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ARTICLE

Land suitability assessment for cassava production in Indonesia using GIS, remote sensing and multi-criteria analysis

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Abstract Sustainable land use is essential for increasing the production of cassava as a diversified crop for ensuring food security in Indonesia. Understanding spatial factors and criteria is required for locating suitable production areas to increase cassava production. In this study, a spatial model was developed to assess the suitability of land for supporting sustainable cassava production. The model was divided into three stages considering different criteria. First, satellite digital images were processed from Landsat-4 Thematic Mapper (TM), Landsat 8 Operational Land Imager (OLI), and Sentinel-2 satellites to create vector data layers and a normalized difference vegetation index (NDVI) database. Second, a spatial analysis was performed to identify highly suitable areas for cassava production using a geographical information system (GIS) and the multi-criteria analysis. Third, a sustainability evaluation was conducted based on land suitability information for a study period of 5 years. Land suitability assessment was performed to increase cassava production. We found that 43.11% (11094 ha) of the study area was highly suitable for cassava production, whereas 30.87% (8233 ha) was moderately suitable and 9.83% (2623 ha) was marginally suitable with incorporating AHP analysis. Moreover, 17.69% (4718 ha) of the land was occupied by residents and settlements. On the other hand, ANP analysis also conducted to confirm the AHP results. We have found approximate similar results with no significant differences in any of the suitability classes. This research recommends that the integrated approach of GIS-based multi-criteria can be extended with satellite remote sensing vegetation datasets to assess regional production and site-specific management of cassava crops.

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1 Introduction

Land suitability assessments are important for sustainable land use and for the selection of potential crops in the changing climates of Indonesia. Indonesia is a developing country with the fifth largest population in the world. The large population increases dependence on rice as a staple food, which could create the threat of food insecurity (Khush 2005). To mitigate this dependency, diversification through the consumption of local foods, such as cassava, is desirable. Cassava is a good alternative that poses fewer risks as a root crop and plays an important role in Indonesia, which is one of Asian countries to support sustainable local food production (Campo et al. 2011; Noerwijati and Budiono 2015; Feenstra 1997; Ariningsih 2018). Cassava can be easily grown, cultivated, and distributed to local communities (Kolawole et al. 2010). The benefits of cassava as a local food could strengthen the food security of developing countries. In the future, cassava has the potential to become a promising crop that can adapt to changing climatic patterns due to its low water and soil acidity requirement compared to rice (FAO 2013; Khumaida et al. 2016). Therefore, sustainable cassava production in Indonesia must ensure maximum benefits for growers. While considering the sustainability of cassava production, criteria related to environmental, ecological, economic, and social indicators must be addressed (Sydorovych and Wossink 2008; Tiwari et al. 1991). Furthermore, food security is one of the major concerns in the context of agricultural sustainability and the sustainable supply of food for the increasing population (Ahamed et al. 2015). Sustainable land use for cassava production significantly drives maximizing the production of cassava to contribute to the food security of Indonesia.

To increase cassava production, suitable areas and ecological conditions must be identified (Heumann et al. 2011). Such important tasks associated with increasing the production of cassava can be addressed through spatial analyses of land use suitability. Suitability classification reflects the suitability of each land unit for cassava production. In the Food and Agriculture Organization's (FAO) 1976 framework for land evaluation, land was divided into four classes: highly suitable ($S1$), moderately suitable ($S2$), marginally suitable ($S3$), and not suitable (N). Spatial assessments of land suitable for cassava production could serve as a starting point for sustainability evaluations. Additionally, interactions between suitability and sustainability have been reported in the FAO's (1976) international framework for evaluating sustainable land management. Environmental factors deemed suitable can reflect the level of sustainability for the same land use over a period of time.

As a spatial tool, geographic information systems (GIS) have been used to conduct spatial analyses of suitability for various purposes, especially land suitability (Ferretti and Pomarico 2013; Malczewski 2006; Smyth and Dumanski 1993). In addition, applications of remote sensing in agriculture include several aspects such as plant phenology, economic features, and land use management

(Ceballos-Silva and Lopez-Blanco 2003). These applications have played an important role and suggest that remote sensing technology is suitable for monitoring agricultural activities. In regional scales of land suitability assessment, satellite remote sensing provides the opportunity to include phonological information of vegetation. The vegetation information can help determine the growth information of cassava plantations and can help inform the decision-making process of land suitability (Vrieling et al. 2011).

Therefore, investigating land suitability depends on multiple criteria and factors in the decision-making process that can largely be assessed using geospatial datasets (Ceballos-Silva and Lopez-Blanco 2003). A key step of land suitability assessment for cassava production is to determine the weight of each factor that influences land suitability. The presence of various and multiple criteria makes land suitability assessment complicated because factors that influence land suitability have unequal levels of significance (Elsheikh et al. 2013). This inequality of weight also varies by location, land use and productivity. The criteria for evaluation are largely dependent on geographical aspects and the socio-economic status of the country. A common rule for choosing a weight is very challenging, as growers have perceptions of weight that match their experiences.

A number of multi-criteria decision rules have been implemented to solve the land-use suitability problems. The decision rules can be classified into multi-objective and multi-attribute decision-making methods (Malczewski 1999, 2004). The multi-objective approaches are mathematical programming model-oriented methods such as linear programming. The single-objective multi-criteria evaluation has a ‘goal’ and computed using multi-attribute analysis. The methodology has several ways to weight the criteria such as, ordered weighted averaging (OWA) using weighted linear combination (WLC), analytic hierarchy process (AHP), and analytic network process (ANP). AHP method introduced by Satty in 1980 has incorporated into the GIS for land-use suitability analysis. As an extension of the criterion importance weighting in WLC, the OWA allows the decision-maker to specify a degree of risk in their approach to decision-making (Rinner and Voss 2013; Feizizadeh and Blaschke 2014). AHP method uses pairwise comparison of each criterion, while WLC directly assigns the weights of relative importance to each attribute map layer and OWA involves two-step weighting (criterion and order weights) (Ahmed 2015).

The analytical hierarchy process (AHP) is a multiple criteria decision-making process that uses analytical hierarchies to determine the importance of criteria and their associated relationships in complex problems (Brandt et al. 2015; Qureshi et al. 2017; Saaty 1980). The analytical hierarchy process has the advantage of assigning weights based on the preferences of experts for the regional concepts. For this reason, the AHP-modelling framework is widely accepted and has been extensively applied for multi-criteria decision analysis (MCDA) purposes and utilized in many decision-making problems regarding land suitability evaluation at a regional level (Zabihi et al. 2015; Akıncı et al. 2013; Zolekar and Bhagat 2015; Malczewski 2004).

Furthermore, GIS and AHP tools have recently been used for land suitability assessment and planning for suitable sites of agricultural land use, major crops and local foods (Pramanik 2016; Akinci et al. 2013; Bunruamkaew and Murayama 2011; Elsheikh et al. 2013; Zolekar and Bhagat 2015; Zabihi et al. 2015; and Widiatmaka 2016). In land suitability analysis, criteria associated with topographic features, vegetation and weather parameters are included. The extension and evaluation of suitability analysis methods can help to assess and improve the sustainability of crop production over time. Selecting the most appropriate model for land suitability assessment is important for current and future land use planning. Several approaches have been used to conduct land suitability assessments. The FAO land evaluation framework (1976) was the first procedure to assess local, regional, and national land-use planning. In recent years, computing technologies combined with GIS have included geospatial criteria to help find solutions for land suitability at the regional scale. Therefore, GIS, remote sensing and AHP can be used in land suitability analysis for various criteria related to ecological conditions or maximizing cassava production at the regional scale in Indonesia. Thus, the aim of this study was to develop a spatial model to assess land suitability levels for cassava production by integrating GIS, remote sensing and AHP.

2 Methodology

The model was built in three stages. First, Landsat-4 Thematic Mapper (TM), Landsat-8 Operational Land Imager (OLI) and Sentinel-2 Multispectral Instrument (MSI) satellites digital images and vector data layers were processed to establish criteria for the suitability analysis. Such criteria included land cover type, topographical features and the normalized difference vegetation index (NDVI). Second, we obtained highly suitable sites for increasing cassava production using GIS and AHP techniques. Third, we evaluated the sustainability levels of cassava production using four categories and images from the satellite database (Fig. 1). Primary data were collected through fieldwork involving questionnaires, interviews, and surveys. Additionally, secondary data from Statistics Indonesia and the Indonesian Geospatial Agency were used. A global positioning system (GPS) receiver was used in our field survey to determine the locations of cassava fields in the city of Serang and to provide ground truth information (Table 1).

