Integrating Expert System, GIS, and Remote Sensing to Evaluate Land Suitability for Yield Prediction of Cassava in Indonesia

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Riska Ayu PURNAMASARI

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Riska Ayu PURNAMASARI

Abstract

Cassava has the potential to be a promising crop that can adapt in changing climatic due to its low water requirement and drought tolerance in Indonesia. However, inappropriate decision on land selection limits the productivity of cassava and increases associated cost to farmers for production. Considering cassava as root crop, prediction of yield using vegetation indices and biophysical properties is very important to maximize yield before harvesting. In this regard, a Decision Support System (DSS) for suitable land selection and a model for yield prediction of cassava correlating with biomass and root yield need to develop. Furthermore, the DSS needs to integrate with expert knowledge's and geospatial variability to identify suitable areas for yield prediction.

Therefore, the purpose of this research is to develop a decision support system to find suitable areas for cassava production and a yield prediction model. The DSS and model integrated expert systems and geospatial technologies such as remote sensing and geographic information systems (GIS) to maximize the productivity of cassava production in Indonesia.

In this research, the methodology was developed in a geographical context from a city to the provincial levels for land suitability analysis (LSA) and yield prediction. The priority indicators were identified using Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP) for LSA. The analysis was scaled up to understand the regional variability of land selection for cassava production in the Banten Province of Indonesia. The Multi-Criteria Decision Method (MCDM) was extended with Fuzzy Expert System to compare with AHP-based analysis using Matlab® and ArcGIS®. Furthermore, the yield prediction method was developed using satellite remote sensing datasets for locating highly suitable areas for cassava production. In this analysis, Sentinel II datasets were collected and analyzed in ArcGIS® environments. First, the sustainability of land use for cassava production in the city level to provincial levels were conducted. Sustainability indicators were classified and discussed with a vision of reflective practice and from multiple views of sustainability. Second, the sustainability of cassava production was analyzed using several indicators: availability, accessibility, affordability and profitability. The results show that the land use for cassava cultivation areas declined annually by 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 in the Banten Province. Third, the suitability analysis using (AHP) and Analytical Network Process (ANP) was performed. The AHP analysis incorporated with suitability analysis for cassava production in the GIS environment. Ground reference data were collected through interviewing farmers in the city to provincial levels. The criteria for suitability assessment of cassava were land use land cover (LULC), slope, elevation, rainfall, soil type, normalized vegetation difference index (NDVI), distance from the river and distance from the road. GIS-based proximity and raster reclassification were conducted into four categories according to the land suitability referred by the United Nations of Food and Agriculture Organization (FAO). The land suitability assessment for cassava production found that 41.6% and 44.6% of Serang City was identified as the most suitable for cassava production using AHP and ANP, respectively. Fourth, the analysis was scaled up to the provincial level to identify most suitable areas using Fuzzy integration with MCDM (F-MCDM). The multi-source database was built using the fuzzy membership function integrated with the application of spectral reflectance of satellite image and mapping system. The MCDM-based AHP method enhanced with fuzzy membership function. Fuzzy set methodologies have proposed as a method for overcoming biased of AHP. The result was showed that 42.17% of land was highly suitable using F-MCDM model, while 35.92% using MCDM Model. In the ground truth data from harvested yield, it was observed that F-MCDM model showed higher accuracy (R^2=0.55) compare to the MCDM (R^2=0.50). Finally, the yield prediction model was develop using the vegetation index from Sentinel II datasets of 10 m resolution. The vegetation indices were used to predict cassava growth, biophysical condition, and phenology status over the growing seasons. The NDVI, SAVI, IRECI, LAI, and fAPAR were used to develop the model of prediction for cassava growth. The generated models were validated using regression analysis of estimate between observed and predicted yield. NDVI showed the higher accuracy in the yield prediction model (R^2=0.62) compared to SAVI and IRECI. The biophysical properties had the accuracy higher prediction accuracy (R^2=0.70). The combined model using NDVI, SAVI, IRECI, LAI and fAPAR reported the highest accuracy (R^2=0.77). The combination model was used to generate the yield prediction map. The ground truth data were referred for evaluation of satellite remote sensing data between the observed and predicted yields.

The developed decision support system was integrated with expert system, GIS, and Sentinel II satellite datasets to evaluate land suitability and prediction of cassava yield from vegetation indices and biophysical properties. The developed model can be used for the regional and country levels in land suitability assessment and yield estimation of cassava to maximize production.

Keywords: *AHP (Analytical Hierarchy Process), ANP (Analytical Network Process, Cassava, GIS (Geographic Information System), Yield Prediction.*

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List of Abbreviations

AHP	Analytical Hierarchy Process
ANP	Analytical Network Process
CI	Consistency Index
CN	Cyanide
CR	Consistency Ratio
ESA	European Space Agency
FAO	Food Agriculture Organization
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation
F-MCDM	Fuzzy Multi Criteria Decision Method
GIS	Geographic Information Systems
GPS	Global Positioning System
HCN	Cyanide Acid
IRECI	Inverted Red-Edge Chlorophyll Index
LAI	Leaf Area Index
LULC	Land Use Land Cover
MCDM	Multi Criteria Decision Method
OLI	Operational Land Imager
OWA	Ordered Weighted Averaging
PAR	Photosynthetically Active Radiation
NDVI	Normalized Difference Vegetation Index
NIR	Near Infra-Red
RS	Remote Sensing
SAVI	Soil Adjusted Vegetation Index
SNAP	The Sentinel Application Platform
SPOT	Satellite pour l'Observation de la Terre
TM	Thematic Mapper
USD	United States Dollar
VI	Vegetation Index
WLC	Weighted Linear Combination

List of Nomenclature

C	Criteria
X	Normalized of Criteria
W	Weight
V	Initial Consistency Vectors
S	Suitability Index
λ	Principal Eigen Value
μ	Fuzzy Membership Value
Σ	Mean Value
CI	Consistency Index
CR	Consistency Ratio
R	Reflectance
f_1	Spread
f_2	Midpoint
L	Soil adjusted factor

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CHAPTER 1
Introduction

1.1 Background

Indonesia is one of the developing countries 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 security (Khush, 2005). To mitigate this dependency and support food security, diversification through the production and consumption of local foods, such as cassava, is one of the potential measure **(Figure 1.1)**. Cassava is a good alternative that poses fewer risks as a root crop and plays an essential role in Indonesia, which is one of few Asian countries to support sustainable local food production (Campo *et al.*, 2011; Noerwijati and Budiono 2015; Feenstra 1997). 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).

As the third most important source of calories after rice and maize in the in the tropical area, cassava has good adaptability in many environments and its ability to produce reasonable yields. This capability is different from most crops. Cassava could make the basis for food security at the household level and a significant source of dietary energy. This crop is an essential part of the diet of people especially in Africa, Asia, and Latin America. Cassava provides an income for millions of farmers, and many processors and traders worldwide. Cassava also has played an important role in Indonesia as well as in most Asian countries (Kolawole *et al.*, 2010; Campo *et al.*, 2011; Noerwijati & Budiono, 2015).

In Indonesia, cassava production utilizes a significant employer of rural labor. It is also has improved the economic condition of rural communities. The role of cassava in the economic area was developed through farm income stabilization and industrial mobilization. However, declining of land use practices and yield of cassava production is a concern in Indonesia nowadays **(Figure 1.2)**. Land use changes have been increased in Indonesia, especially cassava practicing regions has decreased. Inappropriate decision and absence of multi-criteria on land selection also limits productivity.

Furthermore, cassava production can adapt under sustainable use of land by smallholders who gets the effect of most from climate change issue. The impacts of climate change are locally specific and challenging to predict in highly uncertain circumstances. Due to this issue, the optimum window is needed to schedule harvesting of cassava using a yield prediction model for regional inventory planning to ensure food security.

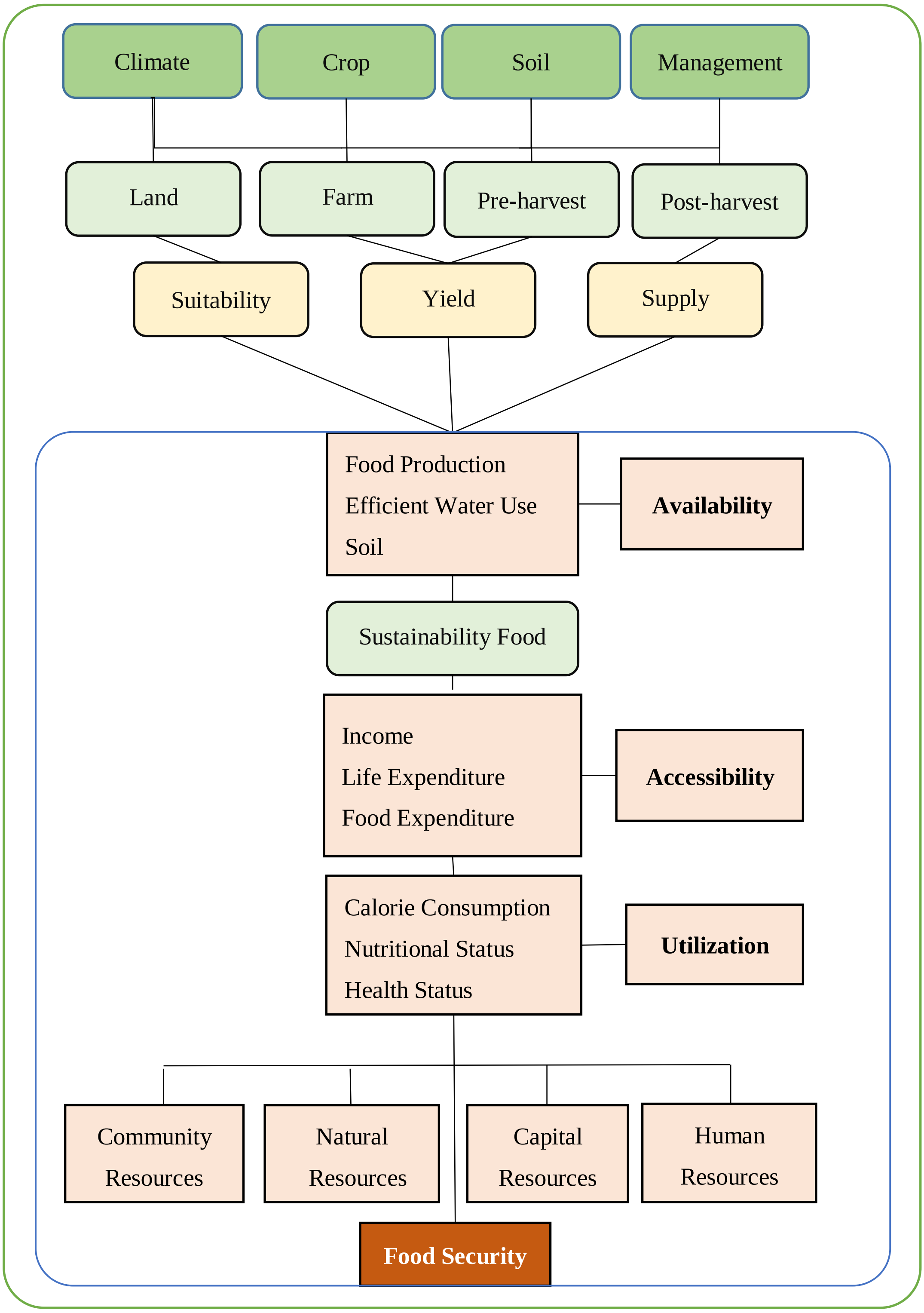
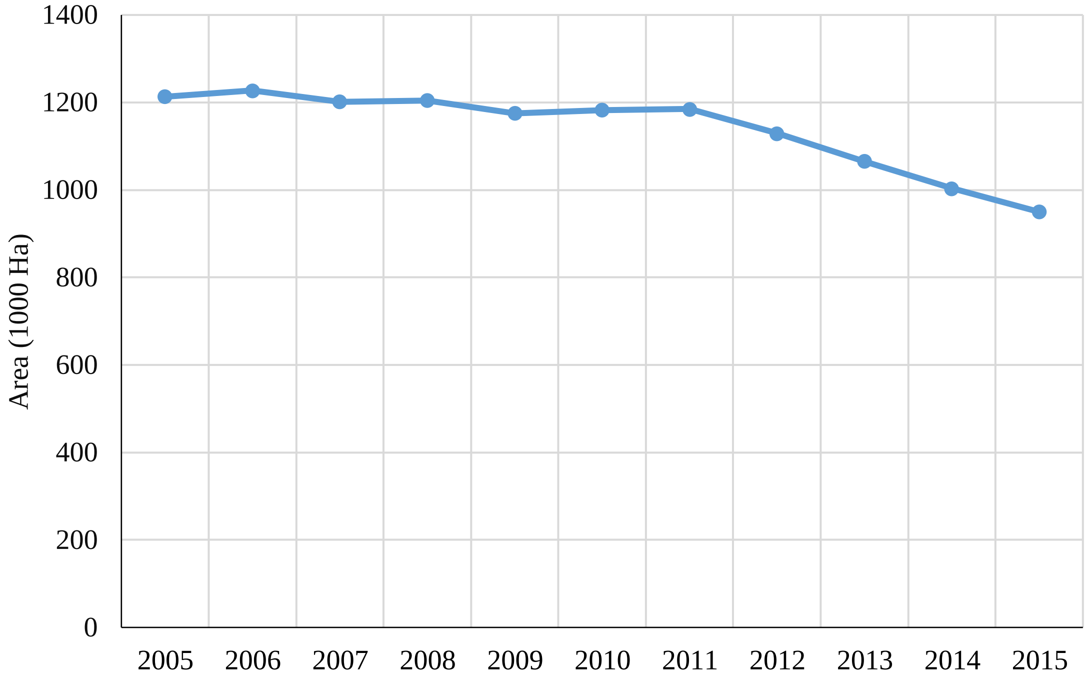
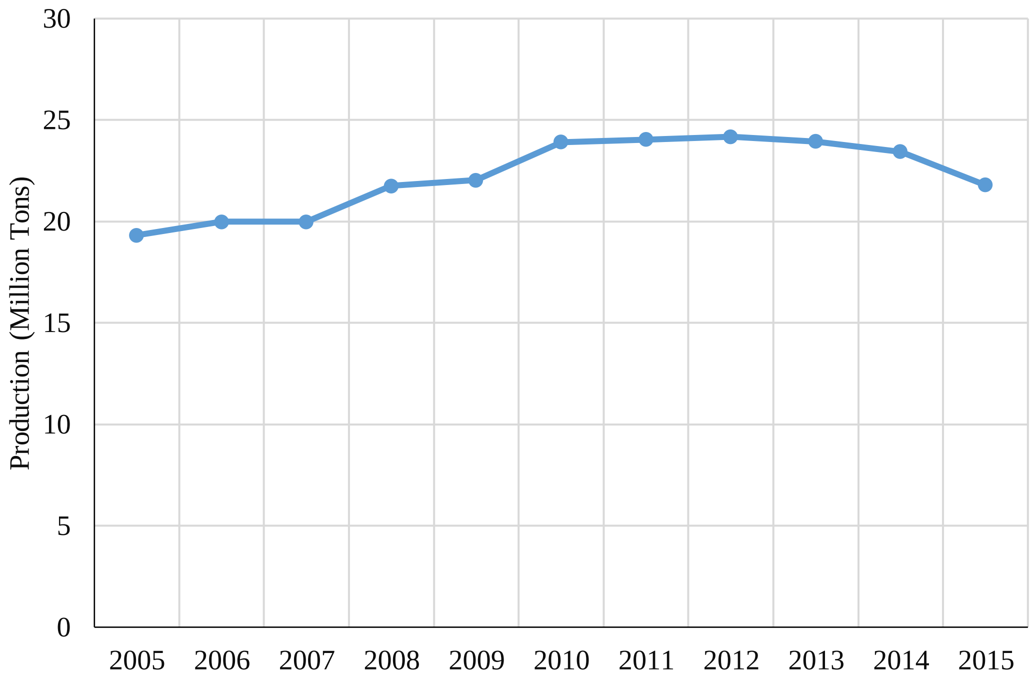


