moderately suitable, 19.26% is marginally suitable, and 1.98~~%, respectively~~% is optimally suitable.

DISCUSSION

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

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

~~Based~~Our experience on ~~our~~ data processing ~~experience, it can be seen~~revealed that when the fuzzy method is used, the threshold set by the researcher (LCP and UCP) in Table 2 becomes a sensitive ~~thing~~aspect that affects the results of individual membership values of land attributes in Table 5. ~~In addition, this~~The threshold is also influenced by the quality of the land itself. ~~This is also emphasized by~~ Qiu et al. (2014) emphasized that thresholds cannot be determined arbitrarily and must be based on expert knowledge of the situation. ~~Based on~~ As shown in Table 5, ~~it can be concluded that~~ some land attributes such us texture in Batang Anai and Bukit Pandan units are optimal for plantation plant growth with individual membership values =1~~, but some other~~. Other land attributes such ~~us~~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 ~~was~~is acidic in the range of 4.56–6.04~~, while for~~. 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 ~~is unable~~they fail to meet the specified threshold~~ and~~, resulting in their low membership values. ~~As for~~For the growth of clove and pepper plants, the individual membership value of pH ~~was~~is quite high ~~with a value >~~ at >0.5 in all land units. ~~This is due to~~All the pH values meet the minimum threshold set for clove and pepper growth based onaccording to the criteria compiled by Ritung et al. (2011). In addition, anotherAnother major limiting factor for cocoa growth in the study area is temperature. –In thisthe present land suitability assessment, temperature is a veryan important factor and is included in the group with the first degree of importance. -This finding is in lineagreement with the opinion of Geo and Saediman (2019) which states), who stated that climatic factors greatly affect cocoa growth. They state that the 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° 26°C to 28° 28°C while most. However, the majority of the research areas havearea has an average daily temperature of <26° 26°C. This resulted in; thus, many sites in the assessment reaching lowerreach low threshold values for temperature. Another land indicator that needs tomust be an important issueconsidered in the research location is CEC. Many land units do not meet the minimum CEC standards for plantthe growth, both for of coffee, cocoa, pepper, and cloves. CEC ranged fromin the study area ranges 12.14 to –21.25 cmol/kg while, and the minimum CEC standard for plant growth is 15 cmol/kg. The main problems in the research area are temperature, pH, and CEC. Temperature is considered to be the main limiting factor for the development of cocoa, clove, and pepper crops asbecause it has the highest importance among the three main limiting factors. However, temperature is an attribute that is difficult to modify byusing any treatment. To overcome the problem of low pH atin the research site, the opinion of Gentili et al. (2018) suggested that the pH can be increased by the addition ofapplying calcium hydroxide can be applied. While the research of. Martinsen et al. (2015) which revealed that the addition of biochars to acid soil can increase pH and CEC can be used to overcome soil fertility problems in the study area.

CONCLUSION

Land suitability for For coffee consists of optimal suitability with an index range of 0.6 to 0.8 coveringgrowth, 23.26% of the study area, moderate suitability is optimally suitable with an index of 0.6–0.8, 76.28% is moderately suitable with an index range of 0.8 to –0.99 covering 76.28% , and marginal suitability covering 0.45% of the area is marginally suitable with an index of 0.52 to –0.6. Meanwhile, Cocoa consists of optimal suitabilityFor cocoa growth, 9.6% of the study area is optimally suitable with an index of 0.8 to –0.88 covering 9.6% of the area , and marginal suitability90% is marginally suitable with an index of 0.6 to –0.8 covering 90% of the area. In addition,. For clove has a marginal suitability coveringgrowth, 19.26% areaof the study area is marginally suitable with an index of 0.4 to –0.6, moderate suitability covering 78.74% areais moderately suitable, and optimal suitability covering only 1.98% areais optimally suitable with index of 0.8 to –0.81. Pepper consists of optimal suitability coveringFor pepper growth, 6.68% of the study area is optimally suitable with an index of 0.8 to –0.87, moderat suitability covering 86.89% area marginal suitability covering is moderately suitable, and 6.41% is marginally suitable with an index of 0.5 to –0.6. Mean annual temperature <–26 °C°C, acidic soil pH, and low CEC were are the main limiting factorfactors for the growth of plantation crops in the study site. As a solution, the addition of biochars and calcium hydroxide to acidcan be supplemented to acidic soils can 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 very simple and easy to implement. Based on the validationValidation tests carried out, it can be concludedshowed that the combination of fuzzy-–PCA models succeeded in objectively revealing the suitability of plantation land well more objectively, so that. Therefore, this model is feasible tocan be applied in other fields of land management. For ~~a more~~ accurate land suitability assessment, further research ~~needs to~~must compare the ability of various methods ~~to calculate~~in calculating the final ~~land suitability index~~LSI.

Figure and Table

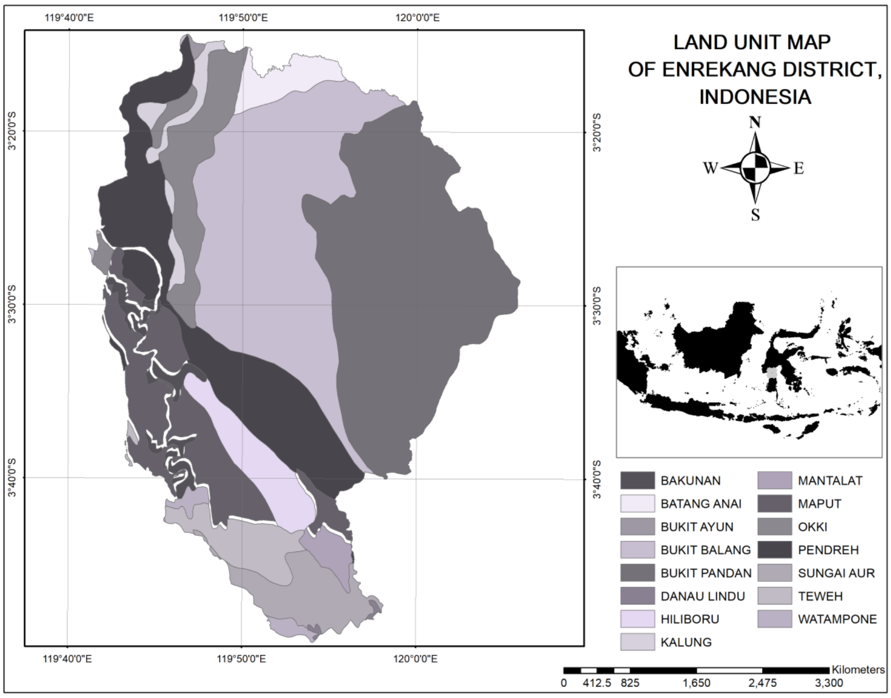

Figure 1. Land unit map of research area.

Commented [Editor6]: Remark: For all tables and figures, consider using the full forms of all acronyms/abbreviations when used only once or at first mention (with the abbreviations or initialisms indicated in a parentheses); use the abbreviations or initialisms in subsequent mentions. Note that the instruction of most journals is that tables and figures should be able to stand on their own (without need for reference to the text).