2.1 Study area

Geographically, the city of Serang is located at 5°99′–6°22′ south and 106°07′–106°25′ east. The city is bordered by the Java Sea to the north and is surrounded by the Serang Regency to the east, south, and west. The city of Serang holds a position as the central government of the Banten Province and is an alternative area for Indonesia's state capital, Jakarta, which is located approximately 70 km away. The city includes six districts and 46 villages and covers a total area of 266.7 km^2. Most of the area is flat land with an elevation of less than 500 meters and is characterized by a tropical climate (Fig. 2a–c). The city includes coastal land to the north, rural areas to the south and north and an urban area in the middle of the region. The urban area includes infrastructural facilities that support socio-economic development.

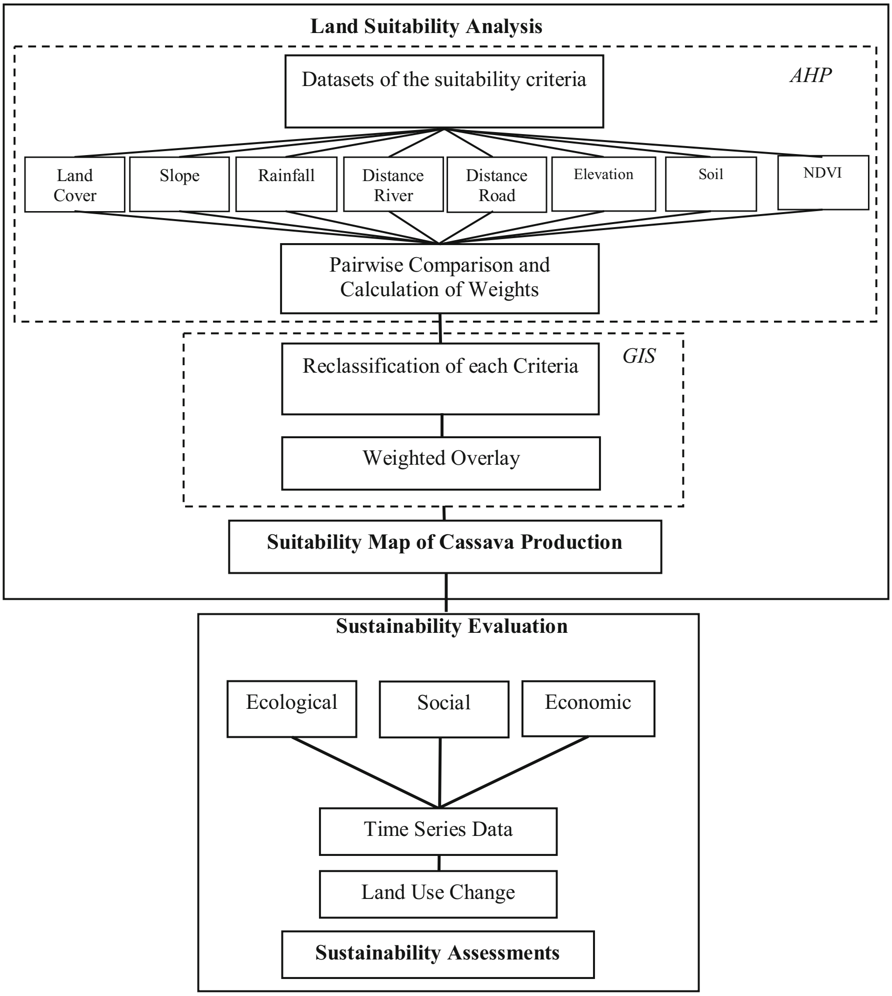


Fig. 1 The framework of site suitability for cassava production

Residences are also concentrated in the central part of the region. Rice cultivation constitutes the main land use in the northern area, whereas fields and dry land are found in the southern area. Cassava is an important alternative source of food, especially for traditional cuisine that is prepared for traditional events. In the city of Serang, cassava has historically been grown by poor farmers with minimal input on poorly managed land. When land is managed poorly, cassava can cause severe erosion on steep slopes (Howeler 1991).

2.2 Criteria for suitability analysis

The criteria for the suitability analysis were land cover, slope angles, elevation levels, soil types, rainfall, distance from rivers, distance from roads and the

Table 1 List of data and original data sources used for land suitability assessment for cassava production

No.	Data	Description	Source
1	Land Use Map	Scale at 1:50.000	2011, Ministry of Environment and Forestry
2	NDVI Map	Extracted from 10-m resolution	2016, Sentinel-2 MSI
3	Slope Map	Derived from 30-m resolution	2015, DEM STRM
4	Elevation Map	Derived from 30-m resolution	2015, DEM STRM
5	Road Map	Scale 1:50.000	2005, Indonesia Geospatial Agency
6	River Map	Scale 1:50.000	2005, Indonesia Geospatial Agency
7	Rainfall Map	Scale 1:50.000	2010, Indonesia Geospatial Agency
8	Location of Market	GPS Data	2014, Survey
9	Cassava Field Location	GPS Data	2014, Survey
10	Cassava Production	Statistics Data	2014, Indonesian Statistics
11	Land Use/Cover Map 2010	Derived from 30-m resolution	2016, Landsat 4 TM
12	Land Use/Cover Map 2016	Derived from 30-m resolution	2016, Landsat 8 OLI

vegetation index (Fig. 3a–h). The details of criteria's characteristics focusing on the Serang city are given in the following sections.

2.2.1 *Land use/land cover*

Land use and land cover (LULC) data files describe the vegetation, water, natural surfaces, and cultural features of a land surface (Akıncı et al. 2013). Most land in the city of Serang is covered by rice fields. Other areas include fields, settlements, forests, plantations, and water bodies. The LULC database was divided into four classes. Class I referred to fields with fertile soils that were easily cultivated for cassava. Class II land was used for rice cultivation with cassava intercropping. Class III referred to plantation and forested land on steep slopes, and class IV land was unsuitable for cassava cultivation due to the presence of settlements, residents, water bodies or mangrove forests.

2.2.2 *Slope*

In the city of Serang, most topography was classified as slopes between 0% and 45% in steepness. On slopes between 0% and 15%, most crops were easily cultivated. For cassava cultivation, slope angles were considered when determining cassava land management. Steep-sloped areas generally undergo soil erosion (Heumann et al. 2011), and soil steepness levels can affect soil formation. Additionally, a slope of 15% is optimal for livestock production and crop planting (FAO 2000). Land