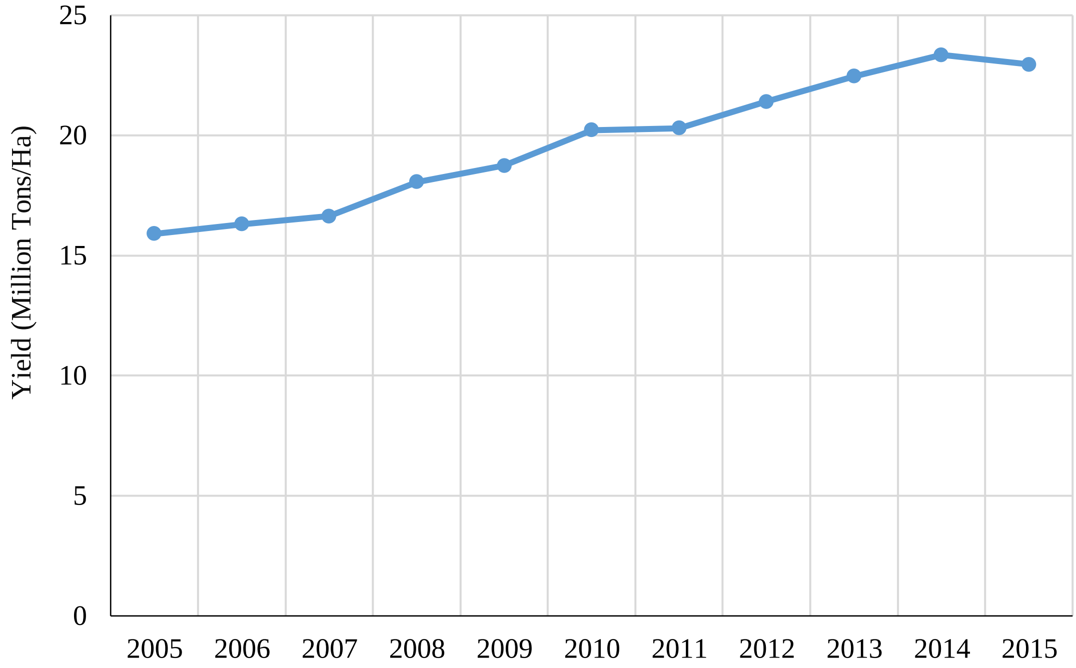
Figure 1.1 Food Security Concepts



(a) Cassava harvested area in Indonesia (2005-2015)



(b) Cassava production in Indonesia (2005-2015)



(c) Cassava productivity in Indonesia (2005-2015)

Figure 1.2 The declining area and yield of cassava production in Indonesia

In this case, suitable areas and ecological conditions of cassava must be identified (Heumann *et al.*, 2011). 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, the land is 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 the time.

Therefore, investigating land suitability depends on multiple criteria and factors in the decision-making process that can be broadly assessed using geospatial datasets (Ceballos-Silva and Lopez-Blanco, 2003). 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). Also, 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 play a significant 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 inform the decision-making process of land suitability (Vrieling *et al*., 2011).

It greatly benefits strategic planning for developing countries when the potential yield of cassava according to their specific environmental, inputs and management needs to analyze the suitability land condition. Monitoring the cassava production, including the potential yield, diseases, and drought conditions within the spatial and temporal knowledge of regions. The monitoring process also could serve for early warning systems. Early assessment of yield reductions could help in strategic planning to forecast the crop production process.

1.2 Problem Statement, Justification and Novelty of Research

The increasing yield of cassava crop is one of the most important issues related to national food policy in Indonesia. Inappropriate decision and absence of multi-criteria on land selection also limits productivity. The most appropriate algorithm for land suitability assessment is essential for current and future land use planning. Several approaches of Multi-Criteria Decision Method (MCDM) using expert's systems have been attempted to conduct land suitability assessment. In recent years, computing technologies combined with GIS have enabled few contributions using the land evaluation FAO framework. Analytical Hierarchy Process (AHP), Analytical Network Process (ANP) & Fuzzy Expert System has the potential to include inland selection procedures for cassava.

Furthermore, considering cassava as the root crop, prediction of yield using vegetation indices (VIs) and biophysical properties is very important to maximize yield before harvesting. The most straightforward approach to estimating crop yields is to establish empirical relationships between ground-based yield measures and VIs measured on a single date or integrated over the growing season (Tucker, 1979). However, the measurement for each field in a large area of a region in the country is time-consuming and not efficient. In this regard, remote sensing technology and GIS applications for monitoring crop condition have been studied during the past several decades, providing timely assessment of changes in growth and development of crops. Numerous approaches developed for estimating crop yields with remote sensing (Sakamoto *et al.*, 2013; Lobell *et al.*, 2015). However, there is a lack of researches for cassava, which is a root crop requires yield estimations based on the canopy and biomass development over the growing seasons. In our best knowledge, there are no research reported about the cassava yield estimation related to find out an optimum window to harvest of cassava. The yield prediction also helps in regional food security policy and inventory to understand the availability of cassava. Therefore, developing an optimum window is needed to schedule harvesting of cassava using a yield prediction model for regional inventory planning to ensure food security.

1.3 Research Questions

The concerning points for declining of land use practices needs to identify and cassava production needs to increase to ensure the food security in Indonesia. Therefore, the following research questions are set to guide our research:

1. How to evaluate the land use changes and cassava production regionally?
2. How to include stakeholders and expert's opinions for land suitability assessment to increase cassava production?
3. How to develop a geo-spatial method considering decision support system (DSS) and multi-criteria for selection of suitable lands to increase cassava production?
4. How to predict yield of cassava with good accuracy before harvesting for inventory planning?

1.4 Research Objectives

A significant research endeavor is required to bring the solution of the research questions to ensure sustainability of cassava production in Indonesia. GIS technology and remote sensing application can be integrated to get the significant model that applicable for stakeholder, farmer, and government to support the regional food security. The remote sensing application through satellite image-based vegetation indices could be used for predicting the cassava yield. An analysis of the availability of suitable land for cassava production and the obtainable yields is essential information for government policymakers and investors. Therefore, to achieve the goal of sustainable cassava production the following objectives are determined to carry out the research:

1. To evaluate land use changes of cassava growing areas in a regional perspective in Indonesia.
2. To develop a geo-spatial land suitability model using Multi-criteria Decision Method (MCDM) based on AHP and ANP for including expert's opinion.
3. To develop a land suitability model for cassava production using Fuzzy Multi Criteria Decision Method (F-MCDM) and compare with MCDM.
4. To predict the yield of cassava for regional inventory planning to ensure food security using satellite imagery.

1.5 Thesis Chapter Layout and Cognitive Summary

This research aims to present sustainability of cassava production that support by the analysis of yield prediction and land suitability analysis. This study discusses the integration of expert system, GIS application using MCDM, and remote sensing technique.

In Chapter 1, background about the potential of cassava production in Indonesia is explained. In this section, the most important issue has described regarding the challenge for cassava as the potential crop in the future related to yield gap and unsuitable land utilization issue. Several methodologies were developed regarding the yield prediction and land suitability analysis. However, as the essential crop in the developing countries in Asia and Africa, the research for cassava is not developed yet. The challenge is to develop the regional method to assess the yield prediction with the suitable land area to ensure the sustainability of cassava production, especially in Indonesia.

Chapter 2 explains the potential of cassava for food security and sustainable agricultural production. Characteristics of cassava, which is the third most important source of calories in the tropics, after rice and maize, is explained. The methodology overall that connects each of the chapter also described. The development of multicriteria analysis, GIS, and remote sensing application in related research contribution also reported.

Chapter 3 evaluates the sustainability of land use for cassava production. Sustainability indicators for ecology, social, and economic categories are discussed with a vision of reflective practice and form multiple views of sustainability. Within the broad concept of the sustainable agriculture, the sustainability of land use and cassava production are discussed.

In the Chapter 4, the suitability analysis using Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP) is discussed. The most appropriate algorithm for land suitability assessment is essential for current and future land use planning. Several approaches of multi-criteria decision method (MCDM) using expert's systems have been conducted to for land suitability assessment. This chapter explained how to evaluate land suitability using AHP and ANP to represent the MCDM.

In chapter 5, the study area extends to a provincial scale for analysis of suitability using Fuzzy integration with MCDM. The use of fuzzy membership classification is used to accommodate the uncertainty in assigning the suitability classes. The fuzzy set theory allows for the concept of these continuous factors to be modeled within a suitability assessment in the GIS environment.

In the Chapter 6, the yield prediction method is developed using vegetation index employed as the application of the remote sensing technology. The method on this research compared the model based on the vegetation indices and biophysical properties to predict the estimated yield using satellite images from Sentinel-2 under the variability of spatial condition for one region.

Overall conclusions are presented in chapter 7 with recommendations for future work.

CHAPTER 2
Review of Literatures

2.1 Literature Reviews

2.1.1 Characteristics of Cassava

Cassava feed around 800 million people in the world (10% of world population), although roots and tubers cover a much smaller area than cereals as human staple. Cassava is the third most important source of calories in the tropics, after rice and maize in the world. Millions of people depend on cassava in Africa, Asia, and Latin America. This crop has good adaptability in many environments and its ability to produce reasonable yields. Cassava has the potential to be a promising crop that can adapt in changing climatic due to its low water requirement in production compare to rice, wheat and maize. Cassava also plays an important role in Indonesia as well as in the most Asian countries (Kolawole, 2010; Campo *et al*., 2011; Noerwijati & Budiono, 2015). This crop is important source of income for small farmer in developing countries. Almost 60 percent of world production of cassava concentrated in five countries Nigeria, Brazil, Thailand, Indonesia and the Congo Democratic Republic **(Figure 2.1 and Figure 2.2)**.