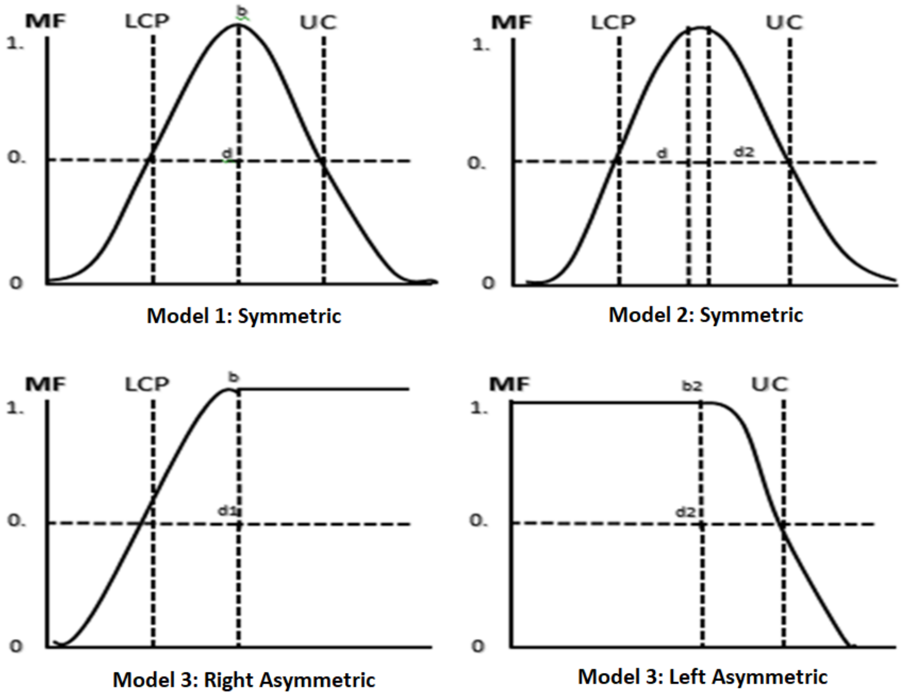

Figure 1. Fuzzy set model for land suitability assessment.

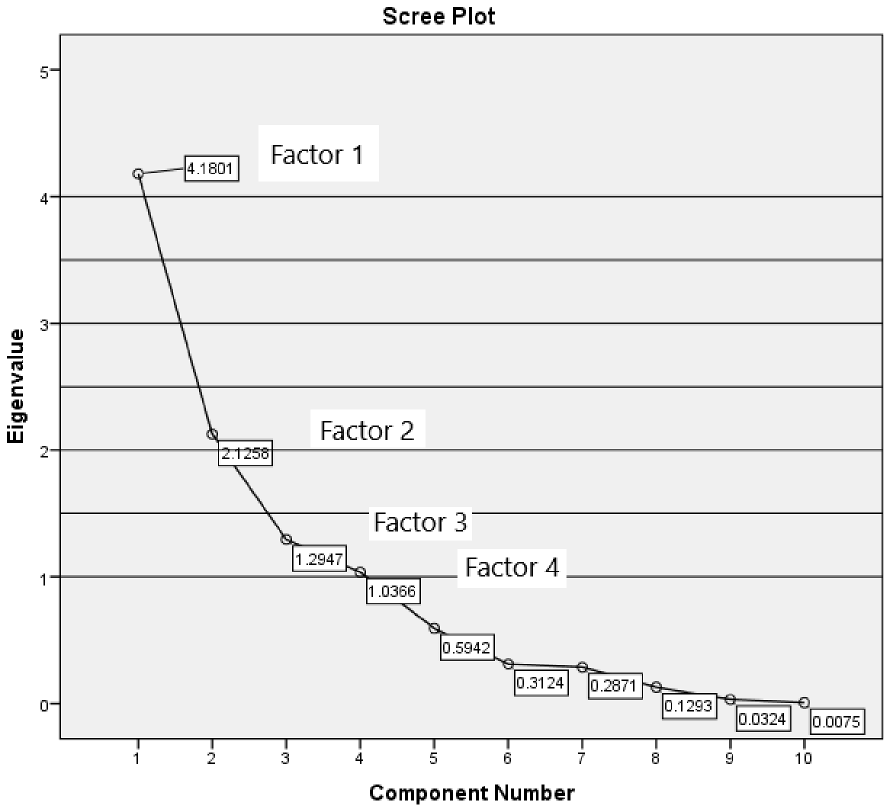

Figure 2. Scree ~~Plot which plots~~plot of the eigenvalue by the component number.

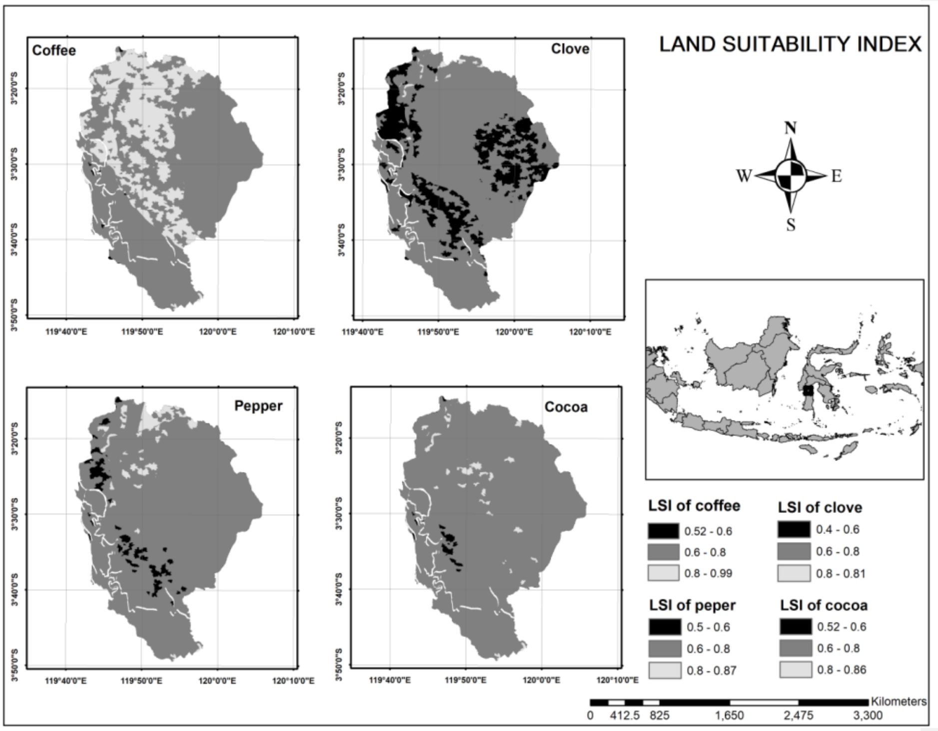

Figure 3. Land suitability index for plantation crops in research area.