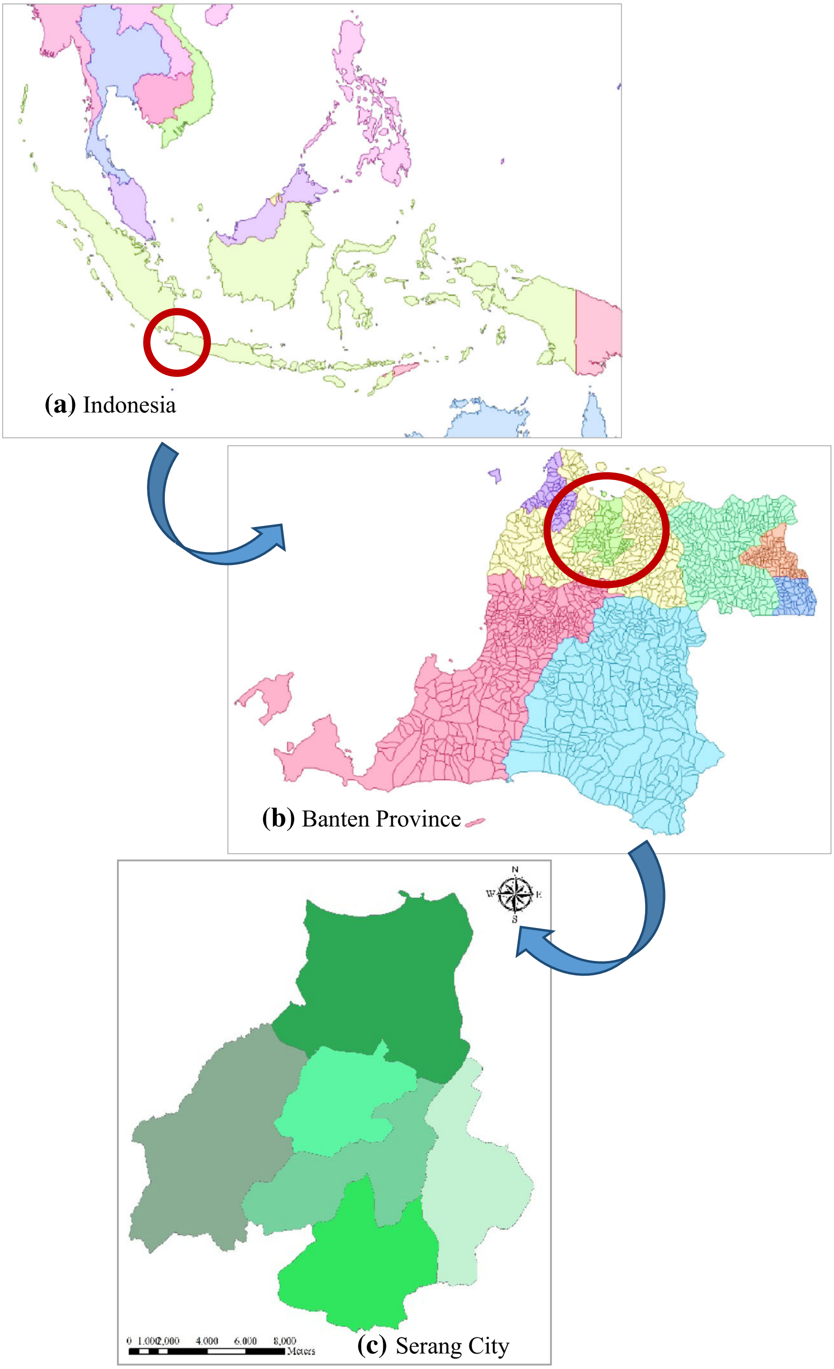
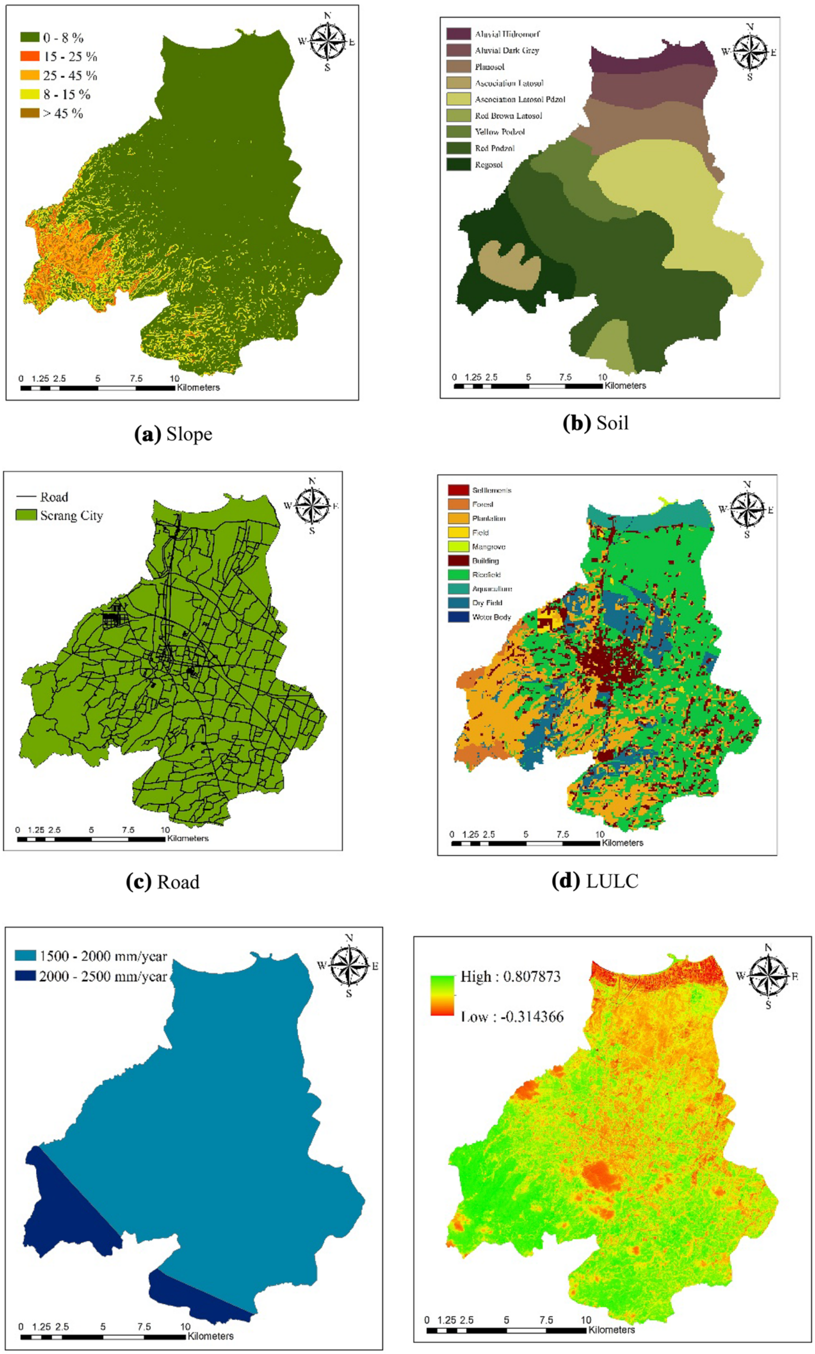


Fig. 2 Geographical extent of study area. **a** Serang City, **b** Banten Province and **c** Indonesia



(a) Slope

(b) Soil

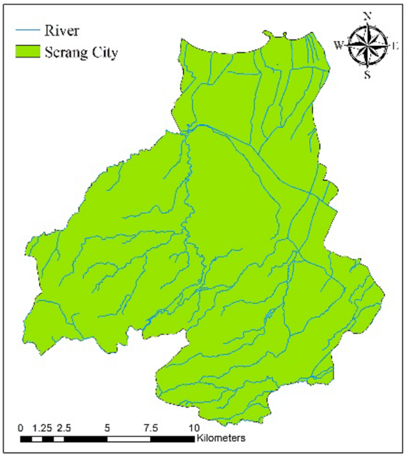
(c) Road

(d) LULC

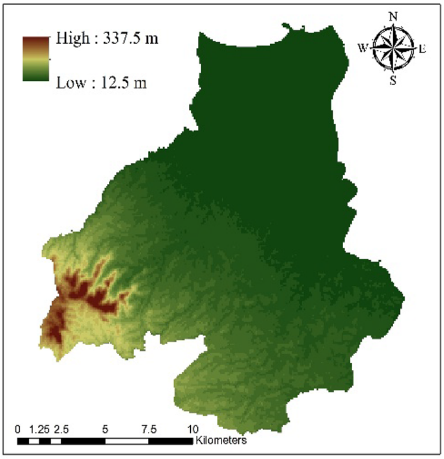
(e) Rainfall

(f) NDVI

Fig. 3 **a–h** Criteria for land suitability analysis for cassava production



(g) River



(h) Elevation

Fig. 3 continued

variety, in terms of slope angles, constitutes an important factor in determining the suitability of cassava production areas.

2.2.3 Distance from rivers

The Ci Banten River, the main river in Serang, supplies irrigation water. Other rivers in the area include the Cilandak, Cikaduan, Cikarang, Cipari, and Pelamunan Rivers. The physical factors associated with water supply, such as the distance from water bodies, streams, rivers, and irrigation zones, were used to determine suitability levels for cassava production. Rice fields were found in plains located close to major water resources, such as large rivers and water bodies, whereas cassava can be planted on sloped areas located farther from water resources.

2.2.4 Rainfall

Serang is characterized by a tropical climate, and significant periods of rainfall occur throughout the year. The average temperature and rainfall levels are 27.4 °C and 1500–2000 mm/year, respectively (BPS 2014). Cassava can also be intercropped with maize, legumes or rain-fed crops in areas of high and well-distributed rainfall (Devendra and Thomas 2002). Cassava can grow in areas that receive as little as 400 mm of average annual rainfall. However, higher yields have been obtained in the presence of greater water supplies (FAO 2013). Moisture stress on cassava roots can result in low yields, especially in years characterized by low rainfall. Therefore, irrigation management should be practiced effectively.

2.2.5 Soil

The major soil types found in Serang are alluvial, red regosol, red yellow podzolic, and latosol soils. Alluvial soils are mostly used in rice-based cropping systems, and regosol soils are used for upland rice and dry land crop cultivation. Regosol soils are found in hilly areas and in the center of mountain slopes. In Java, cassava-growing areas are generally located where soils classified as Mediterranean, alluvial, podzolic, latosols or regosols are found. According to Wargiono (2000), latosol areas are optimal for cultivating cassava. Latosol soils have good physical properties and are deep and tolerant to erosion. However, podzols include low levels of organic matter and tend to erode easily. Wargiono (2000) divided soil types for cassava cultivation into four classes. Class I includes latosol, gray hydromorphic, and planosol soils. Class II includes yellow podzolic soils. Class III refers to yellow regosol and red podzolic soils. Class IV refers to unsuitable soils that consist of gray alluvial hydromorphic soils with high water contents.

2.2.6 Elevation

In Asia, practically no cassava is grown at an elevation of 1000 meters above sea level. In Indonesia, most cassava-growing areas are located in the lowland humid and sub-humid tropics (Heumann et al. 2011). In some areas, cassava can be grown in hilly or mountainous areas, but the sustainability of these systems is compromised when sustained inputs are introduced for maintaining soil fertility and reducing erosion. Additionally, elevation has a strong effect on temperatures in some areas. In the city of Serang, elevation ranges from 12.5 to 375 m. Most of the area is suitable for cassava production, although the optimal elevation for cassava production is approximately 62.5–137.5 m.