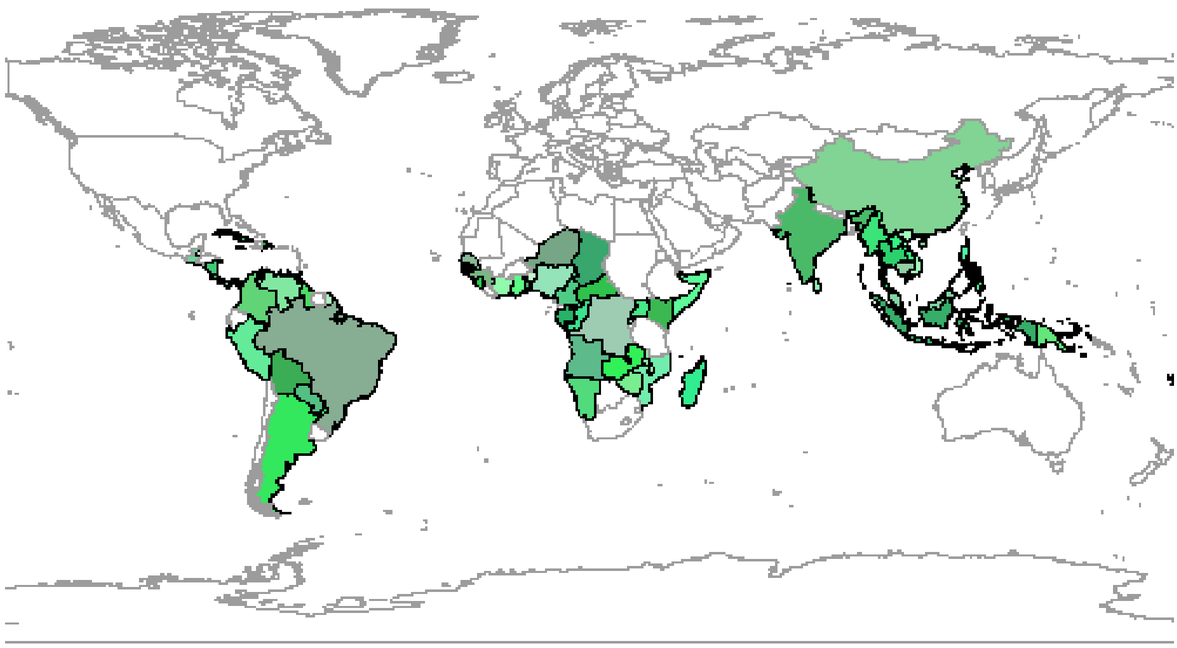


Figure 2.1 Cassava growing area in the world

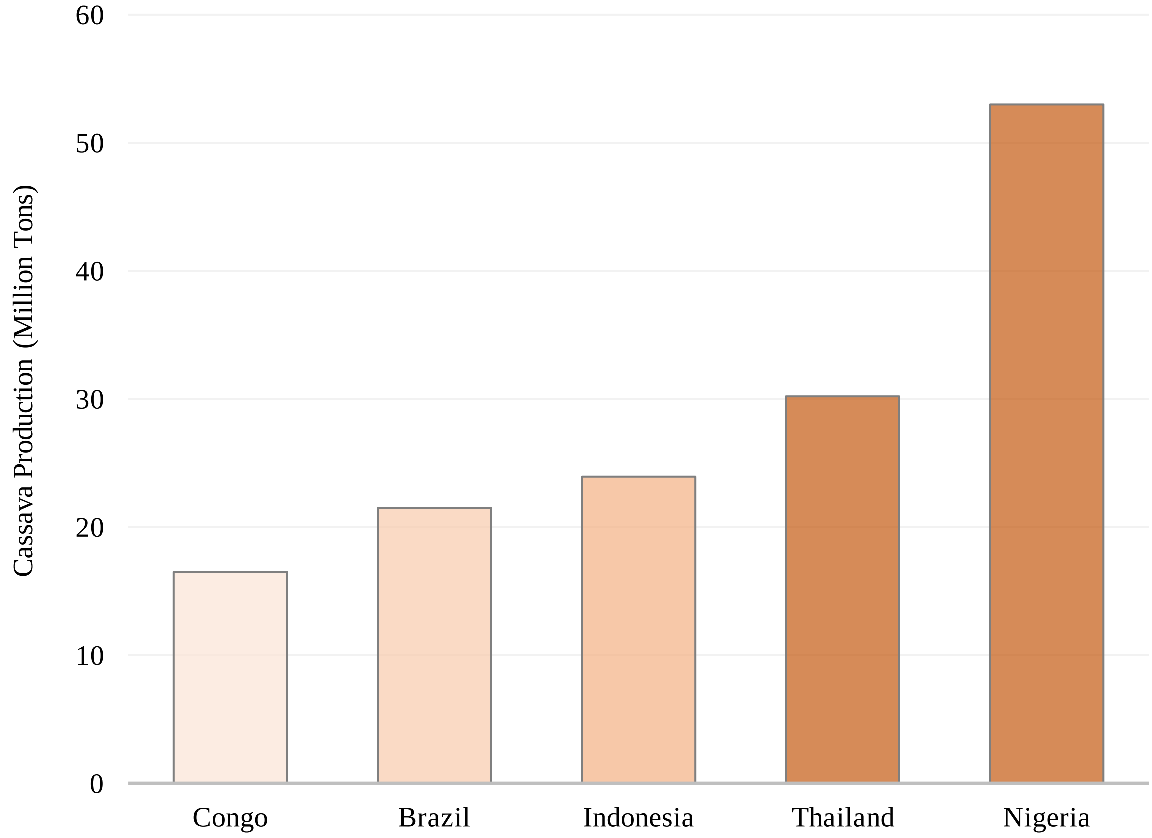


Figure 2.2 Cassava growing dominating regions worldwide

Figure 2.3 Cassava cultivation in Banten province, Indonesia

Cassava roots contain more than 60 percent water. However, that roots also contain high carbohydrates, is about 250 to 300 kg for every ton of fresh cassava roots **(Figure 2.3)**. The optimal time to harvest root as food is about 8 to 12 months after planting, a more extended period produces a higher starch yield. Some varieties of cassava need the post-harvest process to eliminate cyanide (CN). The excellent processing requires to peel, soak, ferment and boil to reduce the HCN (Howeler, 1991).

Indonesia is one of the countries that produces a good amount of cassava. Cassava is one of commodities that the production increases each year and has potential to produce as local and export product**.** As a raw material of some industries, some kind of processed cassava products such as dried chips (namely *gaplek*), tapioca flour, modified cassava flour (mocaf), and cassava rice. Various products of cassava lead to the farmer to plant cassava as potential product with high profit product. Presently, some traditional products of cassava are made by some home industries or small and medium enterprises.

On the contrary, cassava is usually grown by poor farmers in marginal areas. However, the potentially high yields of cassava can guarantee farmers food from small cropped areas, leaving a larger hectarage for crops with high-income potential (Pakpahan *et al*., 1993). The farmer still in the weak position and limited information to produce and market accessibility. The role logistic and supply chain system is needed to increase value addition to cassava.

2.1.2 Land Suitability

Suitability analysis could provide a good starting point for sustainability evaluation of local cassava production. The suitability of land use has defined as the fitness of a given type of land for a specified kind of land use (FAO, 1976). The land evaluation framework can use to explain how the sustainability works. Agricultural suitability analysis is the process of determining the suitability of a given land area for agricultural use and the level of suitability. An essential part of this process is the determination of the criteria that affect the suitability of the land. The utilization of various and multiple criteria makes land-use suitability analysis complex. It is because such criteria as the socio-economic and environmental must be taken to consider the sustainability of land use.

There is no specific standard concerning the criteria to be taken into consideration when assessing land suitability potential for agriculture and that the criteria used in similar studies are usually those that are accessible. In these types of studies, the land use, land cover type, topographical, rainfall, stream, and road distance were used. The suitability classification aims to show the suitability of each land unit for each land use. In FAO's Framework for Land Evaluation, four classes (S1, S2, S3, N) often used to distinguish land that is highly suitable, moderately suitable, marginally suitable, and not suitable for a particular use **(Table 2.1).**

2.1.3 Analytical Hierarchy Process (AHP)

The AHP developed by Saaty (Saaty, 1980). The principles utilized in AHP to solve problems with hierarchies' construction. The Analytic Hierarchy Process (AHP) method commonly used in multi-criteria decision-method (MCDM) exercises was found to be a useful method to determine the weights. multi-criteria decision-method (MCDM) is a set of procedures to analyze the complex decision problems (Malczewski 1999). The AHP has three basic steps. It begins by decomposing the overall goal into a number of criteria and sub-criteria. The goal itself represents the top level of the hierarchy. Major criteria comprise level two, sub-criteria make up level three, and so on.

As the first step the decomposition was designed to solve the problems of the elements into a hierarchy of decision-making process. This hierarchy makes problem more easily to analyze. The form of the decomposition structure; first level (goal), second level (criteria), third level (sub criteria), and fourth level (alternative)

After deciding the criteria and sub-criteria, the second step is deciding and calculate the relative importance between each pair of criteria. The priority of each factor involved in the AHP analysis is determined based principally on the experts and reference opinions. AHP uses a fundamental scale of absolute numbers to express individual preferences or judgment. This scale consists of nine points. In general, nine objects are the most which an individual can simultaneously compare and consistently rank. The score of differential scoring presumes that the row criterion is of equal or greater importance than the column criterion. The reciprocal values (1/3, 1/5, 1/7, 1/9) have been used where the row criterion is less important than the column criterion **(Table 2.2)**.

Then the last step was to ensure the credibility of the relative significance used. AHP provides measures to determine inconsistency of judgments mathematically. Based on the properties of reciprocal matrices, the consistency ratio (CR) can be calculated. CR < 0.10 indicates that level of consistency in the pairwise comparison is acceptable (Saaty, 1980). However, if it is larger than 0.10, then there are inconsistencies in the evaluation process, and the experts should reconsider the judgment.

Table 2.1. Suitability classes

Order	**Class**	**Description**
Suitable	S1 (Highly suitable)	Land having no, or insignificant limitations to the given type of use
	S2 (Moderately suitable)	Land having minor limitations to the given type of use
	S3 (Marginally suitable)	Land having moderate limitations to the given type of use
Not suitable	N (not suitable)	Land having severe limitations that preclude the given type of use, but can be improved by specific management or have so severe limitations that are very difficult to be overcome

Table 2.2. The preference scale for pair wise comparison in AHP

Scale	Degree of preference	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one factor over another	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 the two adjacent judgments	When compromise is needed
Reciprocals	Opposites	Used for inverse comparison

2.1.4 Geographical System Analysis (GIS)

Geospatial technologies such as Remote Sensing (RS), Geographical Information System(GIS) and Global Positioning System (GPS) that use to develop precision agriculture technologies for different crops. Precision agriculture is the application of principles and technologies to manage spatial and temporal variability with all aspects of agricultural production to improve crop production based on environmental friendly. Geographical information system (GIS) is the organized system of computer hardware, software and geographic database that designed to create, store, update, manipulate, analyze and display all forms of geographically referenced information (Peters *et al.*, 2009)

GIS has used in a number of studies examining availability, accessibility, and suitability including environmental and agricultural issues. There are a number of studies have been contributed explicitly through mapping and reported on food and crops production (Bosona *et al.,* 2013; Eckert *et al.*, 2011). Raster GIS has the benefit to collect data for all geographic features, images, and surfaces. In the geographic distribution, GIS has been recognizing widely to integrate the databases of food production, market distribution and community assessment. In this research, raster GIS use to produce the matrix that shows the model of suitable location for local food based on sustainable pillars including ecology, social, and economic.

CHAPTER 3
Sustainability of Land Use Management of Cassava Production to Ensure Regional Food Security in Indonesia

3.1 Background

Cassava production in Indonesia requires detail assessments to increase production and farmers adoption of this low-water intake root crop in regional context of climate change. 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.

The ecological, social and economic indicators need to analyze for sustainable production of cassava in the regional context. Sustainability concept stands for minimizing external inputs, maximizing benefits and maintains the quality of natural resources over the time (Bell and Morse, 2008; Ahamed *et al*., 2015). This concept integrates with the environment, ecology, economy and social aspects, and extends from natural resources to local food production to ensure food security in the changing climates (Sydorovych and Wossink, 2008; Tiwari *et al*., 1999). 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 are required for locating suitable production areas to increase cassava production.

The geo-spatial analysis for time series datasets can ensure monitoring system for land use management in cassava production. The application of satellite database can be used to detect the land use changing over the time to evaluate the sustainable of land use management for cassava production.

3.2 Objectives

Sustainability of land use management is important to increase cassava productivity. Several indicators needed to assess the sustainability evaluation. Therefore, following specific objectives are considered in this chapter to analyses the land suitability management for cassava production.

1. To find the indicators that influence cassava production regionally and increase the productivity to ensure sustainability through maximizing the net economic return with protecting environment.

2. To develop time series datasets for regional cultivation of cassava to understand the sustainability through GIS and satellite remote sensing application.

3.3 Methodology

3.3.1 Study Area

Geographically, the city of Serang located at 5° 99′ -6° 22′ south and 106° 07′ -106° 25′ east. 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 located approximately 70 km away. The city includes six districts and 46 villages and covers a total area of 266.7 km^2 **(Figure 3.1)**. Most of the area is flat land with an elevation less than 500 meters and characterized by a tropical climate. 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. Residences 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 found in the southern area.

3.3.2 The Framework of Sustainability Evaluation

The study begun with measuring the sustainability of cassava for local fod production. There are numbers of indicators and frameworks for sustainability assessment (Hák *et al*., 2007). This research used the pillars from agro-ecological sustainability indicators that has enriched to several criteria such as; availability, accessibility, affordability, and profitability. 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). This study, 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 **(Figure 3.2).**

This research evaluated the sustainability levels of cassava production using four categories and images from the satellite database **(Figure 3.3)**. Primary data were collected through fieldwork involving questionnaires, interviews, and surveys. Additionally, secondary data from Statistics Indonesia and the Indonesian Geospatial Agency were used.