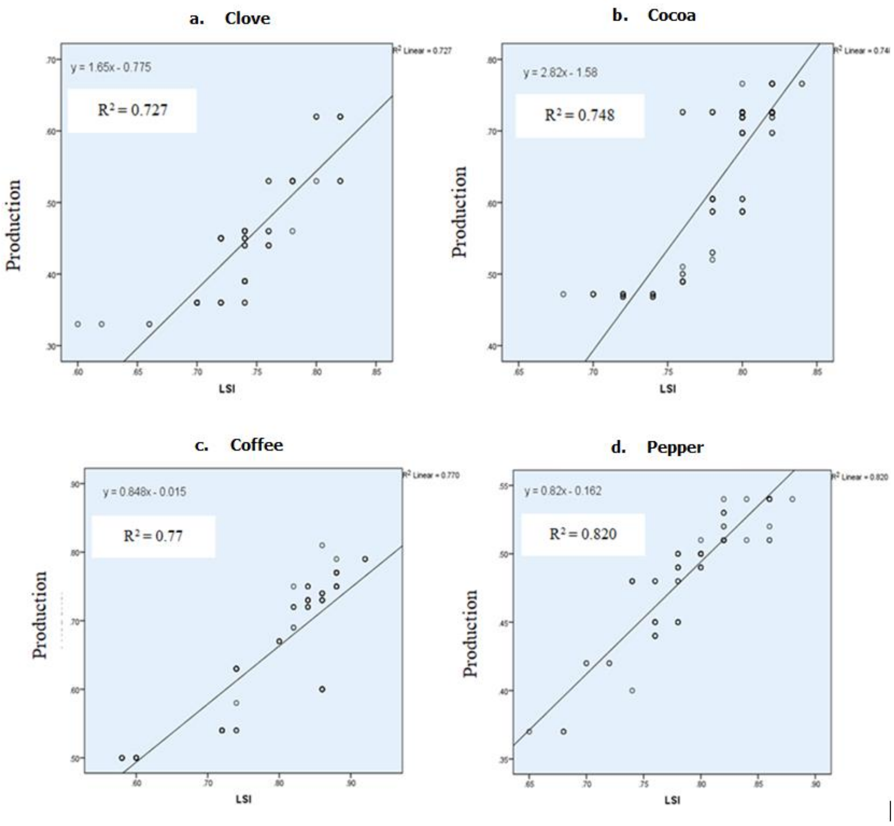

Figure 4. Linear regression between LSI and land production (tonestons/ha)).

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 ~~one to fourteen~~1–14	The results of laboratory analysis
Sum of basic cations ~~(~~(V2)	cmol/kg	The number of basic cations that can be absorbed by the soil include elements of calcium (Ca), magnesium (Mg), 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~~.~~	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 (cm)	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 ~~temperatur~~ 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

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

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

~~Variabel~~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 ~~temperatur~~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		.115		0.945	1.00	.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	

Table 1. Individual membership of land attributes.

Land ~~attribut~~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

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Table 6. ~~Join~~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

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Land Suitability Assessment for Agricultural Crops in Enrekang, Indonesia: Combination of Principal Component Analysis and Fuzzy Methods

ABSTRACT

Land suitability assessment is essential for the efficient use of diminishing fertile agricultural land. Assessment parameters include soil texture, pH, sum of basic cations, base saturation, cation exchange capacity (CEC), organic carbon, soil depth, slope, and mean annual temperature and precipitation data. Results showed that 76.28% and 23.26% of the total area was optimally and moderately suitable for coffee growth, respectively; 9.6% and 90% was optimally and moderately suitable for cocoa growth, respectively; 1.98%, 78.74%, and 19.26% was 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. 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 that the fuzzy method is ideal for converting the numerical data of various magnitudes into membership function values and representing land suitability. Principal component analysis is an effective method to determine the weights of multiple factors in a systematic and objective manner. 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 managements.

Keywords: agricultural land management, crop diversification, fuzzy logic, multi-objective decision-making, principle component analysis

INTRODUCTION

Sustainable agriculture is defined as a comprehensive system of crop production practices with site-specific applications that will persist in the long term (Rigby and Caceres, 1997). 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 in designing sustainable land use. Land suitability is the eligibility of a specific type of land for a specific purpose (FAO, 1976) 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 et al. (2020), the evaluation of agricultural land suitability is critical to increase production and plan 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 (Mosleh et al., 2017; Cartwright et al., 2020; 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) (Leake & Malczewski, 2000; Zimmermann & Gutsche, 1991). 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., 2016; Ananda & Herath, 2009). 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 et al. (2019) 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 and 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, Chastain, and Zhou (2014), land suitability maps generated using this method are informative and accurate. Many studies used fuzzy methods for land use optimization (Morteza et al., 2019; Vavatsikos et al., 2020; Arabsheibani., 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. (2015) 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 (Bas, Das & Pal, 2020). According to Pennsylvania State University (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 (Mosadeghi et al., 2015; Keshavarzi et al., 2020; Nasery et al., 2021; Zalhaf et al., 2021 Kelic et al., 2022; Paul and Ghosh, 2022; Sengupta et al., 2022) 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.

MATERIAL 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 km^2 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 (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.

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 (FAO, 1976). 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 (Blasi et al., 2008). According to Zonneveld (1989), 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 (NH4-Acetat 1N, pH 7) in dry soil sample at 105°C for the analysis of sum of basic cations, CEC, and base saturation.

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.

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 (2011) and Sys (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 (Pearson, 1901; Hotelling, 1933). 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.

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

$$MF(x_i) = 1, \text{ if } (b_1 + d_1) \le xi \le (b_2 - d_2) \quad \text{(fuzzy model 2)},$$

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

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

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 (W_f) and an individual land indicator (W_i), the following must be considered: loading factor of each indicator (y_i), total loading factor ($\sum y$), variance component of each factor (m), and total variance component ($\sum m$).

$$W_i = \frac{|y_i|}{\sum |y|} \quad (2)$$

$$W_f = \frac{|m_i|}{\sum |mi|} \times 100$$

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:

$$\text{JMF}(X_{i....z}) = \sum_{i=1}^{n} Wi\,(MFi)\,. \quad (3)$$

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 5:

$$\text{LSI} = \sum_{i=1}^{n} \text{Hf}i\,(JMFxi)\,. \quad (5)$$

RESULTS

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 (Mg), 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. 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. 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 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.

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 (W_i) 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 (W_i) of each factor is 1. This rule is also applicable to other land attributes. The following classification is based on the maximum corresponding 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.

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. 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.

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.

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.

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 Atnafu (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, and the minimum CEC standard for plant growth is 15 cmol/kg. 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.

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.