2.2.7 Distance from roads

The number of vehicles in the city has increased due to economic growth, but road networks have not been expanded at the same rate. Therefore, traffic congestion in the city has increased. Regarding socio-economic factors, main roads are needed to sell fresh cassava at any distance from areas of cultivation. In selecting areas suitable for cassava production, the distance from roads must be considered because such distances affect transportation costs for supply processes. Shorter distances between fields and roads facilitate access to the transportation infrastructure and link farmers and farming activities to marketing channels.

2.2.8 Normalized difference vegetation index (NDVI)

To avoid soil erosion during cassava production, land covered by low vegetation can reduce the rate of surface runoff. Vegetation index variations were assessed using a satellite-based measure: the normalized difference vegetation index (NDVI). The NDVI is a vegetation index that is correlated with several important biophysical properties and that generates different crop indices (Ahamed et al. 2013; Elhag

2014). The proportion of vegetative biomass in the area being sensed or captured in satellite data is important for crop monitoring. Additionally, crop stages can be determined from NDVI data. In Indonesia, cassava production begins with planting at various times, but most field harvests occur during June or July. In this study, the NDVI was calculated for each cassava field using temporal information from Sentinel-2 MSI images acquired at the end of the growing period and before the harvest in May.

2.3 Digital image processing

We used image data for each criterion. A 1:50,000 map of land cover types, rainfall levels, distances from rivers, soil types, elevations, distances from roads, and NDVI data were used for the analysis. Basic vector data layers were collected from the Geospatial Information Agency of Indonesia. Landsat-4 TM, Landsat-8 OLI, and Sentinel-2 MSI vegetation index (VI) datasets were used for field-level crop monitoring in conjunction with NDVI data.

2.3.1 NDVI computation technique

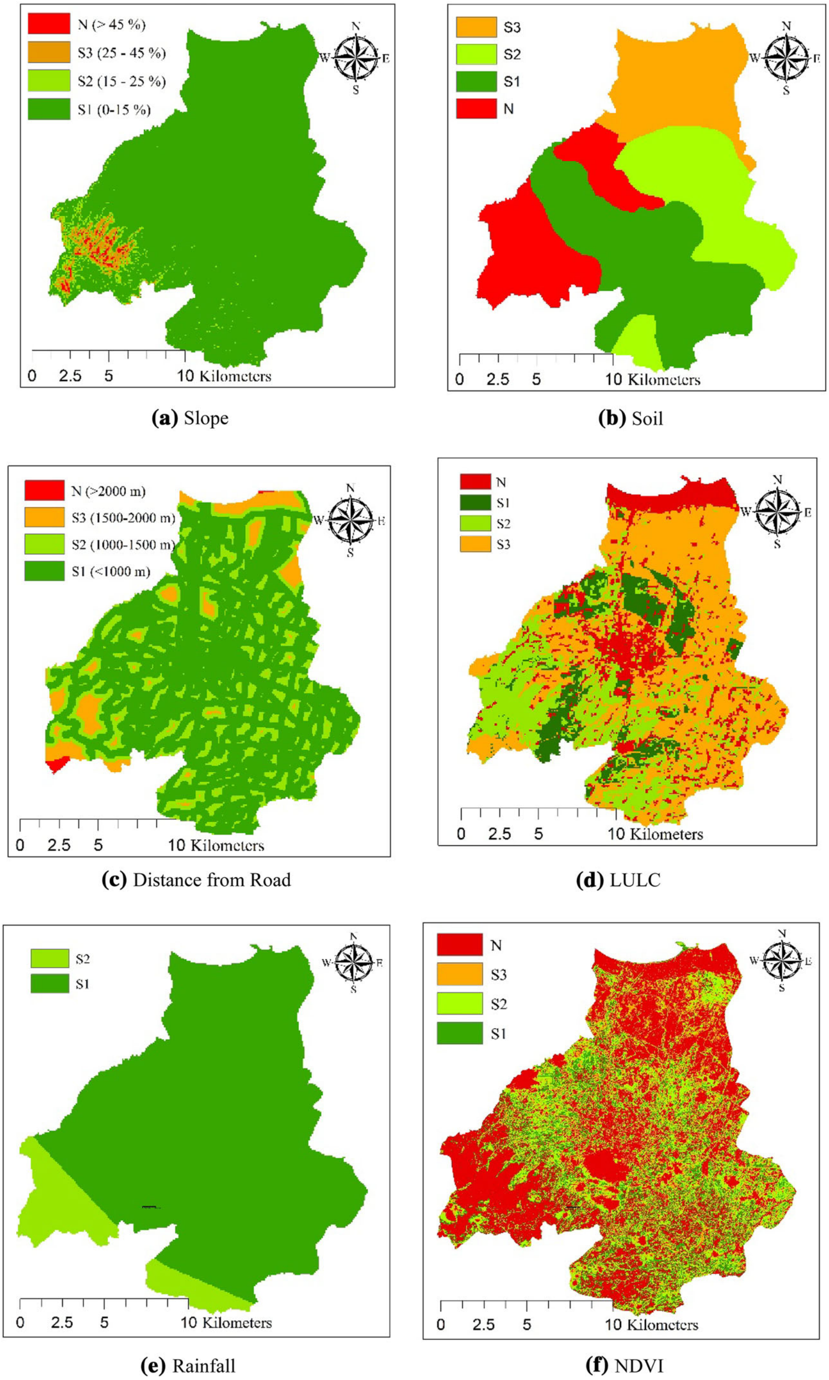
The NDVI was proposed by Rouse et al. 1973, and it has become the most popular indicator for studying vegetation health and crop production. The NDVI is developed from two important wave bands: the red and near infrared (NIR) bands. It has been widely used for agricultural mapping and yield monitoring. The NDVI is calculated as follows:

$$\mathrm{NDVI} = \frac{\mathrm{RNIR} - \mathrm{Rred}}{\mathrm{RNIR} + \mathrm{Rred}} \tag{1}$$

We acquired all available cloud-free Sentinel-2 scenes and calculated the NDVI from band combinations corresponding to the red and NIR reflections using Band 4 and Band 8. The Sentinel-2 mission combines two satellites—Sentinel-2A and Sentinel-2B—equipped with identical multispectral instruments capable of acquiring data in 13 bands at different spatial resolutions (between 10 m and 60 m). These satellites provide continuity for the Satellite pour l’Observation de la Terre (SPOT) missions of the European Space Agency (ESA).

2.4 Reclassification of criteria

Reclassification was used to simplify or change our interpretation of raster data by changing a single value to a new value or by grouping ranges of values into single values. Each criteria source map was reclassified into four classifications. The classification used the following suitability classes: highly suitable ($S1$), moderately suitable ($S2$), marginally suitable ($S3$), and not suitable (N) (Fig. 4a–h). Spatial data were converted into raster layers and then processed in ArcGIS® (ESRI, USA). They were then classified into four classes as integer rasters that represented



(a) Slope

(b) Soil

(c) Distance from Road

(d) LULC

(e) Rainfall

(f) NDVI

Fig. 4 a–h Reclassification of criteria

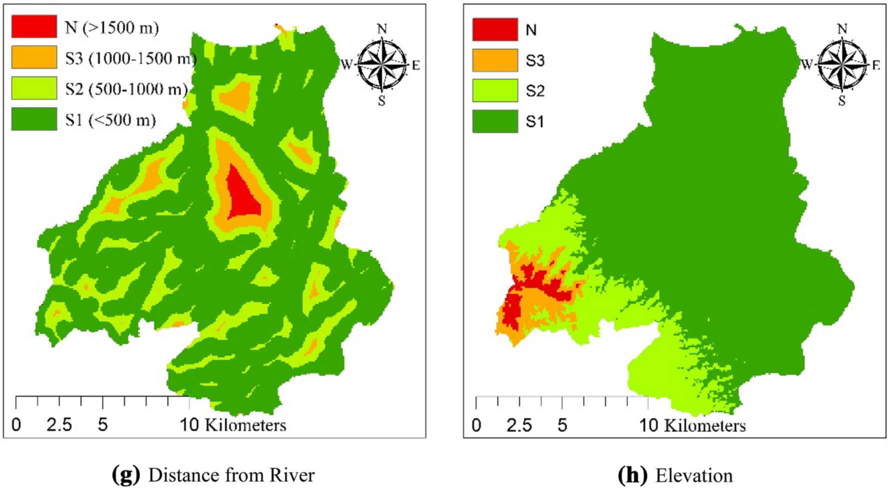


Fig. 4 continued

different suitability levels based on assigned threshold values (Table 2) (Tienwong et al. 2009).