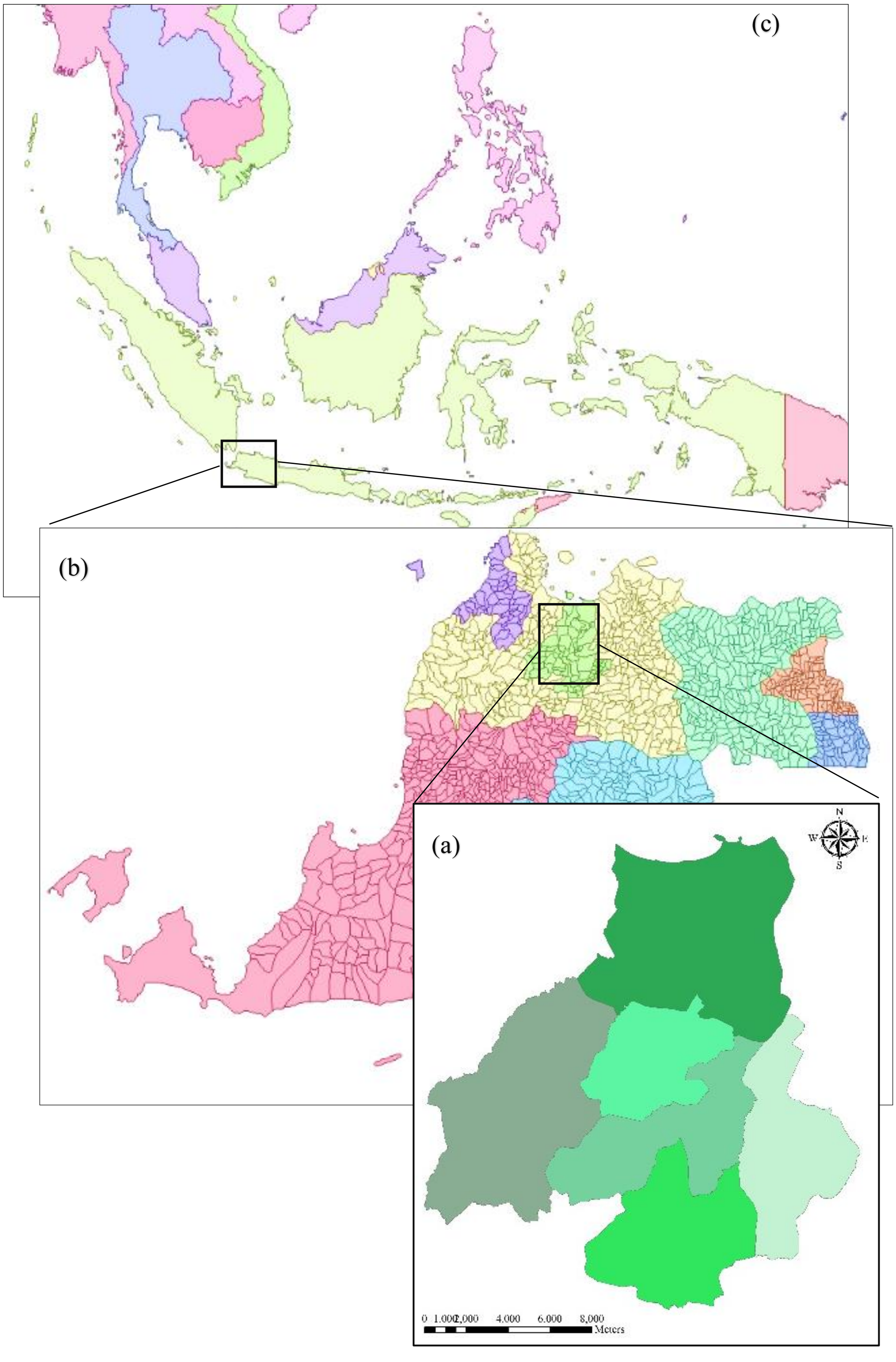


Figure 3.1. Study area selection at Serang city (a), Banten province (b), Indonesia (c)

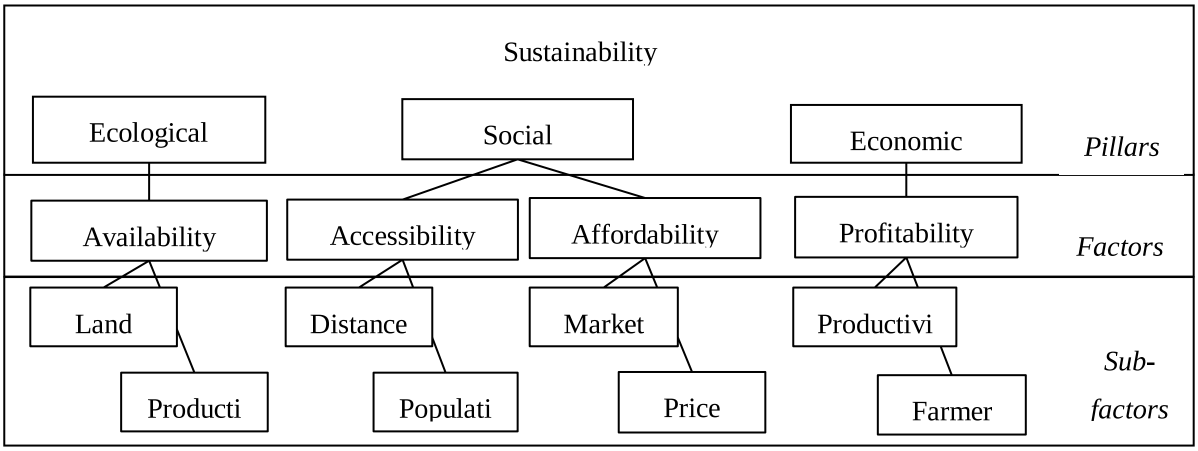


Figure 3.2 Criteria of sustainability evaluation of cassava production

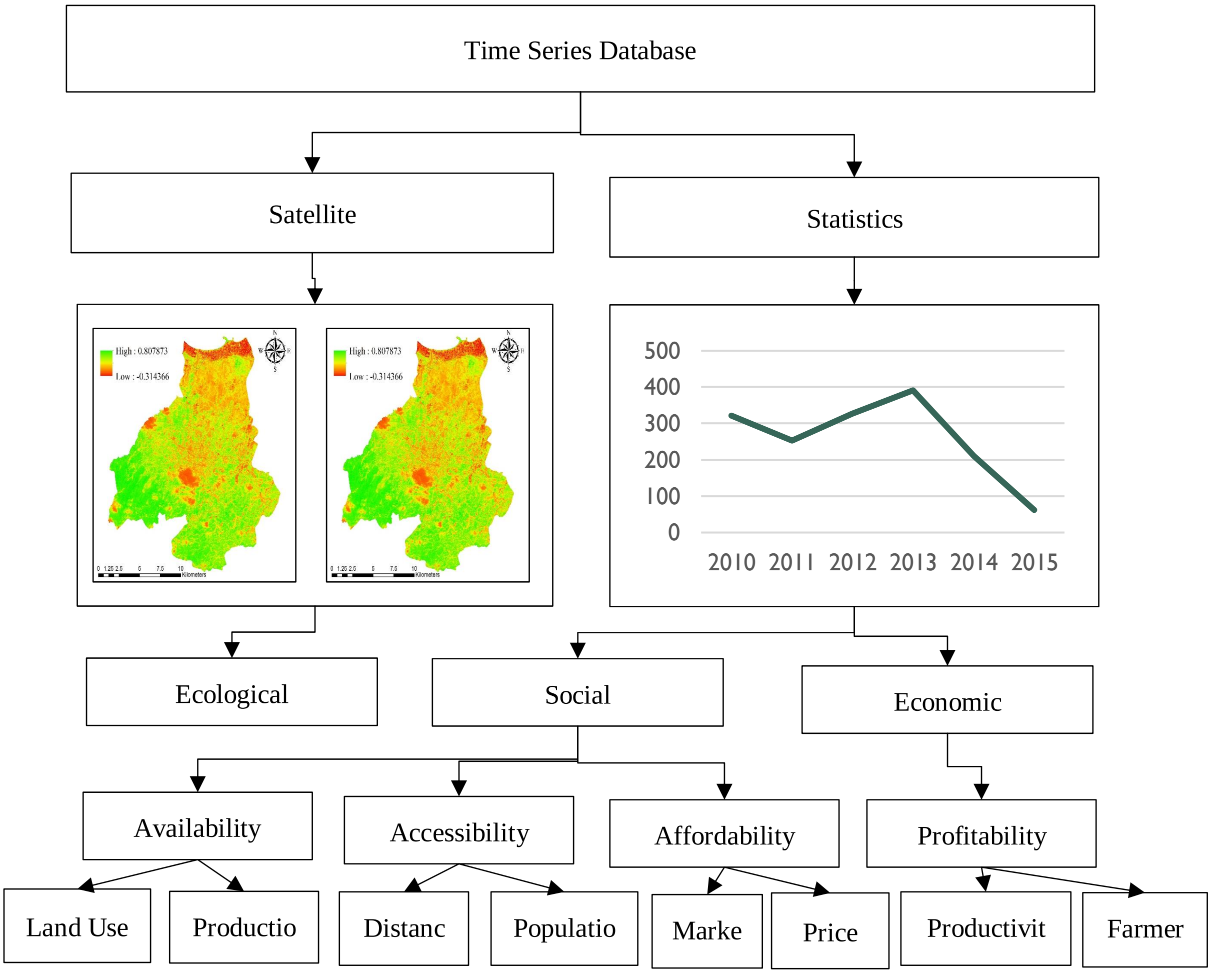


Figure 3.3. Sustainability evaluation framework

3.4 Results

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. The primary assessment developed from field surveys and discussion with experts. Then the secondary data from 2010 to 2015 were collected from Indonesian statistics. Using the sustainability approach, the criteria and factors developed used for monitoring the cassava production over the 2011-2015 years in the Serang city. Those criteria and factors are very important components in achieving cassava production as an integral part of the sustainable development in the Serang city. Over the period examined, production and land use were under sustainable due to a shift from agricultural to settlement land use. The land of cassava fields from 2010 to 2015 was decreased 3.38% annually based on our collected data **(Table 3.1 and Figure 3.4)**.

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) **(Figure 3.5)**. 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.

The criteria were under sustainable such as Land use, Production, and Productivity. These criteria were used to further analysis of suitability. This result was used for the reason to identify the suitable land use for cassava production. This research can be extended to enhance for the socio-techno entrepreneurship for local foods with the partnership of government, famers market, and local entrepreneur who were involved with processing of local food and distribute throughout the city. The GPS local access points for the farmers market and entrepreneur places must be identified to perform the network analysis and the local food matrix of identically location throughout the Serang city.

Table 3.1. Agricultural data assessment from 2010 to 2015 (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	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