Figure and Table

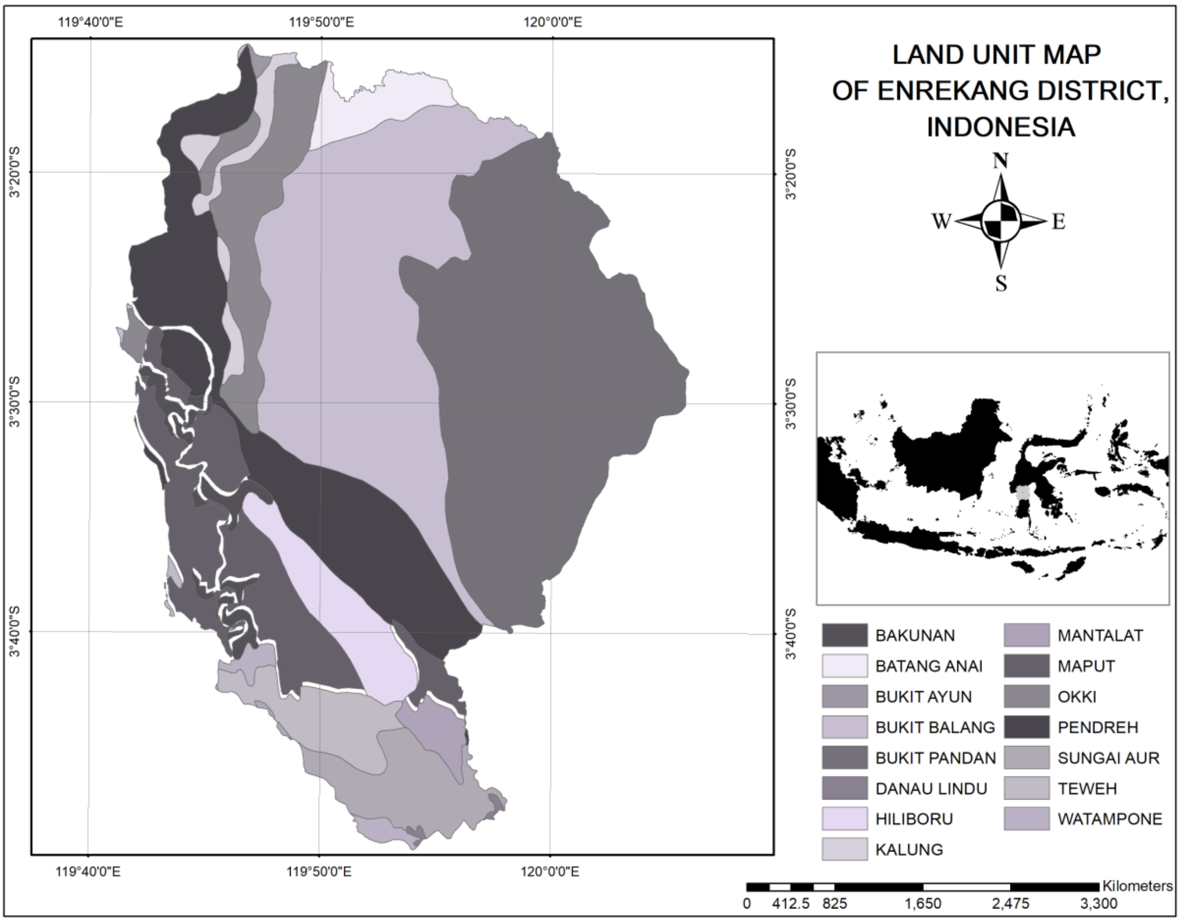

Figure 1. Land unit map of research area.

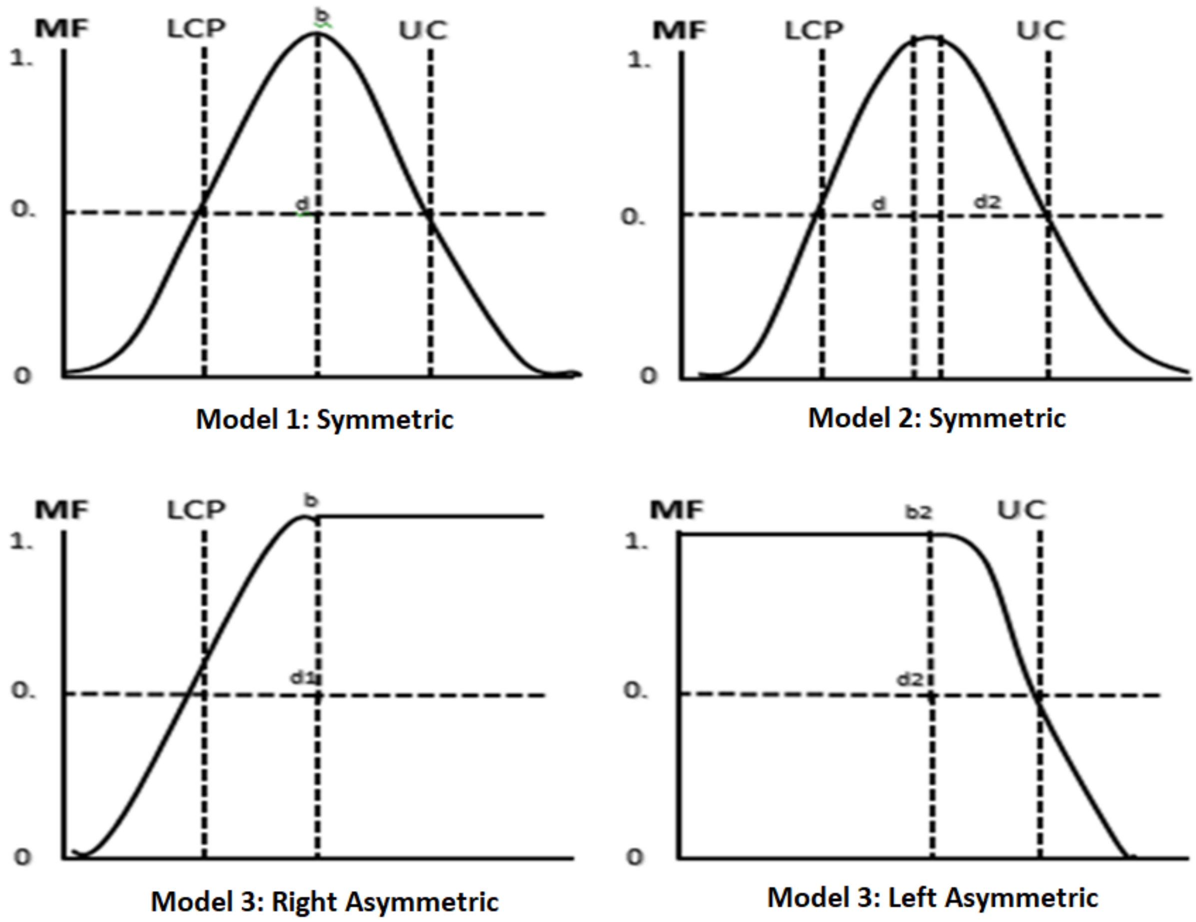

Figure 1. Fuzzy set model for land suitability assessment.