For each of the suitability levels, we chose a suitability score. The suitability score is a way of computing values across the source layers so that there is a common standard. All source layer values are placed on the same scale with the same units. The same scale is used for all individual suitability layers and for the final overall suitability layer. In this study, we used a score of 9 for highly suitable areas, a score of 6 for moderately suitable areas, a score of 3 for marginally suitable areas, and a score of 1 and a restricted value for unsuitable areas.

2.5 Land suitability assessments

The land suitability assessment for the cassava production model was developed using the classification categories of land suitability proposed by the FAO (FAO 1976). The suitability classification is designed to determine the suitability of each land unit for a particular use. In the FAO's framework for land evaluation, land, the first class, is designated as suitable (*S*) or not suitable (*N*). These suitability classes can then be further sub-divided as needed. In practice, three classes (*S*1, *S*2 and *S*3) are often used to identify land that is highly suitable, moderately suitable, or marginally suitable for cassava production. The AHP application was used to support our weighted overlay calculations in the GIS environment. The AHP results were obtained from experts in related fields and from literature reviews. Through this process, the consistency ratio (CR) was calculated and was used in the land suitability analysis. The AHP method was applied to determine the relative importance of all of the selected criteria and factors (Ahamed et al. 2013).

A set of questionnaires within the AHP framework was developed. In the questionnaire, respondents can determine the relative importance of each criterion

Table 2 Reclassification of criteria of land suitability assessment for cassava production

Criteria	Suitability class	Sub-criteria	Percentage area (%)	Area (ha)
LULC	S1	Class I	11.38	3059
	S2	Class II	43.27	11,631
	S3	Class III	27.61	7422
	N	Class IV	17.74	4767
Slope (%)	S1	0–8%	83.81	22.352
	S2	8–15%	10.25	2.734
	S3	15–25%	3.07	818
	N	> 25%	2.87	765
Rainfall (mm.)	S1	1000–1500	89.22%	23.794
	S2	1500–2000	10.78%	2.875
Distance from roads (m)	S1	< 1000	88.31	23.794
	S2	1000–2000	10.51	2.803
	S3	2000–3000	1.11	296
	N	> 3000	0.07	18
Distance from rivers (m)	S1	< 500	72.4	19.309
	S2	500–1000	20.76	5536
	S3	1000–1500	4.66	1.242
	N	> 1500	2.18	581
Elevation (meters)	S1	12.5–62.5	76.93	20,517
	S2	62.5–137.5	17.14	4571
	S3	137.5–212.5	4.14	1104
	N	212.5-337.5	1.79	477
Soil type	S1	Latosol	37.93	10,115
	S2	Podzolic	21.36	5698
	S3	Regosol	20.48	5462
	N	Alluvial hydromorphic	20.23	5395
NDVI	S1	Vegetation	10.06	1829
	S2	Rice field	13.83	2514
	S3	Forest	43.94	7986
	N	Waterbody, settlements	32.16	5845

with respect to others, for example, the importance of soil with respect to land use, water, roads and markets, and vice versa. Sets of questionnaires were disseminated to five experts with relevant backgrounds (cassava experts, agriculture experts, and agriculture planners) during the field trip. The AHP is widely used by decision-makers and researchers. Calculation of criteria weights is central in the AHP method and depends on experts' opinions and determination for each criterion.

The study results are fully dependent on the applied AHP evaluation, how the criteria were defined and how the criteria were measured. The structured interviews were performed with relevant experts who were working for the cassava production in Indonesia for more than 10 years. Through this process, the consistency ratio

(CR) was calculated and used in the land suitability analysis. The AHP method was applied to determine the relative importance of all of the selected criteria and factors (Ahamed et al. 2013). The total suitability score (Si) of each land unit was calculated using the following expression:

$$S_i = \sum_{i=1}^{n} W_i \times R_i. \tag{2}$$

2.5.1 Analytical hierarchy process (AHP)

Weights were used to determine the priorities of criteria (land cover, distance from rivers, rainfall levels, distance from roads, slope angles, elevation levels, soil types and vegetation index data) and to identify the suitability of different land uses for cassava production. The resultant AHP weights were used to determine the priority of each criterion for weighted overlay applications using GIS.

In the first stage of the analysis, we organized elements of the decision model into a hierarchy that included first level (goal), second level (criteria), and third level (alternative) elements. The first level involved selecting the goal. The second level of the hierarchy considered rules or criteria associated with the goal. The lowest level considered alternative decisions (Fig. 5).

The second phase involved scoring the criteria via pairwise comparisons and scoring scales of relative importance (Table 3). Questionnaires were used to gather expert opinions on the relative importance of the considered criteria and factors. Comparative results (for each factor pair) were described as integer values of 1 (equal value) to 9 (extremely different), where a higher number denotes that the chosen factor was considered to be more important than other factors to which it was compared. For example, when comparing land cover and slope angle criteria, a score of 1 indicates that both were equally relevant to evaluating suitability, and a score of 9 indicates that land cover is more important than the slope angle. All scores were assembled in a pairwise comparison matrix with diagonal and reciprocal scores located in the lower left-hand triangle. Reciprocal values (1/3, 1/5, 1/7, and 1/9) were used where the row criterion was found to be less important than the column criterion (Table 4).

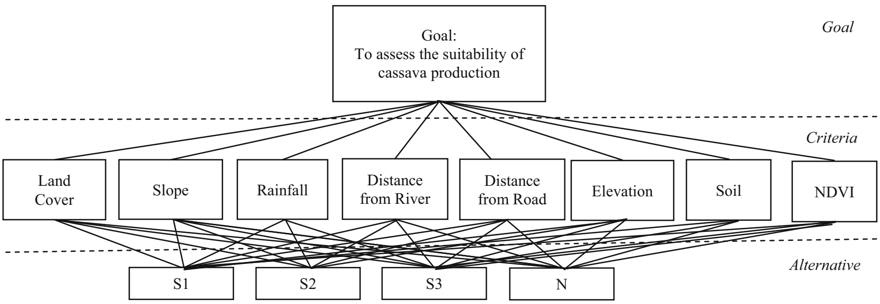


Fig. 5 The AHP framework to select suitable areas for cassava production

Table 3 Preference scale for AHP pairwise comparison (Saaty 1989)

Scale	Degree of preference	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgments slightly favor one activity over another
5	Strong or essential importance	Experience and judgments strongly favor one activity over another
7	Very strong importance	An activity is favored very strongly over another
9	Extreme importance	The evidence favoring one activity over another is the highest possible order of affirmation
2,4,6,8	Intermediate values between two adjacent judgments	When compromise is needed
Reciprocals	Opposites	Used for inverse comparisons

Table 4 Pairwise comparison for the AHP model among the criteria selected for cassava production

	Soil	Land Cover	Elevation	Slope	Rainfall	Distances from roads	River	NDVI
Soil	**1**	3	5	5	7	9	9	3
Land cover	0.33	**1**	3	3	7	7	9	1
Elevation	0.2	0.3	**1**	1	3	5	7	0.3
Slope	0.2	0.3	1	**1**	3	3	5	0.3
Rainfall	0.14	0.14	0.33	0.33	**1**	3	3	0.14
Distance from roads	0.11	0.14	0.2	0.33	0.33	**1**	1	0.14
Distance from rivers	0.11	0.11	0.14	0.2	0.33	1	**1**	0.11
NDVI	0.33	1	3	3	7	7	9	**1**

Third, we calculated the matrix and ensured the consistency of the pairwise comparison criteria. The AHP also provided measurements for calculating normalized values of each criterion and alternatives and for determining the normalized principal Eigen factors and priority vectors. The pairwise matrix was calculated and is given by the following expression:

$$\begin{bmatrix} C_{11} & C_{12} & \ldots C_{1n} \\ C_{21} & C_{22} & \ldots C_{2n} \\ . & . & . \; . \\ . & . & . \; . \\ C_{n1} & C_{n2} & . \, C_{nn} \end{bmatrix}. \tag{3}$$

The sum of each column of the pairwise matrix was denoted as follows:

$$C_{ij} = \sum_{i=1}^{n} C_{ij}. \tag{4}$$

We then divided each element of the matrix by its column total to generate a normalized pairwise matrix:

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}} = \begin{bmatrix} X_{11} & X_{12} & \ldots X_{1n} \\ X_{21} & X_{22} & \ldots X_{2n} \\ . & . & . \quad . \\ . & . & . \quad . \\ X_{n1} & X_{n2} & . \, X_{nn} \end{bmatrix}. \tag{5}$$

Finally, we divided the sum of the normalized matrix column by the number of criteria used (n) to generate the weighted matrix of priority criteria:

$$W_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{n} = \begin{bmatrix} W_{11} \\ W_{12} \\ . \\ . \\ W_{1n} \end{bmatrix}. \tag{6}$$