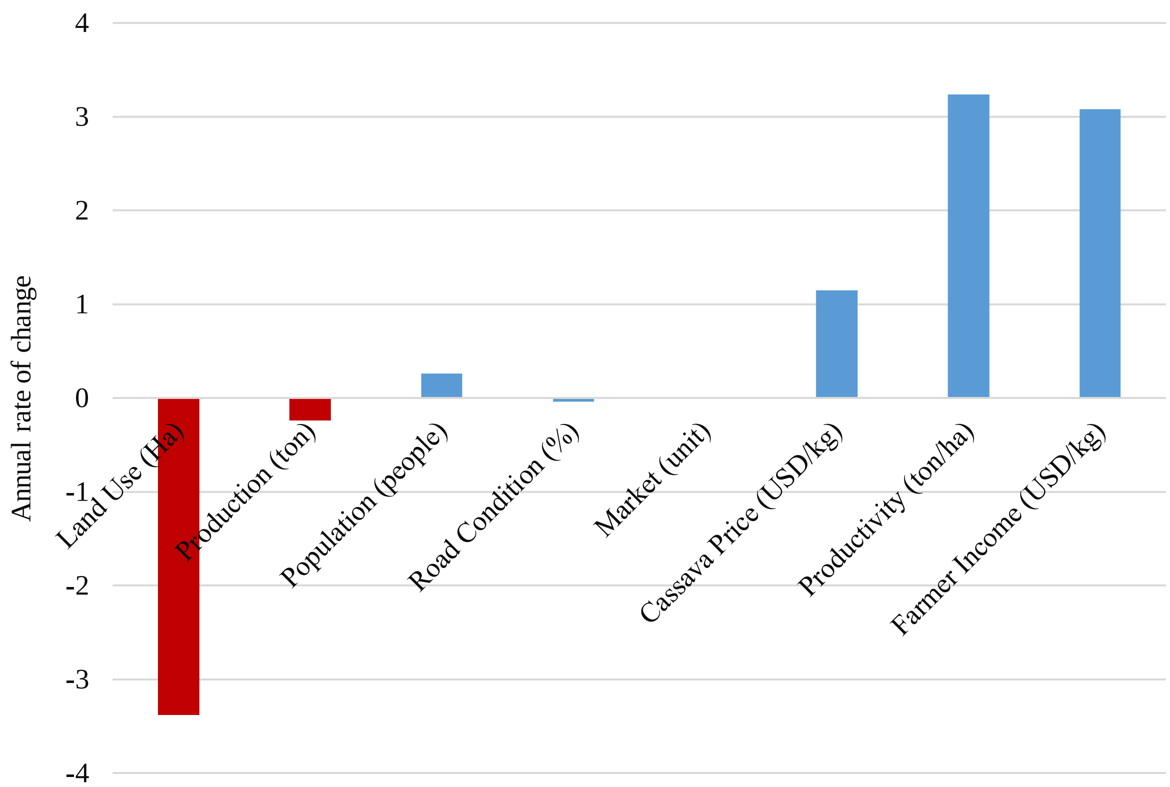
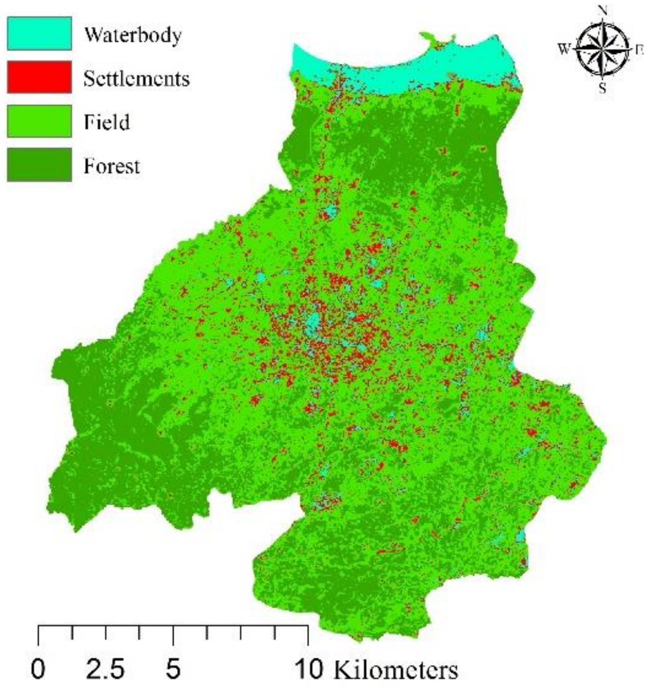
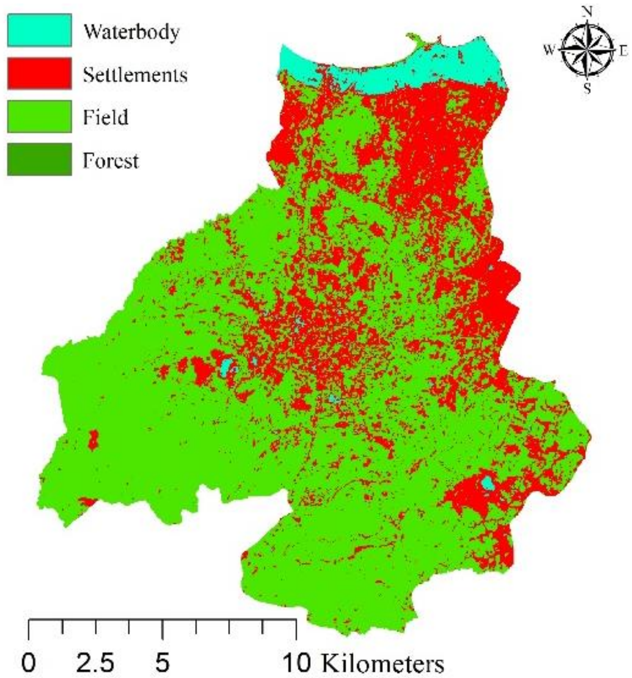


Figure 3.4 Annual rate of change for agriculture sustainability assessment in Serang city



(a) Serang city in 2010



(b) Serang city in 2016

Figure 3.5 (a-b). Land use changes in Serang city drawn from Landsat satellite information for 2010 and 2016

3.5 Discussion

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 by 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 criteria and factors for sustainability assessment are very important components in achieving cassava production as an integral part of the sustainable development in the Serang city. Therefore, from the result of the sustainability approach, the factors were not sustainable was land use. This result was used for the reason to identify the suitable land use for cassava production. Because land use efficiency will support higher economic returns.

3.6 Summary

The main contribution of this part was the identification of the sustainability. The result of this study appeared as practically useful for the development of local food system utilization. Additionally, final output of this study could be used for generating alternative scenarios of local food management based upon the social, economic, and ecology aspects. This logistic model could serve as a significant role to government and entrepreneur to identify the most suitable locations to increase local food capacity against the changing climates. This research can be extended to enhance for the socio-techno entrepreneurship for local foods with the partnership of government, famers market, and local entrepreneur who were involved with processing of local food and distribute throughout the city. The GPS local access points for the farmers market and entrepreneur places must be identified to perform the network analysis and the local food matrix of identically location throughout the Serang city. In the further part, the suitability of land analysis need to be developed. Hence, the spatial assessments of land suitable for cassava production could serve as a starting point for sustainability evaluations.

CHAPTER 4

Land Suitability Model for Cassava Production Using GIS, AHP and ANP (MCDM)

4.1 Background

Land suitability assessments are essential for sustainable land use and the selection of cassava in the changig climates of Indonesia. Sustainable land use for cassava production significantly drives maximizing the production of cassava to contribute to the food security of Indonesia. To support the suitability analysis, geographic information systems (GIS) have been used to conduct spatial studies of suitability for various purposes, mainly land suitability (Ferretti and Pomarico, 2013; Malczewski, 2006; Smyth and Dumanski, 1993).

The investigating of land suitability depends on multiple criteria and factors that can be assessed using geospatial datasets (Ceballos-Silva and Lopez-Blanco, 2003). A critical method of land suitability assessment for cassava production is to determine the weight of each factor that influences land suitability. The presence of various and multi-criteria decision-method (MCDM) in land suitability assessment is complicated (Elsheikh *et al*., 2013). The complication of weight also varies by location, land use, and productivity. The criteria for evaluation are sometimes dependent on geographical aspects and the socio-economic status of the country. There is the number of multi-criteria decision rules has been implemented to solve the land-use suitability problems.

The MCDM rules can be classified into multi-objective and multi-attribute decision-making methods (Malczewski 1999, 2006). The multi-objective approaches are mathematical programming model-oriented methods such as linear programming. The single-objective multi-criteria evaluation had a 'goal' and computed using multi-attribute analysis. The methodology has several ways to weight the criteria such as ordered weighted averaging (OWA) using a 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 (Feizizadeh and Blaschke, 2014). AHP method uses the 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 AHP is a MCDM 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). Meanwhile, ANP is a nonlinear structure with bilateral relationships (Azizi *et al*., 2014). The

AHP and ANP have the advantage of assigning weights based on the preferences of experts for the regional concepts and can be 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 2006).

Furthermore, GIS and MCD tools have recently been used for land suitability assessment and planning for suitability of agricultural land use, major crops and local foods (Pramanik, 2016, Akinci *et al*., 2013; Bunruamkaew and Murayama, 2011; Elsheikh *et al*., 2013, 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.

4.2 Objectives

In recent years, computing technologies combined with GIS have included geospatial criteria to help find solutions for land suitability at the regional scale. GIS, remote sensing and MCDM can be used in land suitability analysis for various criteria related to ecological conditions or maximizing cassava production at the regional scale in Indonesia. Therefore, following specific objectives are considered in this part of the research to develop a spatial model to assess land suitability levels for cassava production.

1. To develop a geo-spatial model to assess land suitability levels for cassava production in the sub-district level integrating GIS, remote sensing and multi criteria analysis.
2. To determine the weight of each criteria that influences land suitability using MCDM employing AHP.
3. To determine the influence of each criteria and interaction that influences geo-spatial land suitability model using MCDM employing ANP.

4.3 Methodology

4.3.1 Study Area

The studied area, Serang City was one of the seven districts of Banten Province. The city was 70 km away from the Jakarta city and located towards the north of Banten province. Location of Serang City, using the coordinate system is UTM (Universal Transfer Mercator) located at coordinates 618,000 m up to 638 600 from west to east and 9,337,725 m up to 9,312,475 m from north to south. The total area of Serang city was 266.7 km2 which was bounded by: North: Java Sea, East: Serang Regency, West: Serang Regency, South: Serang Regenc. Serang City consists of 6 districts, 20 urban village and 46 village. The names of the districts as follows; district of Cipocok Jaya (8 sub districts), district of Curug (10 villages), district of Kasemen (10 villages), district of Serang (12 sub districts), district of Taktakan (12 villages), and district of Walantaka (14 villages) **(Figure 4.1)**.

4.3.2 The Framework of Suitability Analysis

Geographic proximity had been related to sustainability for a variety of reasons, encompassing the ecological, economic and social dimensions of the food system (Gatrell *et al.*, 2011). This work was assessed the potential suitable areas for local food production and distribution using GIS, AHP and ANP. The data, boundary maps, land use and land cover, topography map were collected from Indonesia Geospatial Agency. The statistical data of demographic and socio-economic aspect like number of gender, age of workers and number of educated people were collected from the population census. This research was divided into three parts: first, was predicted the sustainability, second, was decided the criteria for suitability analysis, and third was analyzed to obtain the most suitable area for developing cassava as local food with GIS based AHP and ANP method **(Figure 4.2).**