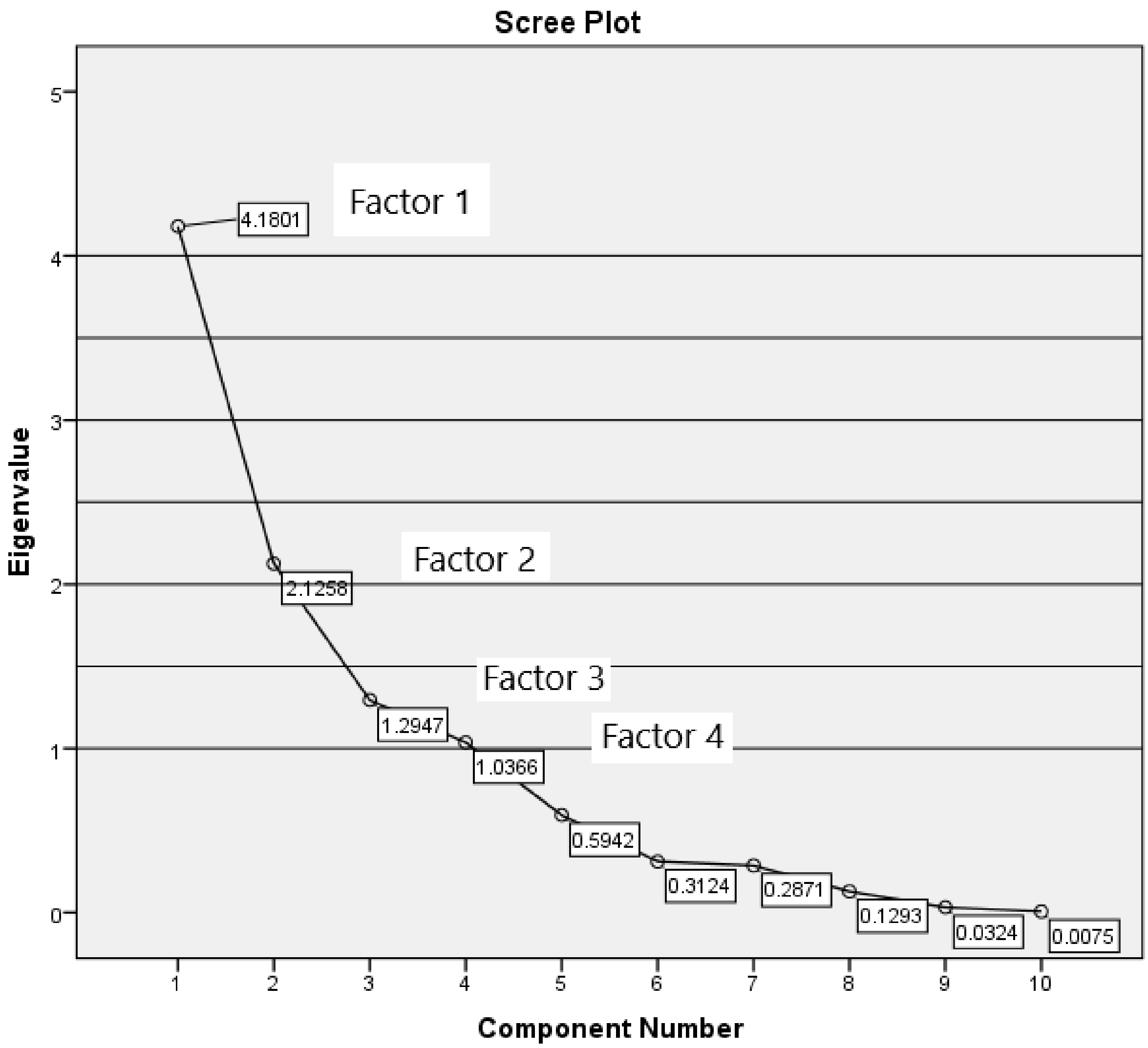

Figure 2. Scree plot of the eigenvalue by the component number.

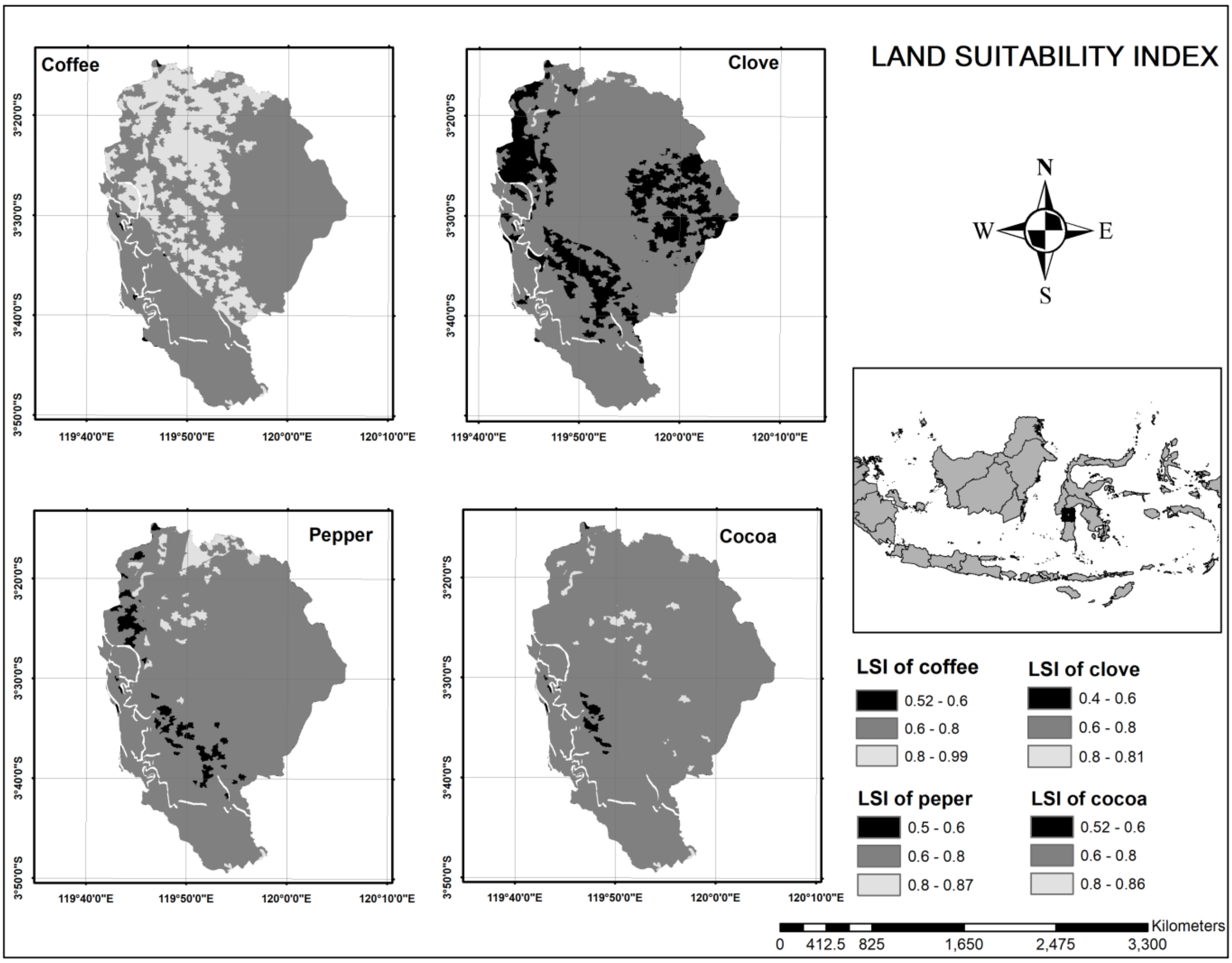

Figure 3. Land suitability index for plantation crops in research area.