The initial consistency vectors were derived by multiplying the pairwise matrix by the vector of weights:

$$\begin{bmatrix} C_{11} & C_{12} & \ldots C_{1n} \\ C_{21} & C_{22} & \ldots C_{2n} \\ . & . & . \quad . \\ . & . & . \quad . \\ C_{n1} & C_{n2} & . \, C_{nn} \end{bmatrix} \times \begin{bmatrix} W_{11} \\ W_{12} \\ . \\ . \\ W_{1n} \end{bmatrix} = \begin{bmatrix} C_{11}W_{11}+ & C_{12}W_{11}+ & \ldots + C_{13}W_{11} \\ C_{21}W_{12}+ & C_{22}W_{12}+ & \ldots + C_{23}W_{12} \\ . & . & . \quad . \\ . & . & . \quad . \\ C_{n1}W_{1n} & C_{n1}W_{1n} & . \, C_{n1}W_{1n} \end{bmatrix}$$
$$= \begin{bmatrix} V_{11} \\ V_{12} \\ . \\ . \\ V_{1n} \end{bmatrix}. \tag{7}$$

The principal eigenvector ($\lambda_{\max}$) was then calculated by averaging the values of the consistency vector:

$$\lambda_{\max} = \sum_{i}^{n} \mathrm{CV}_{ij}. \tag{8}$$

Eigen values were calculated by averaging the rows of each matrix. Eigen values were also referred to as relative weights. The largest Eigen value was equal to the number of criteria, and when $\lambda_{\max} = n$, judgments were consistent. Normalized Eigen values were generated as weights of priority criteria. The principle value suggests that eight criteria were consistent, as the calculation results reveal a maximum value of 8.34 (Table 5). The judgments were also checked to determine the consistency index (CI), which was calculated as:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{9}$$

Table 5 Normalized matrix for the criteria selected for cassava production

	Soil	Land Cover	Elevation	Slope	Rainfall	Distance from roads	Distance from rivers	NDVI	Total	Average	Consistency measure
Soil	0.413	0.500	0.365	0.360	0.244	0.25	0.204	0.500	2.840	0.355	8.649
Land cover	0.136	0.166	0.219	0.216	0.244	0.194	0.204	0.166	1.549	0.193	8.621
Elevation	0.082	0.050	0.073	0.072	0.104	0.138	0.159	0.050	0.730	0.091	8.238
Slope	0.082	0.050	0.073	0.072	0.104	0.083	0.113	0.050	0.629	0.078	8.411
Rainfall	0.057	0.023	0.024	0.023	0.034	0.083	0.068	0.023	0.338	0.042	7.977
Distance from roads	0.045	0.023	0.014	0.023	0.011	0.027	0.022	0.023	0.192	0.024	8.167
Distance from rivers	0.045	0.018	0.010	0.014	0.011	0.027	0.022	0.018	0.168	0.021	8.023
NDVI	0.136	0.166	0.219	0.216	0.244	0.194	0.204	0.166	1.549	0.193	8.621

Table 6 Random consistency index (RI) to determine consistency ratio (CR) (Saaty 1989)

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Here n is the total number of criteria. Saaty (1989) also introduced the consistency ratio (CR) and compared it to the consistency index and the random index (RI) value, which is the calculated value for matrices of different sizes (Table 6). The consistency ratio was calculated as:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}. \tag{10}$$

A lower CR ratio indicates a higher degree of consistency. Further confirmation and understanding about weight and influences among the criteria, ANP also employed in this research.

2.5.2 Analytical network process (ANP)

ANP is an extension of the AHP and proposed by Satty 1980 and 2001. ANP is a nonlinear structure with bilateral relationships (Azizi et al. 2014). In this research, ANP was used to obtain the weight of the criteria to compare with the weight from AHP. In the ANP analysis, first, the construction of a conceptual model was developed to determine relationships among the criteria and alternatives. If no relationship exists among the criteria, then there is influence among the criteria and alternatives. The, criteria were compared pairwise by Super Decisions Software® to form an un-weighted super-matrix. Then, the priorities derived from pairwise comparison matrices were entered as parts of the columns referred as the evaluation matrix U for criteria ($C1$, $C1$, $C3$, $C4$, $C5$, $C6$, $C7$, $C8$) and alternatives ($A1$, $A2$, $A3$, $A4$). The evaluation matrix for the criteria can be expressed as follows:

$$U = \begin{bmatrix} U_{11} & U_{12} & \ldots U_{18} \\ U_{21} & U_{22} & \ldots U_{28} \\ . & . & . \; . \\ . & . & . \; . \\ U_{41} & U_{42} & . \, U_{48} \end{bmatrix}. \tag{11}$$

In contrast, the evaluation matrix V in which alternatives ($A1$, $A2$, $A3$, $A4$) are evaluating according to the criteria ($C1$, $C1$, $C3$, $C4$, $C5$, $C6$, $C7$, $C8$) can be expressed as follows:

$$V = \begin{bmatrix} V_{11} & V_{12} & V_{13} V_{14} \\ V_{21} & V_{22} & V_{23} V_{24} \\ . & . & . \quad . \\ . & . & . \quad . \\ V_{81} & V_{82} & V_{83} \; V_{84} \end{bmatrix}. \tag{12}$$

Then, the weighted supermatrix is expressed as a function of the evaluation matrices U and V. The supermatrix S should be a probability matrix and irreducible. The weighted supermatrix can be expressed follows:

$$S_{weighted}\begin{bmatrix} 0 & U \\ V & 0 \end{bmatrix} = \begin{array}{c} \\ \mathrm{A}_1 \\ \vdots \\ \mathrm{A}_4 \\ \mathrm{C}_1 \\ \vdots \\ \mathrm{C}_8 \end{array} \begin{array}{c} \begin{array}{cccccc} \mathrm{A}_1 \cdots & \mathrm{A}_4 & & \mathrm{C}_1 & \cdots & \mathrm{C}_8 \end{array} \\ \begin{bmatrix} 0 & \dots & 0 & U_{11} & \dots & U_{18} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & U_{41} & \dots & U_{48} \\ V_{11} & \dots & V_{14} & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ V_{81} & \dots & V_{84} & 0 & \dots & 0 \end{bmatrix} \end{array} \tag{13}$$

After that, limit supermatrix was obtained by raising the weighted supermatrix to powers by multiplying the matrix itself (Table 8). The limit supermatrix can be expressed as follows:

$$S_{\text{limited}} = \lim_{n \to \propto} S^{n}_{\text{weighted}}. \tag{14}$$

Examples of weighted supermatrix and limit supermatrix are given to show the relations among the criteria and alternatives for one expert's opinion (Tables 7 and 8). At the end, the weighted overlay approach was used for applying a weight priority of the criteria to generate a land suitability map for cassava production in the GIS environment.

2.5.3 GIS analysis

Suitability assessment criteria were used as the reclassified raster data layers for land cover, slope angles, elevation levels, soil types, rainfall levels, distance from rivers, distance from roads and the vegetation index. All of the reclassified raster data were combined with weighted overlay tools. This reclassification was used to simplify or change our interpretation of raster data by changing a single value to a new value or by grouping ranges of values into single values. Each criteria source map was reclassified into four classifications. The classification used the following suitability classes: highly suitable ($S1$), moderately suitable ($S2$), marginally suitable ($S3$), and not suitable (N). Spatial data were converted into raster layers and were then processed in ArcGIS® (ESRI, USA). They were then classified into four classes as integer rasters that represented different suitability levels based on the assigned threshold values (Tienwong et al. 2009). Weighted overlays are overlay analysis tools used to identify the best or most preferable locations for cassava production. The criteria included in the weighted overlay analysis were not equal in importance. The weights of key criteria were calculated using the AHP/ANP application. Using the reclassification and weighted overlay method, a spatial analysis was conducted, and a suitability map for cassava production was created (Eckert and Sujata 2011; Gatrell et al. 2011).

Table 7 The weighted supermatrix for determining the relation among the criteria and alternatives for cassava production using ANP

Alternatives					Criteria								
		N	*S*1	*S*2	*S*3	Elevation	LULC	NDVI	Rainfall	River	Road	Slope	Soil
Alternatives	*N*	0.000	0.000	0.000	0.000	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.055
	*S*1	0.000	0.000	0.000	0.000	0.565	0.565	0.565	0.565	0.565	0.565	0.565	0.565
	*S*2	0.000	0.000	0.000	0.000	0.262	0.262	0.262	0.262	0.262	0.262	0.262	0.262
	*S*3	0.000	0.000	0.000	0.000	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118
Criteria	Elevation	0.089	0.090	0.089	0.089	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	LULC	0.194	0.194	0.194	0.194	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	NDVI	0.194	0.194	0.194	0.194	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Rainfall	0.040	0.035	0.040	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	River	0.020	0.023	0.020	0.020	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Road	0.023	0.024	0.023	0.023	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Slope	0.078	0.079	0.078	0.078	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 8 The limited supermatrix for determining the relation among the criteria and alternatives for cassava production using ANP

Alternatives						Criteria							
		N	*S*1	*S*2	*S*3	Elevation	LULC	NDVI	Rainfall	River	Road	Slope	Soil
Alternatives	*N*	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028
	*S*1	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283
	*S*2	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131
	*S*3	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059
Criteria	Elevation	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
	LULC	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097
	NDVI	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097
	Rainfall	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018
	River	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
	Road	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012
	Slope	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
	Soil	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181

2.6 Ground truth information and field survey

Primary data from the field survey were collected through questionnaires, interviews, and surveys. GPS data for cassava production locations were collected. Ground references were collected to determine the locations of cassava fields located in the highly suitable areas of Serang city. A field survey and a focus group discussion held with cassava farmers and regional sellers were completed in November 2016.