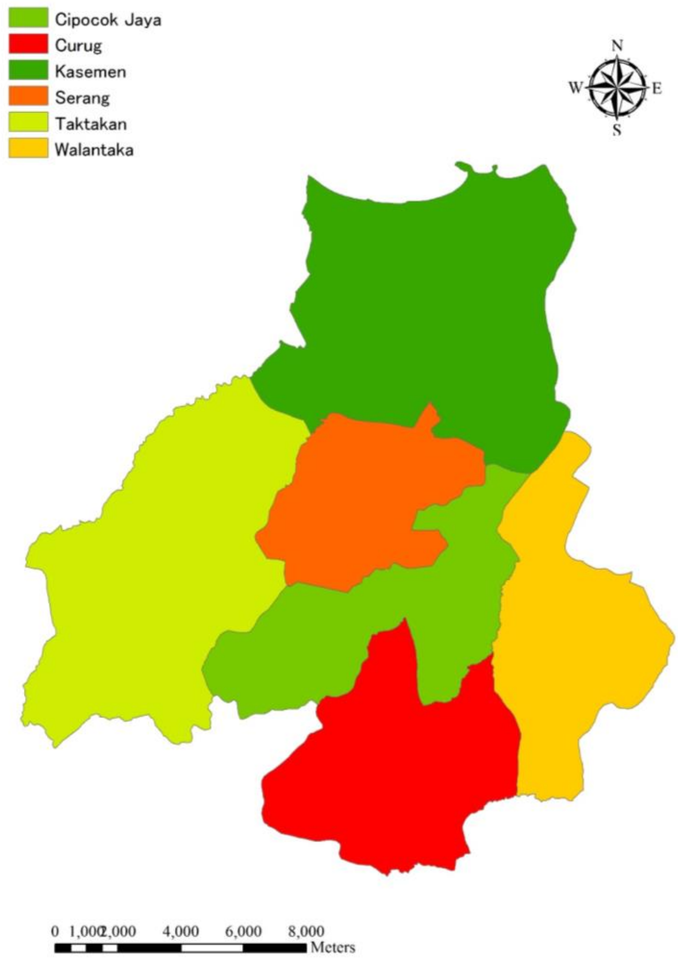


Figure 4.1 Map of Serang city, Banten province, Indonesia

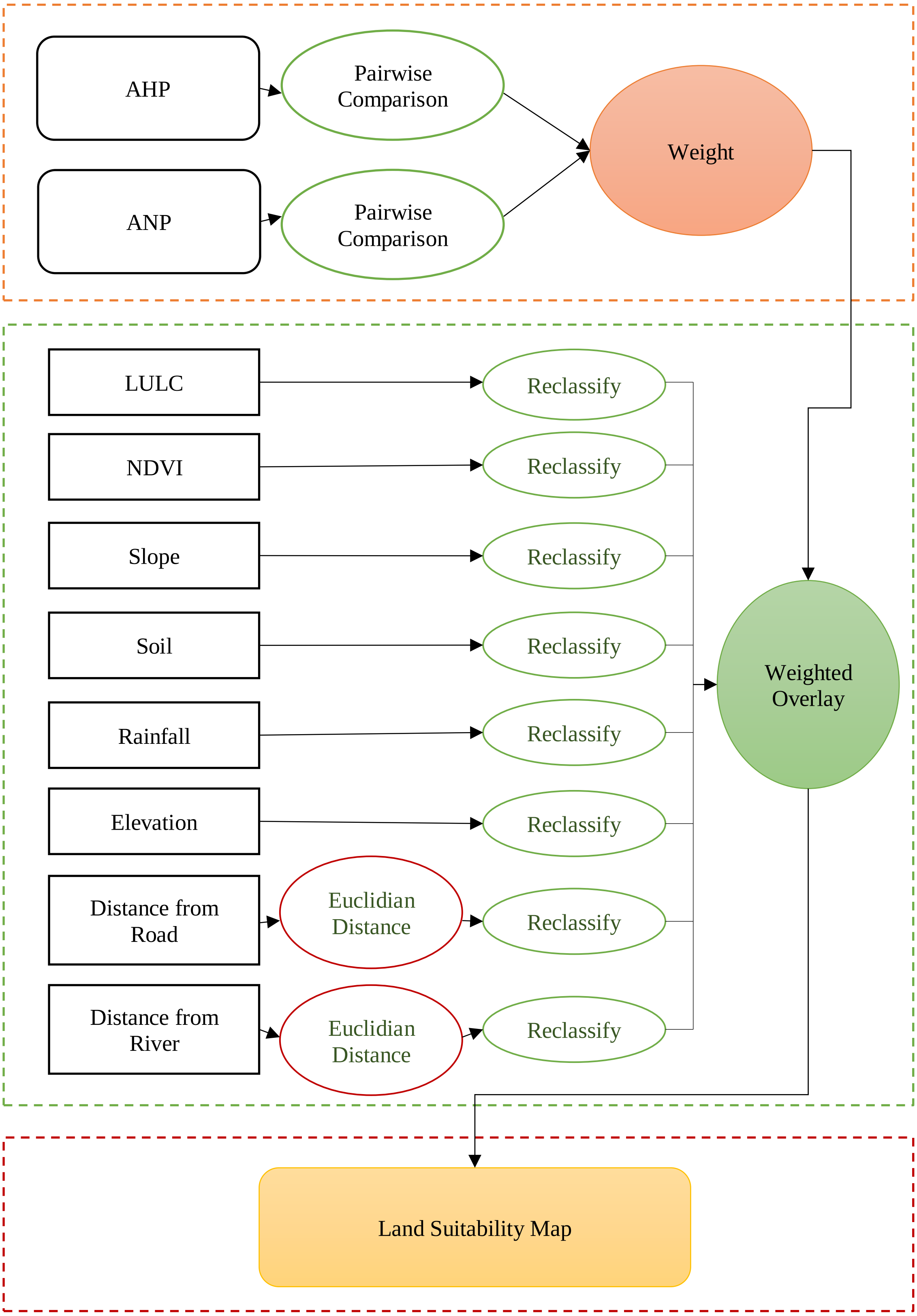


Figure 4.2. The framework of land suitability analysis

4.3.3 Geographical Extent of Serang City

4.3.3.1 Land Use/Land Cover

The land of Serang city had coastal land in North area, rural area both in South and North part and urban area in the middle of the city. The urban area consisted of facilities related with infrastructure to support the socio-economic aspect. Residence was also concentrated in the central part of the city. In the north, the land use was dominated for rice land, while a field and dry land located in the southern part.

4.3.3.2 Slope

Serang city area mostly flat land area with elevation less than 500 meter. Most of topography contour at Serang City classified as variety of flat with slopes of between 0% and 45% steepness. The variety of the area in terms of slope was a factor in the suitability analysis for cassava production. This factor was affected a varying degree, a complexity and slope of area.

4.3.3.3 Distance from River

Cibanten, the main river of the Serang city had a multifunctional dam. The purpose of this river was to supply the clean water and also for the irrigation system supply. There were the others river named Cilandak, Cikaduan, Cikarang, Cipari, and Pelamunan.

4.3.3.4 Rainfall

Serang has a tropical climate. There is significant rainfall throughout the year in Serang. Even the driest month still has a lot of rainfall. The temperature here averages 27.4 °C. The rainfall here averages 1500-2000 mm/year.

4.3.3.5 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 and Sudaryanto (2000), latosol areas are optimal for cultivating cassava.

4.3.3.6 Elevation

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.

4.3.3.7 Distance from Road

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.

4.3.3.8 Vegetation Index

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).

4.3.4 Suitability Assessment

The utilization of various and multiple criteria makes land use suitability analysis increasingly complex because such criteria as the socio-economic and environmental must be taken to consider the sustainability of land use. There is no certain standard concerning the criteria to be taken into consideration when assessing land suitability potential for agriculture and that the criteria used in similar studies are usually those that are accessible.

In these types of studies, the land cover, topographical, rainfall, stream, and road distance were used. This suitability evaluation for local food system focused on the agricultural suitability criteria based on the FAO classification. The method was used GIS, AHP and ANP application of MCDM (Multi Criteria Decision Method) (Maczewski 1999) to determine the suitable location for production of local food especially for cassava. For this suitability analysis the data was gathered from field surveys, expert interview, and secondary data collection from various sources **(Table 4.1 and Figure 4.3)**.

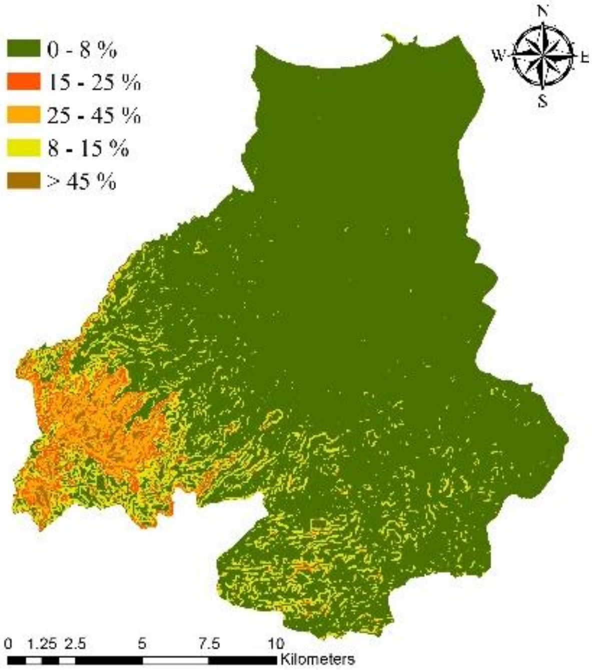
The land suitability classification consists of assessing and grouping the land types in orders and classes according to their aptitude. The order defines the suitability and expressed by highly suitable (S1), Moderately Suitable (S2), Marginally Suitable (S3), and Not Suitable (N).

4.3.5 Questionnaires, Interview, and Survey

The primary data from the field survey were collected through questionnaires, interviews and survey. This research also used the questionnaire to interview the expert and community. The expert selects according to their knowledge in sustainable agriculture and experience in cassava production **(Appendix 1).** In addition, a GPS receiver was used for field survey to know about the location of cassava fields, government offices, markets, and community centers in the Serang City.

Table 4.1 List of data used and their original sources

No	Data	Scale	Source
1	Boundary Map	1:50.000	Indonesia Geospatial Agency
2	Land Use Map 2013	1:50.000	Indonesia Geospatial Agency
3	Topography (Slope) Map	1:50.000	Indonesia Geospatial Agency
4	Road Map	1:50.000	Indonesia Geospatial Agency
5	Population Map	1:50.000	Indonesia Geospatial Agency
6	Stream Map	1:50.000	Indonesia Geospatial Agency
7	Rainfall Map	1:50.000	Indonesia Geospatial Agency
8	Location of Market	GPS Data	Survey
9	Location of the cassava field	GPS Data	Survey
10	Cassava Production	Statistics	Indonesian Statistics

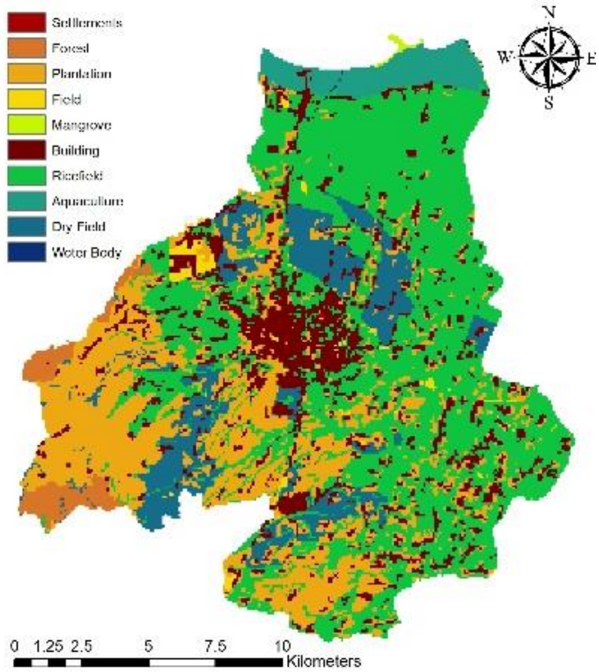


(a) Slope

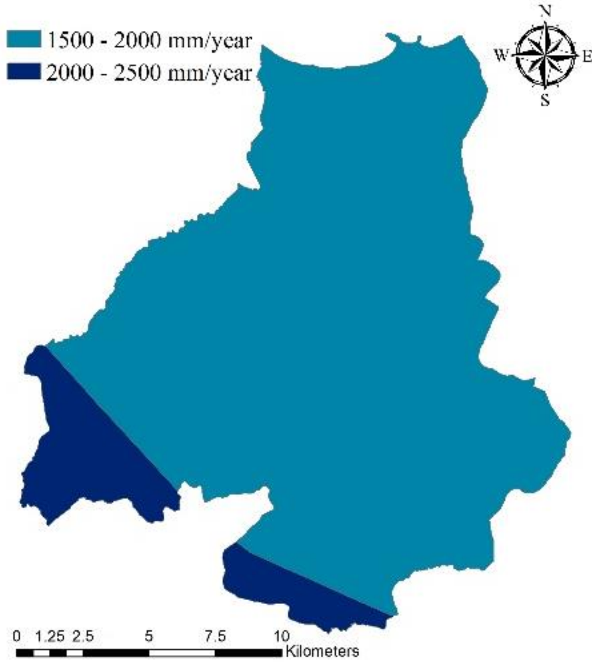
(b) Soil


Road
Serang City
N
W
E
S
0 1.25 2.5 5 7.5 10
Kilometers

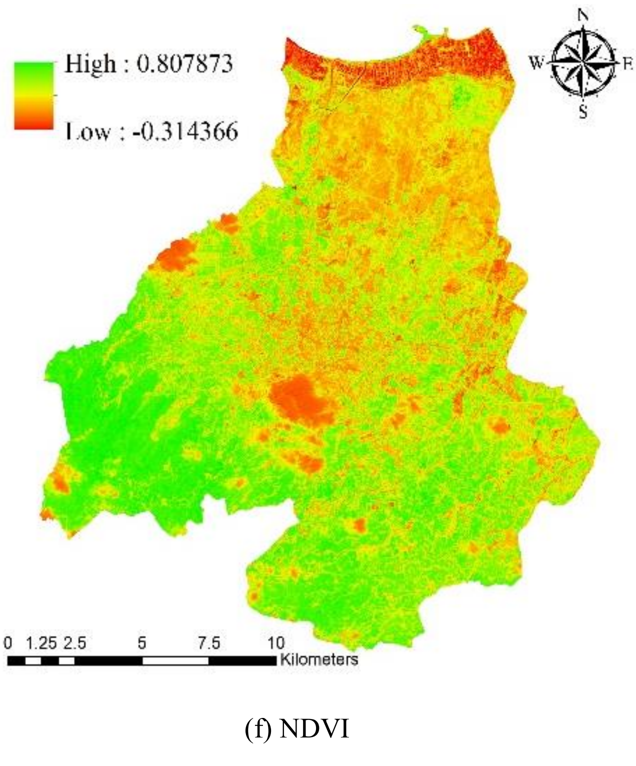
(c) Road


Settlements
Forest
Plantation
Field
Mangrove
Building
Ricefield
Aquaculture
Dry Field
Water Body
N
W
E
S
0 1.25 2.5 5 7.5 10
Kilometers

(d) LULC

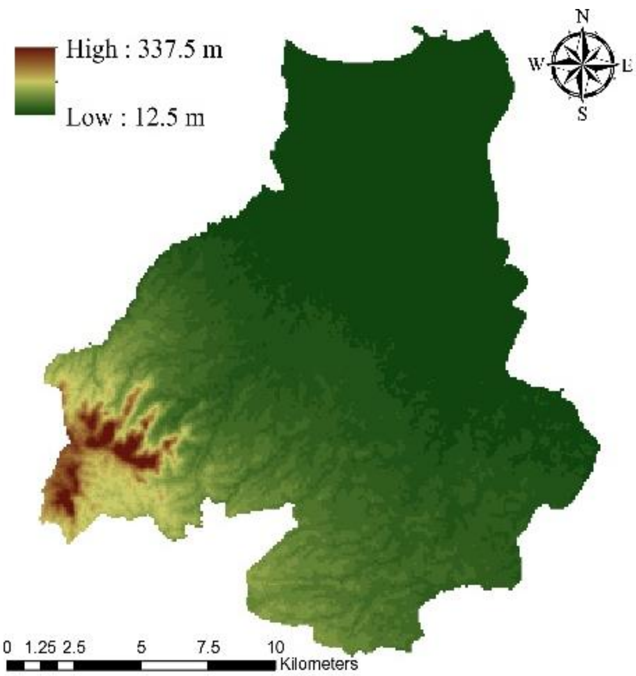


(e) Rainfall



(f) NDVI

(g) River



(h) Elevation

Figure 4.3 (a-h). Criteria for land suitability analysis for cassava production

4.3.6 AHP Aplication

In this research, the weights were used to determine the priority for each criteria to identify suitability of land use for cassava production. The form of the decomposition structure consisted with first level (goal), second level (criteria), third level (alternative) **(Figure 4.4).**

4.3.6.1 Decision Elements (Goal, Criteria and Alternatives)

The first step of the analysis was to set up the elements of the decision model into a hierarchy consisted with first level (goal), second level (criteria), third level (alternative). The first level cointains the goal of selecting the best alternative. The second level of the hierarchy includes rules or criteria that contribute to the goal. The lowest level contains the alternative decision will select (Estoque, 2011) **(Figure 4.4).**