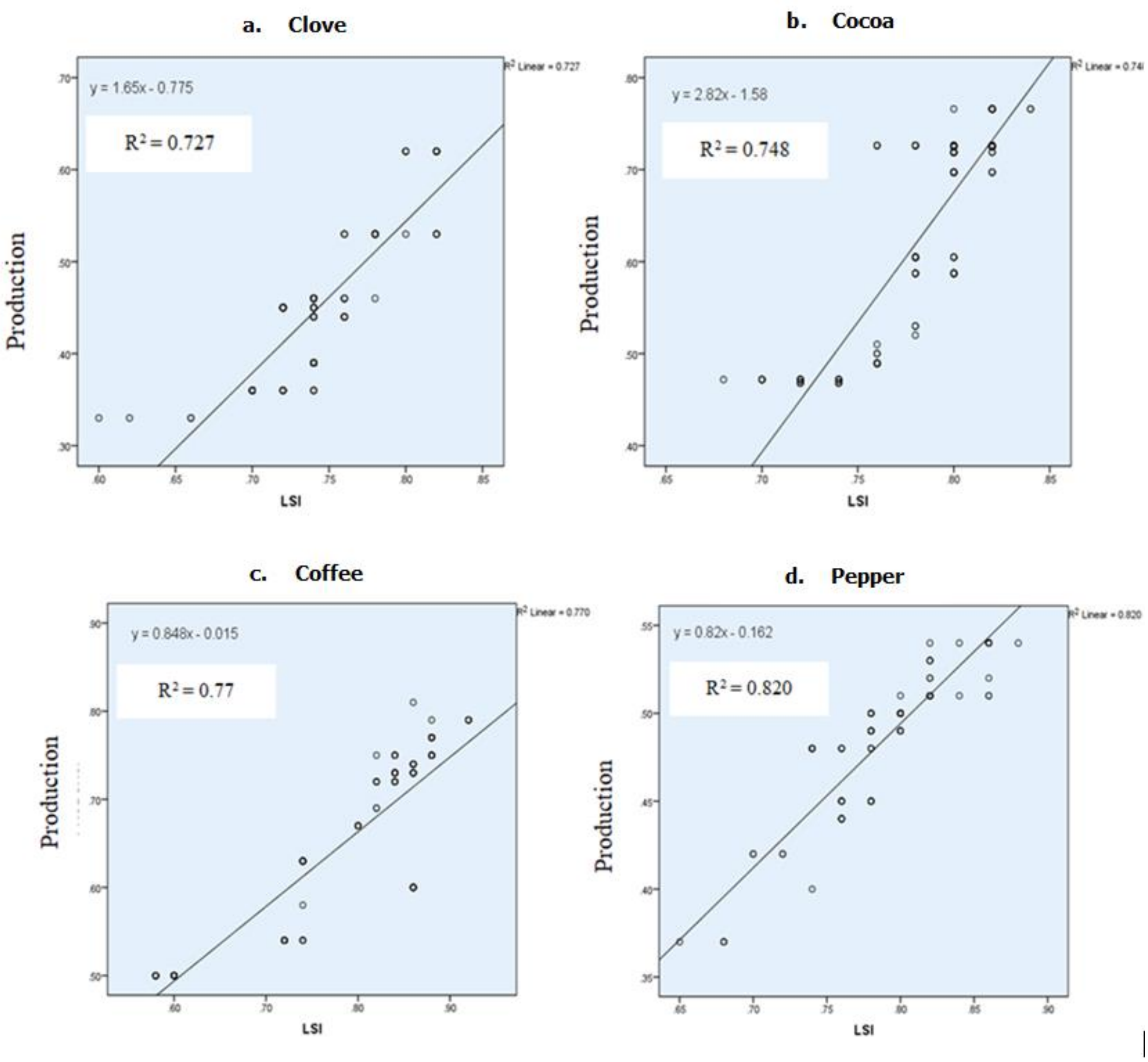

Figure 4. Linear regression between LSI and land production (tons/ha).

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	The number of basic cations that can be absorbed by the soil include elements of calcium (Ca), magnesium (Mg), 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	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 (cm)	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

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

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		.115		0.945	1.00	.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

Table 1. 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

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

Nurfadila Jamaluddin Sappe[1], Sumbangan Baja[2], Risma Neswati[2*], Didi Rukmana[3]

[1] Faculty of Post-Graduate, Hasanuddin University, Indonesia
[2] Department of Soil Science, Faculty of Agriculture, Hasanuddin University, Indonesia
[3] Department of Agriculture Socio-Economics, Hasanuddin University, Indonesia

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***** *Corresponding Author*
Email address:
neswati76@gmail.com

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.