2.7 Sustainability evaluation

Several indicators and frameworks are commonly used for sustainability evaluation (Ahamed et al. 2009; Bell and Morse 2008; Ahamed et al. 2015; Von Wirén-Lehr 2001). In this study, we focused on pillars of agro-ecological sustainability indicators that are related to ecological, social, and economic factors and are associated with several criteria, such as availability, accessibility, affordability, and profitability. These criteria were considered to evaluate the sustainability of cassava production between 2010 and 2015 (Fig. 6).

3 Results

In the GIS analysis, the reclassified rasters were used with AHP and ANP weights and ranked accordingly. The CR was the indicator of judgments to refer to the AHP weight, whether consistent or not. In the AHP analysis, a CR of 6.1% was found, which was less than 10%, referred the consistency of expert opinions was acceptable. Among the eight sub-criteria identified, the AHP application ranked soil as the first priority (34%) followed by land cover (18%), the vegetation index (16%), rainfall (11%), elevation level (8%), slope (7%), distance from roads (3%), and distance from rivers (3%) when selecting suitable lands for cassava (Table 9). The ANP model also included a consistency test and observed 6.3%, which was also less than 10% to assess the degree of consistency of the experts. The ANP application ranked soil as the first priority (36%) followed by land cover (18%), the vegetation index (14%), rainfall (11%), elevation (8%), slope (6%), distance from rivers (4%) and distance from roads (3%) (Table 9).

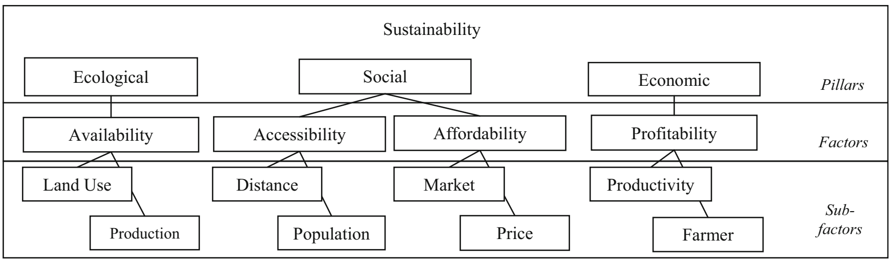
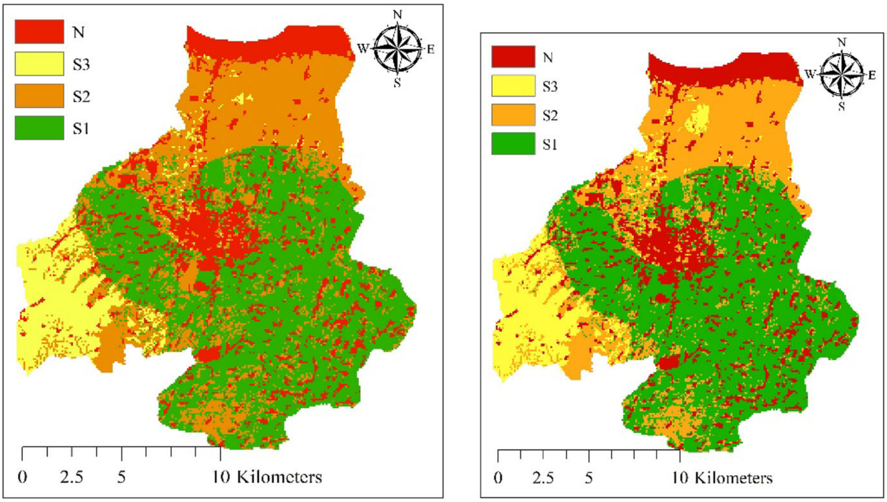


Fig. 6 Criteria of sustainability evaluation of cassava production

Table 9 Priority criteria weights according to expert's opinions for selecting land suitability in cassava production

Criterion names	Weights of criterion											
	Experts initials											
	(Experience of experts, years)											
	Expert A		Expert B		Expert C		Expert D		Expert E		Mean	
	(11 years)		(10 years)		(20 years)		(21 years)		(15 years)			
	AHP	ANP	AHP	ANP	AHP	ANP	AHP	ANP	AHP	ANP	AHP	ANP
Soil	0.356	0.387	0.408	0.436	0.339	0.345	0.355	0.361	0.244	0.246	0.340	0.355
LULC	0.214	0.223	0.181	0.175	0.198	0.198	0.194	0.194	0.102	0.100	0.178	0.178
NDVI	0.184	0.156	0.170	0.165	0.198	0.198	0.194	0.089	0.067	0.064	0.162	0.134
Elevation	0.109	0.100	0.085	0.069	0.099	0.096	0.091	0.089	0.034	0.032	0.083	0.077
Slope	0.074	0.059	0.072	0.037	0.080	0.080	0.079	0.079	0.038	0.039	0.069	0.059
Rainfall	0.031	0.036	0.042	0.022	0.043	0.040	0.042	0.037	0.398	0.407	0.111	0.108
Road	0.014	0.022	0.023	0.019	0.024	0.023	0.024	0.024	0.054	0.052	0.028	0.028
River	0.020	0.017	0.021	0.078	0.021	0.020	0.021	0.022	0.063	0.061	0.029	0.040
CR	0.080	0.080	0.058	0.065	0.033	0.039	0.043	0.040	0.091	0.091	0.061	0.063



(a) AHP based weighted overlay **(b)** ANP based weighted overlay

Fig. 7 **a**, **b** Land suitability distribution using a weighted overlay

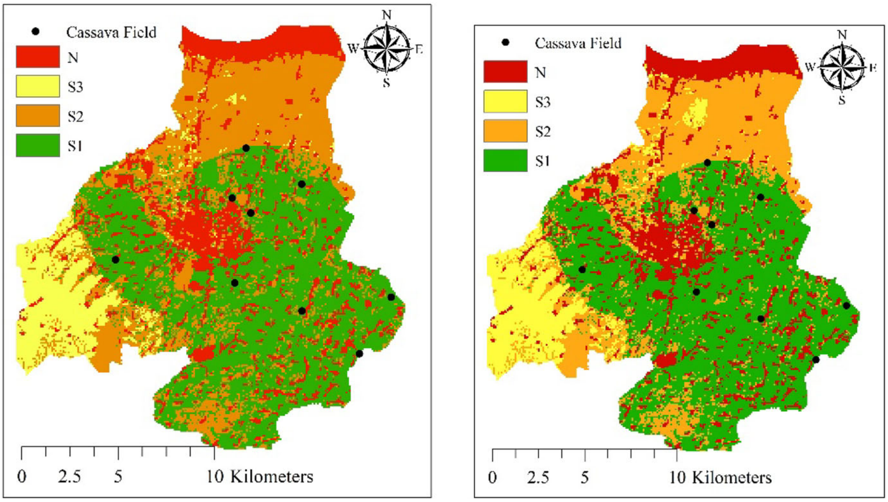
The weighted overlay was used for applying a weight priority of the criteria to generate the land suitability map for cassava production. The reclassified raster data layers of land cover, slope angles, elevation levels, soil types, rainfall, distance from rivers, distance from roads and the vegetation index were combined with weighted overlay tools and AHP/ANP weights to generate suitability map (Fig. 7). A suitability map for cassava production was created from a weighted overlay, and we found in the AHP analysis that 41.60% (11094 ha) of the study area was highly suitable for cassava production, 30.87% (8233 ha) was moderately suitable and 9.83% (2623 ha) was marginally suitable. Whereas, the result of ANP analysis found that 44.62% (11901 ha) of the study area was highly suitable for cassava production, 27.17% (7246 ha) was moderately suitable and 10.51% (2803 ha) was marginally suitable. Additionally, the same result of AHP and ANP show 17.69% (4718 ha) of the land area was found occupied by residences and settlements (Fig. 7 and Table 10). Highly suitable areas for cassava production covered 41.60% (11094 ha) of the total area of the Serang city. These areas were mainly dry lands with moderately well-drained soils. Soils in this group were loamy with topsoil that was leveled and bounded for paddy rice. There is high possibility to use these areas and can be used to grow cassava after they are drained to avoid waterlogging. The moderately suitable area covered 30.87% (8233 ha) of the total area of Serang. These areas were poorly drained and coarsely textured with alluvial terraces. Marginally suitable areas for cassava production cannot support cassava plantations. Only 9.83% (2623 ha) of the land area was categorized as marginally suitable. Deep and coarsely textured soils positioned on slopes of less than 20% of the mentioned areas. Soil fertility levels were moderately low. Upland crops and fruit trees are often found with low levels

Table 10 Suitable area for cassava production in the Serang City, Banten Province, Indonesia

Suitability Class	AHP		ANP	
	Percentage area (%)	Area (ha)	Percentage area (%)	Area (ha)
Highly suitable	41.60	11094	44.62	11901
Moderately suitable	30.87	8233	27.17	7246
Marginally suitable	9.83	2623	10.51	2803
Not suitable	17.69	4718	17.69	4718

of fertility, a lack of water during dry seasons, soil erosion on steep slopes, and high levels of acidity in some areas.