4.3.6.2 Priorities to Decision Elements

This step is to gather the score of the criteria using pair-wise comparison technique and the scoring scale of relative importance. The score of differential scoring presumes that the row criterion is of equal or greater importance than the column criterion. The reciprocal values (1/3, 1/5, 1/7, 1/9) have been used where the row criterion is less important than the column criterion **(Table 4.2 and Table 4.3).**

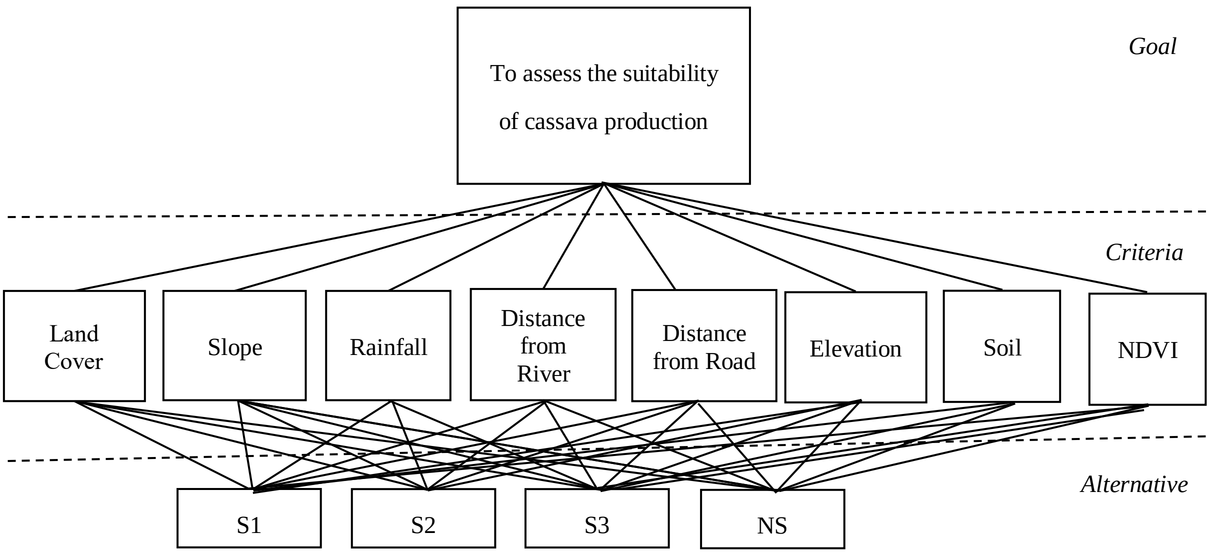


Figure 4.4 The AHP model for suitability cassava location

Table 4.2. The preference scale for pair wise comparison in AHP (Saaty, 1989)

Scale	Degree of preference	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one factor over another	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 the two adjacent judgments	When compromise is needed
Reciprocals	Opposites	Used for inverse comparison

Table 4.3. The pairwise comparison for AHP model

	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

This analysis was used the questionnaires for expert's opinions to determine the relative importance of the involved criteria and factors. Results of the comparison (for each factors pair) were described in term of integer values from one (equal value) to 9 (extreme different) where higher number means the chosen factor was considered more important in greater degree than other factor being compared with (Saaty, 1980).

4.3.6.3 Relative Weights to Decision Element

To ensure the credibility of the relative significance used, AHP provides the measuement with calculating the normalized values for each criterion and alternative and determining the normalized pricipal eigenfactors or priority vectors.

AHP provided a structural basis for quantifying the comparison of decision elements and criteria in a pair wise technique. The pair wise matrix was calculated and given by the following expression:

$$\begin{bmatrix} C_{11} & C_{12} & \ldots C_{1n} \\ C_{21} & C_{22} & \ldots C_{2n} \\ \cdot & \cdot & \cdot \quad \cdot \\ \cdot & \cdot & \cdot \quad \cdot \\ C_{n1} & C_{n2} & \cdot \quad C_{nn} \end{bmatrix} \tag{4.1}$$

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

$$C_{ij} = \sum_{i=1}^{n} C_{ij} \tag{4.2}$$

Each element of the matrix was divided by its column total to generate a normalized pairwise matrix:

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}} = \begin{bmatrix} X_{11} & X_{12} & \ldots X_{1n} \\ X_{21} & X_{22} & \ldots X_{2n} \\ \cdot & \cdot & \cdot \quad \cdot \\ \cdot & \cdot & \cdot \quad \cdot \\ X_{n1} & X_{n2} & \cdot \quad X_{nn} \end{bmatrix} \tag{4.3}$$

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

$$W_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{n} = \begin{bmatrix} W_{11} \\ W_{12} \\ \cdot \\ \cdot \\ W_{1n} \end{bmatrix} \tag{4.4}$$

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

$$\begin{bmatrix} C_{11} & C_{12} & \ldots C_{1n} \\ C_{21} & C_{22} & \ldots C_{2n} \\ \cdot & \cdot & \cdot \quad \cdot \\ \cdot & \cdot & \cdot \quad \cdot \\ C_{n1} & C_{n2} & \cdot \quad C_{nn} \end{bmatrix} \text{x} \begin{bmatrix} W_{11} \\ W_{12} \\ \cdot \\ \cdot \\ W_{1n} \end{bmatrix} = \begin{bmatrix} C_{11}W_{11} + & C_{12}W_{11} + & \ldots + C_{13}W_{11} \\ C_{21}W_{12} + & C_{22}W_{12} + & \ldots + C_{23}W_{12} \\ \cdot & \cdot & \cdot \quad \cdot \\ \cdot & \cdot & \cdot \quad \cdot \\ C_{n1}W_{1n} & C_{n1}W_{1n} & \cdot \quad C_{n1}W_{1n} \end{bmatrix} = \begin{bmatrix} V_{11} \\ V_{12} \\ \cdot \\ \cdot \\ V_{1n} \end{bmatrix} \tag{4.5}$$

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

$$\lambda_{max} = \sum_i^n CV_{ij} \tag{4.6}$$

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 **(Table 4.4).**

Table 4.4. Normalized matrix for the criteria selected for cassava production

	Soil	Land Cover	Elevation	Slope	Rainfall	Distance from roads	Distance from rivers	NDVI	Consistency measure
Soil	0.413	0.500	0.365	0.360	0.244	0.25	0.204	0.500	8.649
Land Cover	0.136	0.166	0.219	0.216	0.244	0.194	0.204	0.166	8.621
Elevation	0.082	0.050	0.073	0.072	0.104	0.138	0.159	0.050	8.238
Slope	0.082	0.050	0.073	0.072	0.104	0.083	0.113	0.050	8.411
Rainfall	0.057	0.023	0.024	0.023	0.034	0.083	0.068	0.023	7.977
Distance from roads	0.045	0.023	0.014	0.023	0.011	0.027	0.022	0.023	8.167
Distance from rivers	0.045	0.018	0.010	0.014	0.011	0.027	0.022	0.018	8.023
NDVI	0.136	0.166	0.219	0.216	0.244	0.194	0.204	0.166	8.621

Table 4.5. 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

The judgments were also checked to determine the consistency index (CI), which was calculated as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{4.7}$$

Here, n is the total number of criteria. Saaty (2012) 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 4.5).** The consistency ratio was calculated as:

$$CR = \frac{CI}{RI} \tag{4.8}$$

The principle value suggests that eight criteria were consistent, as the calculation results reveal a maximum value of 8.34. Additionally, a *CR* of 3.4% was calculated, which was less than 10%. A lower *CR* ratio indicates a higher degree of consistency. Thus, the consistency of expert opinions was acceptable. Among the eight sub-criteria identified, the AHP application ranked soil as the first priority (36%) followed by land cover (19%), the vegetation index (19%), elevation level (10%), slope (8%), rainfall (4%), distance from roads (2%), and distance from rivers (2%) when selecting suitable lands for cassava production.

4.3.7 ANP Application

In the present study, ANP is used to obtain the weight of the criteria to compare with the weight from AHP method. The application steps of ANP can be described in the following steps. In step 1, the construction of a conceptual model is produced to determine relationships. Since, there is no relationship among the criteria, the ANP was used only for the relationship between criteria and alternatives.

In step 2, criteria are pair-wisely compared using Super Decisions software in order to form an un-weighted super-matrix same as the AHP. The pairwise matrix was calculated and is given by the following expression:

$$\begin{bmatrix} C_{11} & C_{12} & \ldots C_{1n} \\ C_{21} & C_{22} & \ldots C_{2n} \\ \cdot & \cdot & \cdot \quad \cdot \\ \cdot & \cdot & \cdot \quad \cdot \\ C_{n1} & C_{n2} & \cdot \quad C_{nn} \end{bmatrix} \tag{4.9}$$

In step 3, the priorities derived from pairwise comparison matrices are entered as parts of the columns of a supermatrix. The supermatrix use the evaluation matrix U for criteria (C1, C1, C3, C4, C5, C6, C7, C8) evaluating alternatives (Ai, A2, A3, A4) expressed as follows,

$$U = \begin{bmatrix} U_{11} & U_{12} & ...U_{18} \\ U_{21} & U_{22} & ...U_{28} \\ \cdot & \cdot & \cdot \quad \cdot \\ \cdot & \cdot & \cdot \quad \cdot \\ U_{41} & U_{42} & . \quad U_{48} \end{bmatrix} \tag{4.10}$$

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) is expressed as follows.

$$\mathrm{V} = \begin{bmatrix} V_{11} & V_{12} & V_{13} & V_{14} \\ V_{21} & V_{22} & V_{23} & V_{24} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ V_{81} & V_{82} & V_{83} & V_{84} \end{bmatrix} \tag{4.11}$$

Then, the weighted supermatrix **(Appendix 3)** is expressed as a function of the evaluation matrix U and the evaluation matrix V as follows. Supermatrix S should be a probability matrix and should be irreducible.

$$S_{weighted} = \begin{bmatrix} 0 & U \\ V & 0 \end{bmatrix} = \begin{array}{c|c} & \begin{array}{cccccc} \mathrm{A}_1 & \cdots & \mathrm{A}_4 & \mathrm{C}_1 & \cdots & \mathrm{C}_8 \end{array} \\ \begin{array}{c} \mathrm{A}_1 \\ \vdots \\ \mathrm{A}_4 \\ \mathrm{C}_1 \\ \vdots \\ \mathrm{C}_8 \end{array} & \begin{bmatrix} 0 & \dots & 0 & U_{11} & \dots & U_{18} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & U_{41} & \dots & U_{48} \\ V_{11} & \dots & V_{14} & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ V_{81} & \dots & V_{84} & 0 & \dots & 0 \end{bmatrix} \end{array} \tag{4.12}$$

In step 4, limit supermatrix **(Appendix 4)** is obtained by raising the weighted supermatrix to powers by multiplying the matrix itself.

$$S_{limited} = \lim_{n \to \propto} S_{weighted} \tag{4.13}$$

4.3.8 GIS Application

The data used in GIS analysis were in digital format, however some of them were in analogue format. Topographical map (and any hardcopy map) was an example of analogue data, the conversion of GIS involved scanning, geo-referencing, and digitizing. ArcGIS 10 software were used to analyze and visulaize the mapfor features and rasters.

4.3.8.1 Reclassification

The reclassification is a analytical process to reclassify or change cell values to alternative values using a variety of methods. The process of taking input cell values and replacing them with new output cell values. Reclassification was used to simplify or change the interpretation of raster data by changing a single value to a new value.

Each source map of the Serang city was reclassified into four classifications. The classification used the value group ranges of the class of suitability. There were Highly Suitable (S1), Moderately Suitable (S2), Marginally Suitable (S3), and Not Suitable (N). The range of suitability collected from Tienwong *et al.* (2009) as shown on the **(Table 4.6).**

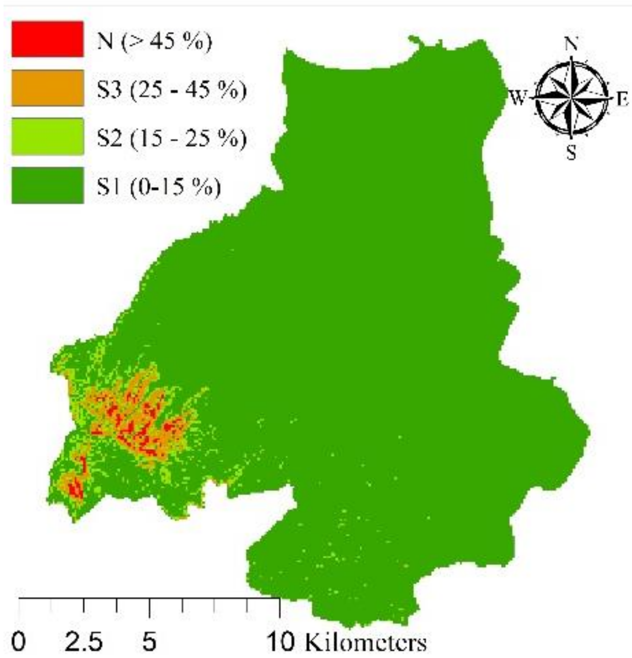
4.3.8.2 Weighted Overlay

Weighted Overlay was one of the Overlay Analysis tools included in the Spatial Analyst extension. Commonly was used to solve multi-criteria problems such as optimal site selection or suitability modeling. It was the technique for applying a common scale of values to diverse and dissimilar inputs to create an integrated analysis. This tool was used to identify the best or most preferred locations for cassava production. In order to decide the class of suitability, AHP analysis was used as quantitative method for ranking decision alternatives and selection the one given multiple criteria. The criteria that related with land use suitability has been using to decide the suitability of location with the Weighted Overlay tools. All the data raster (land cover, stream, rainfall, road, and slope) was combined with the weighted overlay tools.