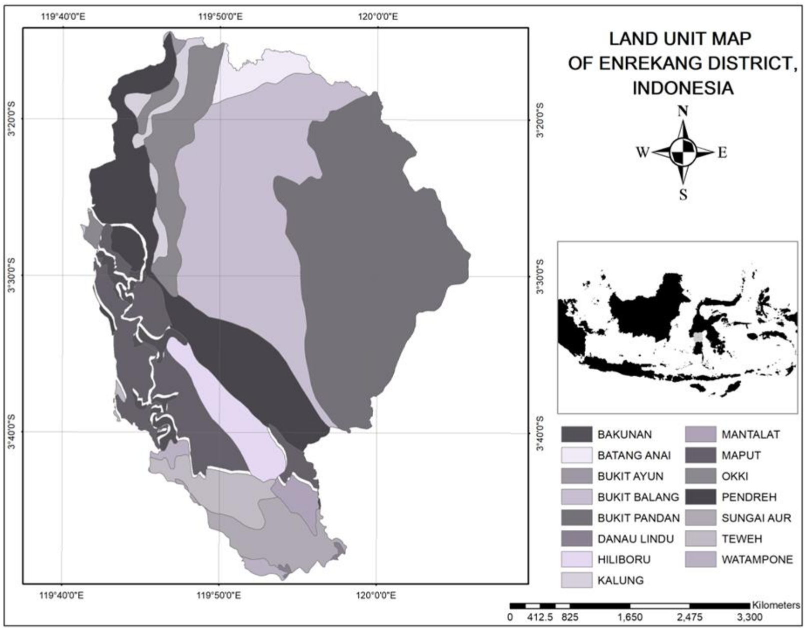

Figure 1. Land unit map of research area

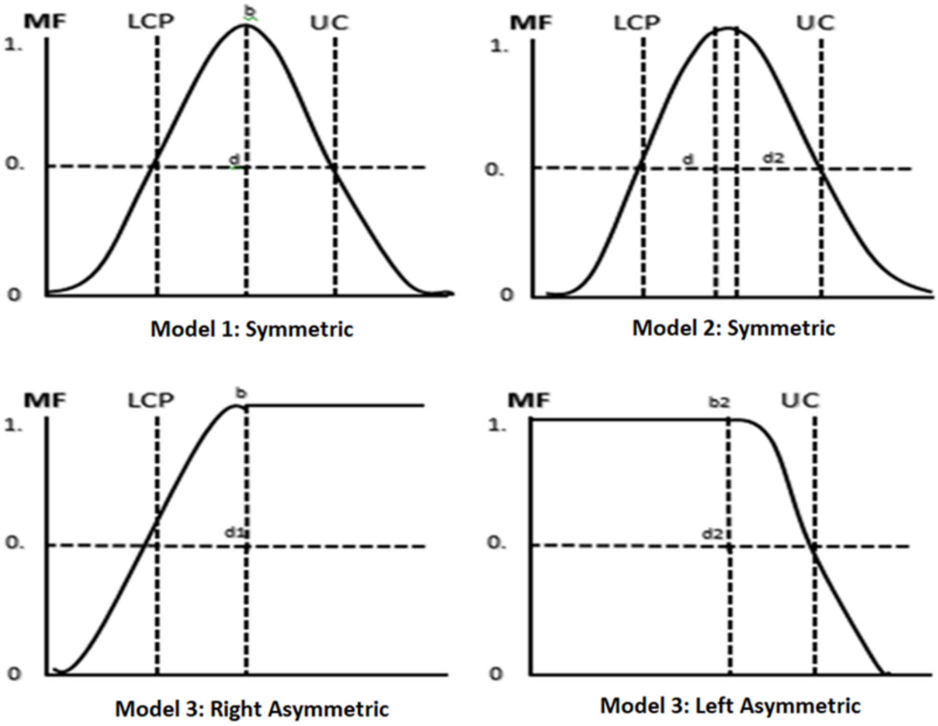

Figure 2. Fuzzy set model for land suitability assessment

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.

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

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

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

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

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).

$$W_i = (|y_i|)/(\Sigma|y|) \quad [2]$$

$$W_f = (|m_i|)/(\Sigma|m_i|) \times 100$$

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:

$$JMF(X_i \ldots z) = \sum_{i=1}^{n} W_i(MF_i) \quad [3]$$

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:

$$LSI = \sum_{i=1}^{n} Hf_i(JMFx_i) \quad [4]$$

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

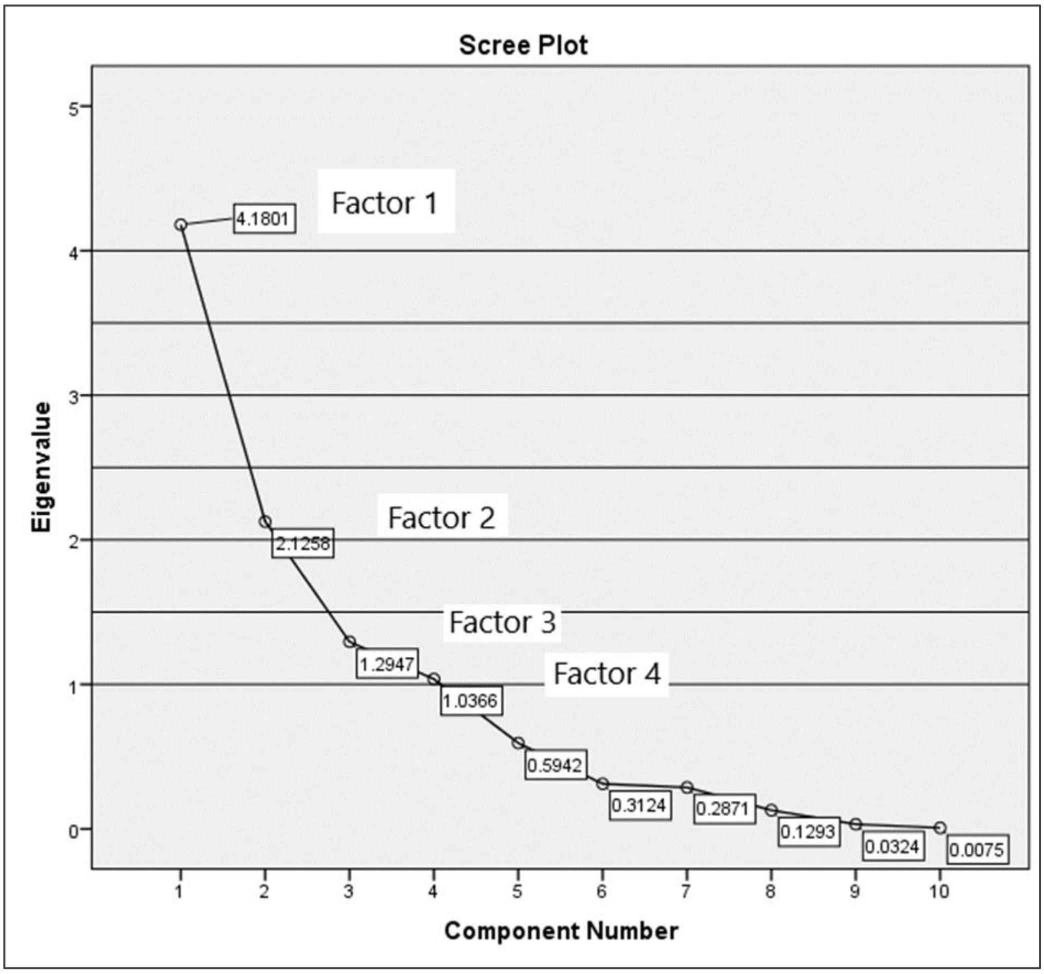

Figure 3. Scree plot of the eigenvalue by the component number

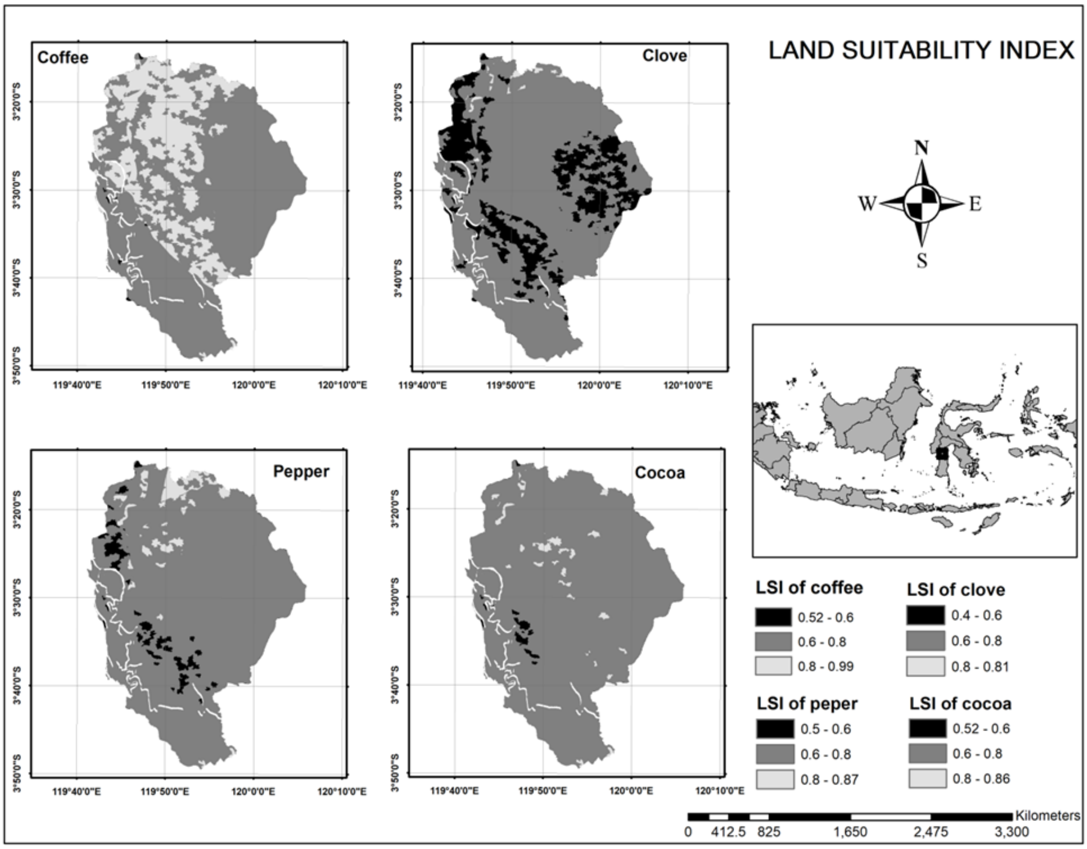

Figure 4. Land suitability index for plantation crops in research area

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.