The 4718 ha (17.69%) area of land that was classified as unsuitable for cassava production due to the presence of settlements and residences cannot be replaced with cassava fields. This area included the coastal area in the northern part of Serang and is characterized by sandy soils with high mineral contents. Although cassava can grow under high nitrogen (N), potassium (K) and organic matter (OM) application conditions, to obtain high-quality yields, appropriate management strategies must be applied to boost cassava production in coastal areas. The weighted overlay map used to locate suitable cassava production areas could serve as a reference map for predicting production methods that could support measures to increase local food production in the city of Serang. According to the GPS locations for cassava production recorded in November 2016, most cassava-growing areas were concentrated in the southern part of the region (Fig. 8).



(a) AHP based weighted overlay **(b)** ANP based weighted overlay

Fig. 8 **a**, **b** Validation of land suitability analysis using ground reference information

In the sustainability evaluation, several sub-criteria (e.g., land use, production, population, distance, market, price, productivity, and income) were considered. These data were collected from primary and secondary sources. Over the period examined, production and land use were unsustainable due to a shift from agricultural to settlement land use. Although cassava production has been located in the most suitable areas, we found that the land of cassava fields from 2010 to 2015 decreased 3.38% annually based on our collected data (Table 11). Furthermore, the NVDI images based on Landsat-4 TM and Landsat-8 OLI showed the vegetation conditions, which reflect the land use change and physical features that cover the Earth's surface (land cover) (Fig. 9). Most land in the city of Serang was cultivated land with plantation fields, irrigated paddy fields, and rain-fed areas. Additionally, protected areas were occupied by settlements.

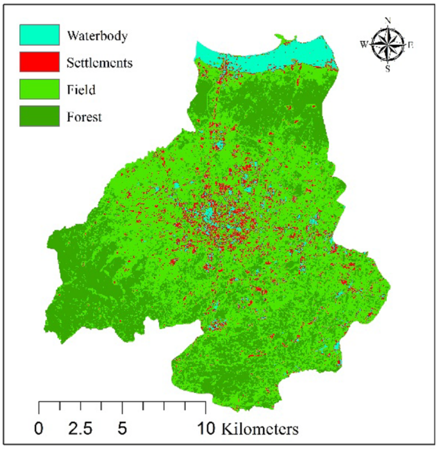
4 Discussion

We found that most land areas suitable for cassava production were located in the southern part of Serang in the Banten province. This result could be because the soil steepness levels in this area are less than 15%, and this condition could affect soil formation. From the ground truth survey, cassava farmers can grow cassava in rotation with other crops to prevent depletion of nutrients from soil. The production of cassava in new areas has faced several barriers, especially regarding labor and the conversion of peat land and forests in agricultural areas. Future yields can be maximized through the implementation of several management practices (e.g., minimum tillage, contour ridging, fertilization, strip-cropping, and intercropping with government support and rural appraisals from experts). Our study results illustrate the effectiveness of spatial assessments for evaluating suitable land use for sustainable cassava production. Therefore, geospatial technologies that combine GIS, remote sensing and AHP could be used to support land suitability assessments of cassava production. Geospatial modeling has limitations in obtaining highly accurate validation results due to a lack of ground reference information of previous years. As such, future studies should integrate several indicators based on high-resolution spatial and temporal remote sensing data.

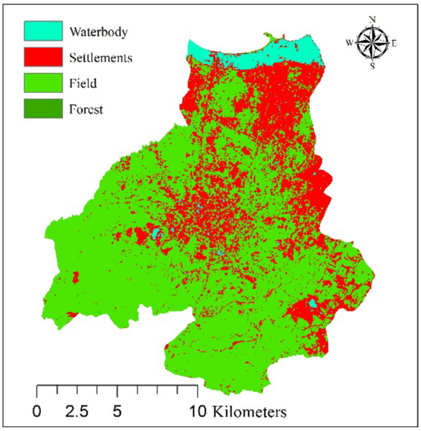
Furthermore, this empirical method accepted key input from experts through AHP-based questionnaires and structured questionnaire surveys for cassava growers and agricultural production officers in the study area, which significantly enhanced the decision-making capabilities of the land-use plan. However, the AHP method has limitations in that it employs suitability determinations that can be subject to bias in both the scope and quality of outputs for the variation of weights. We thought of many ways to provide equal weights after fieldwork was conducted extensively in the city of Serang. Inequality usually varies for site-specific cases and crop selection (such as with cassava) in regional contexts. The judgment of pertinent criteria is complicated, and there are preferences of priority among the criteria. In such a case, AHP has the advantage of weighting the criteria based on experts' opinions. However, it is very difficult to judge the subjectivity of decision-making during the modeling stages. To overcome the limitation and influences of criteria,

Table 11 Agricultural data assessment from 2010 to 2015 for Serang City, Banten Province, Indonesia (BPS 2017)

Factors	Sub-factors	2010	2011	2012	2013	2014	2015	Trend of change (%)	Annual rate of change (%)
Availability	Land use (Ha)	321	253	327	391	211	62	− 67.62	− 3.38
	Production (ton)	4600	3289	4400	6374	3175	4162	− 5.00	− 0.24
Accessibility	Population (people)	577785	598407	611897	618802	631101	643205	5.35	0.26
	Road condition (%)	54.87	54.87	54.87	52.25	55.50	53.83	− 0.95	− 0.04
Affordability	Traditional market (unit)	6	6	6	6	6	6	0	0
	Cassava price (USD/kg)	0.075	0.075	0.075	0.09	0.12	0.12	23.07	1.15
Profitability	Productivity (ton/ha)	14.33	14.52	14.58	15.33	15.03	67.12	64.81	3.24
	Farmer income (USD/kg)	0.036	0.076	0.114	0.152	0.152	0.152	61.70	3.08



(a) Landsat 4 TM, 2010



(b) Landsat 8 OLI, 2016

Fig. 9 **a**, **b** Land use changes in Serang City Drawn from Landsat

we have also employed ANP for further confirmation of weights. Additionally, consistency ratio was introduced for AHP and ANP to validate the judgment of experts. The consistency ratio indicates the degree of coincidence between the AHP or ANP models and experts' opinions for weighting the criteria in the model. The weights were given to identify the preferences of criteria to analyze in the GIS environment.

In the GIS analysis, weights from AHP and ANP were used to develop the weighted overlay using the criteria. The ground truth information validated the weighted overlay and confirmed the suitable locations of cassava fields in the Serang city. Most of the fields were located in the highly suitable areas and some were in the marginally suitable areas. The validation was required to understand spatial variability of cassava production for regional perspective and identify the causes of decreasing production of cassava. Along with spatial variability, socio-economic factors should be included for increasing cassava production. Present research shows the results of suitable areas for cassava production in the Serang city to establish cassava as an alternate crop to minimize the climate risk of rice production in Indonesia.

5 Conclusions

This study identified suitable areas to evaluate the sustainability of land use for cassava production using a multi-criteria model integrating with GIS, remote sensing and AHP. The multi-criteria model for suitability assessment used eight criteria: LULC, rainfall, distance from rivers, slope angle, elevation level, soil type, distance from roads and NDVI. From these criteria, we found that priority criteria, such as the soil type, LULC, and NDVI, influenced the sustainability of cassava production. All of the criteria were processed through a weighted overlay using AHP to calculate the weights of each criterion. To cut on the bias of AHP, the results also confirmed with the ANP. The land suitability assessment for cassava production indicated that 41.6 and 44.6% of the study area was highly suitable using AHP and ANP, respectively. Furthermore, the sustainability of cassava production was analyzed using several indicators classified into four categories: availability, accessibility, affordability, and profitability. The results show that the land use for cassava cultivation areas declined annually 3.38% between 2010 and 2015. The results obtained from this research are very significant in the decision-making processes to increase the production of cassava in suitable areas of the Serang city. The production scenario is one of the most important points for the suitability understanding for increasing regional production of cassava in Indonesia. The model can be further expanded spatially by including a fuzzy approach with AHP and ANP to overcome the limitation of the multi-criteria model.

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