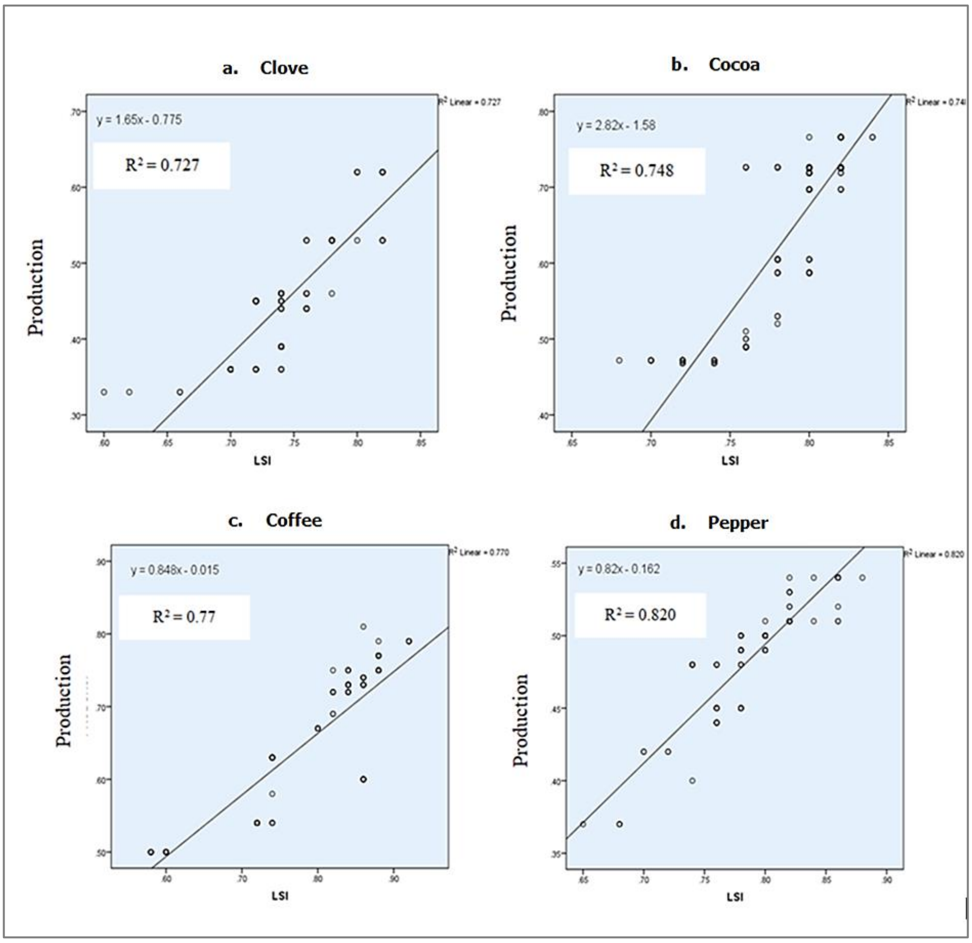

Figure 5. Linear regression between LSI and land production (ton ha^{-1}).

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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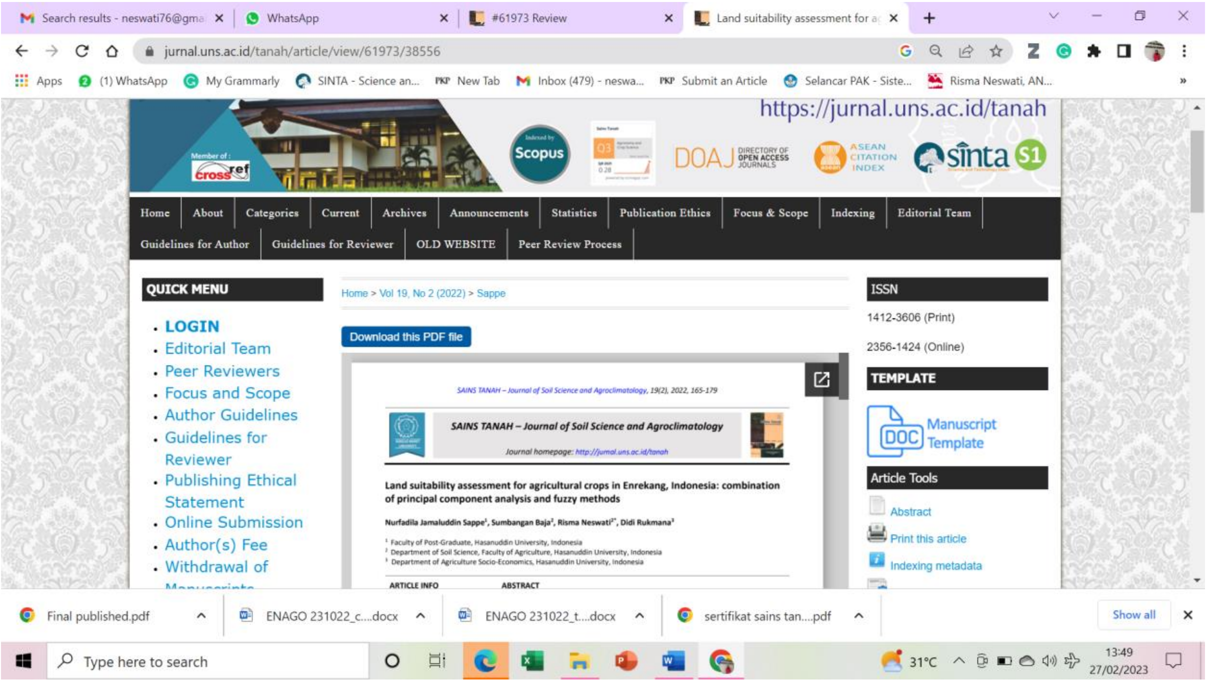
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Land suitability assessment for agricultural crops in Enrekang, Indonesia: combination of principal component analysis and fuzzy methods
Nurfadila Jamaluddin Sappe1, Sumbangan Baja2, Risma Neswati2*, Didi Rukmana3
1 Faculty of Post-Graduate, Hasanuddin University, Indonesia
2 Department of Soil Science, Faculty of Agriculture, Hasanuddin University, Indonesia
3 Department of Agriculture Socio-Economics, Hasanuddin University, Indonesia
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