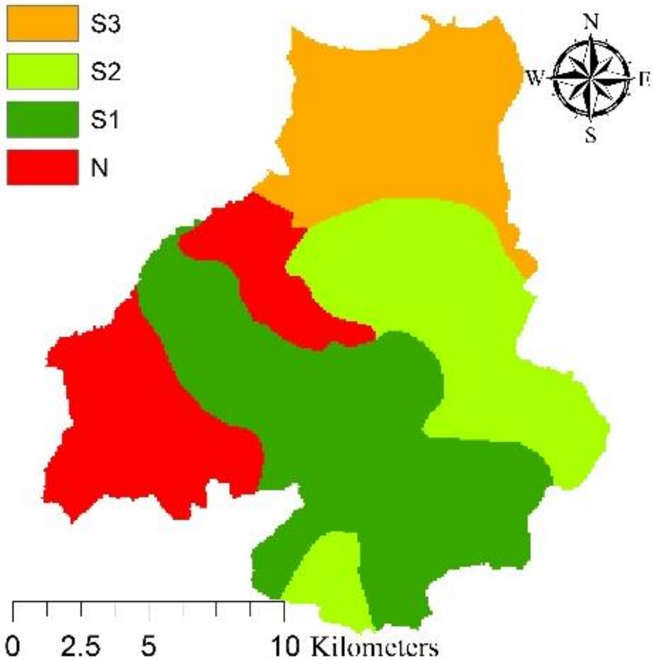
The input criteria layers were in different numbering systems with different ranges, to combine them in a single analysis, each cell for each criterion was reclassified into a common preference scale such as 1 to 10, with 10 being the most favorable **(Figure 4.5).** Each of the criteria in the weighted overlay analysis was not equal in importance. The weight of the important criteria was calculated by the previous AHP application.

Table 4.6. The classification for cassava suitability assessment

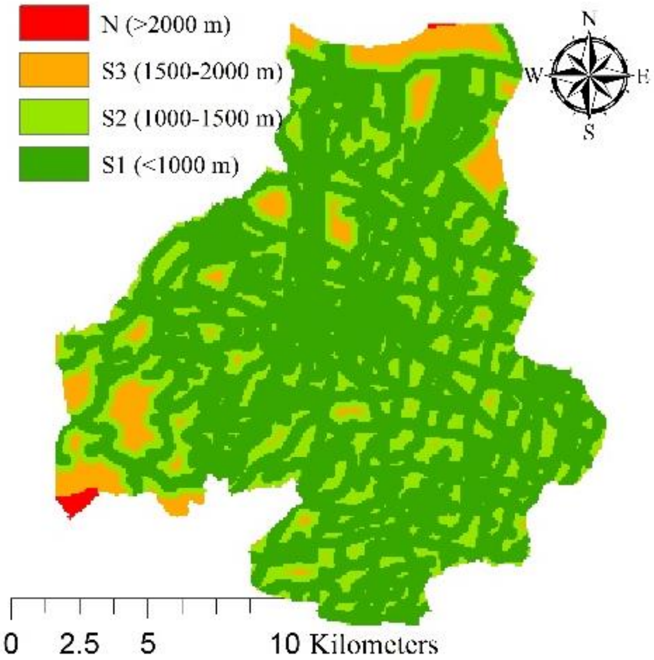
Criteria	Suitability Class	Sub-criteria	Percentage area (%)	Area (ha)
LULC	S1	Class I	11.38	3059
	S2	Class II	43.27	11631
	S3	Class III	27.61	7422
	N	Class IV	17.74	4767
Slope (%)	S1	0-8%	83.81	22.352
	S2	8-15%	10.25	2.734
	S3	15-25%	3.07	818
	N	> 25%	2.87	765
Rainfall (mm.)	S1	1000-1500	89.22%	23.794
	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	20517
	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	10115
	S2	Podzolic	21.36	5698
	S3	Regosol	20.48	5462
	N	Alluvial Hydromorphic	20.23	5395
NDVI	S1	Vegetation	10.06	1829
	S2	Ricefield	13.83	2514
	S3	Forest	43.94	7986
	N	Waterbody, Settlements	32.16	5845



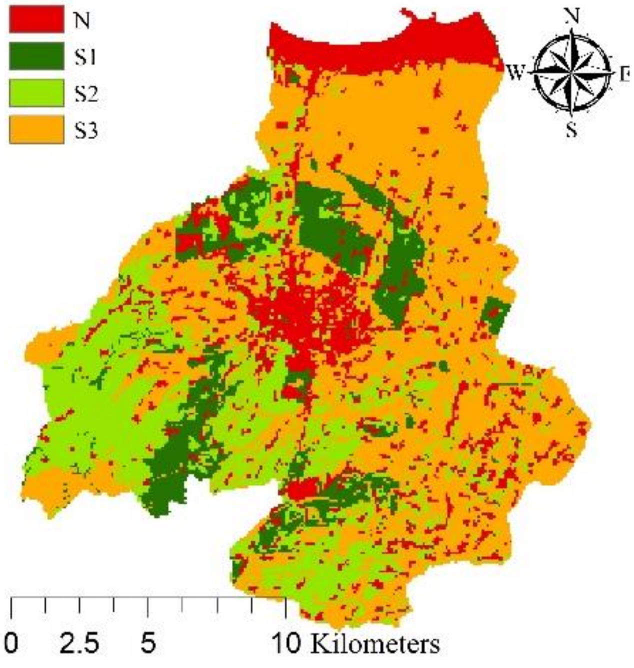
(a) Slope



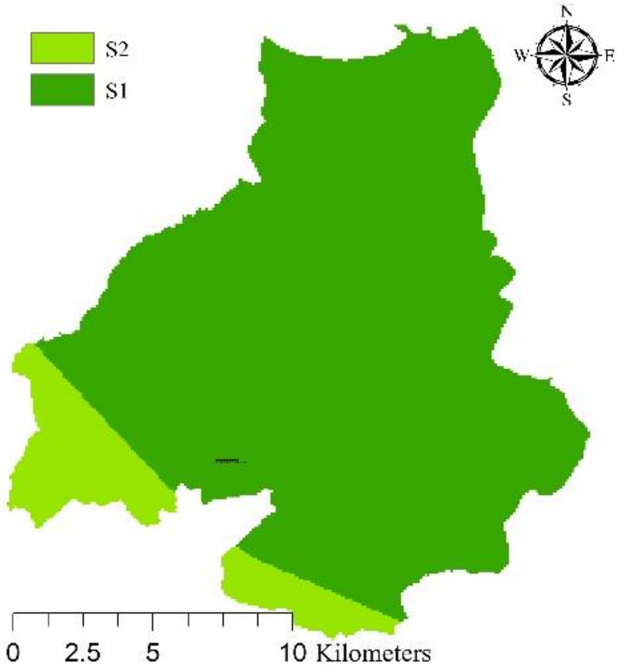
(b) Soil



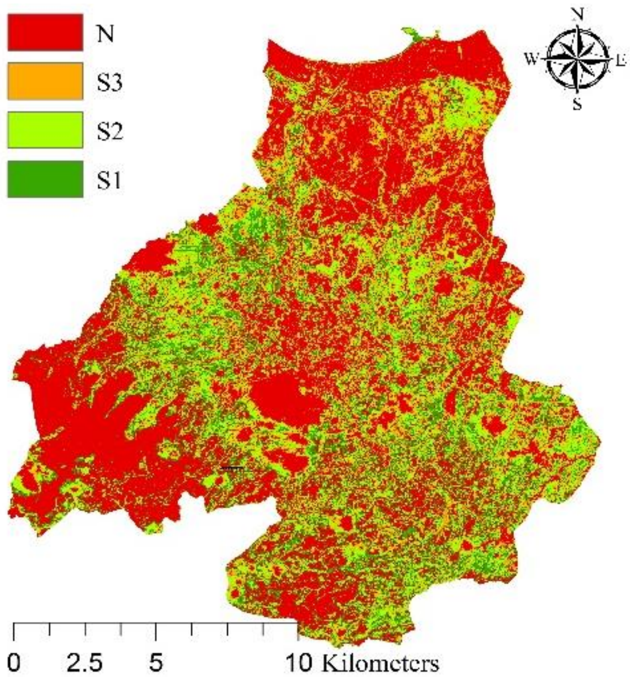
(c) Distance from road



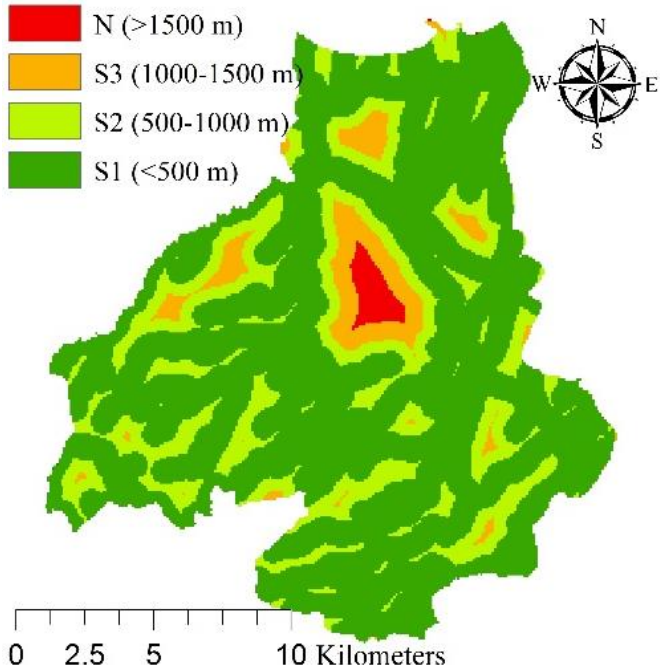
(d) LULC



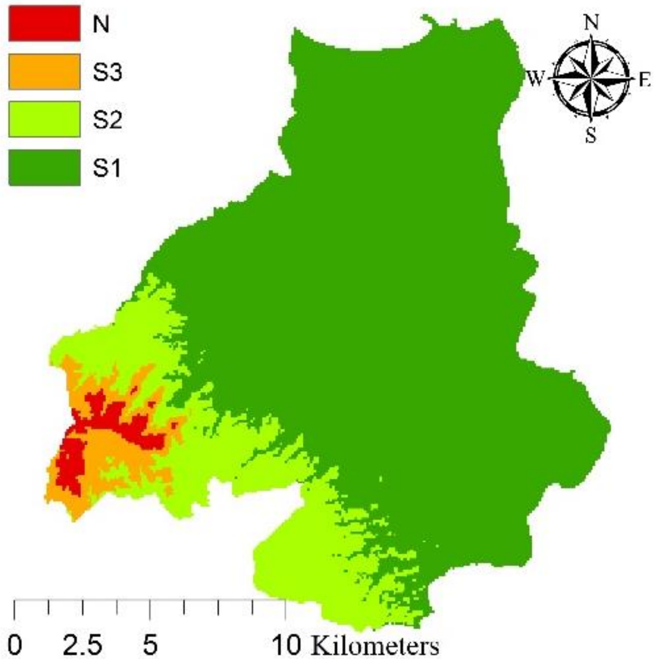
(e) Rainfall



(f) NDVI



(g) Distance from river



(h) Elevation

Figure 4.5 (a-h) Reclassification of the criteria

4.4 Results

4.4.1 Suitability Analysis

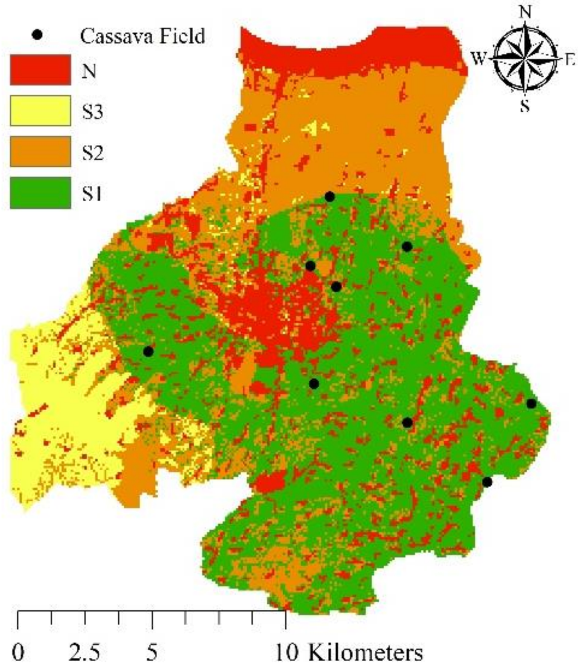
The suitability classification aimed to show the suitability of each land unit for particular land use. In FAO's Framework for land evaluation, land is the first class as suitable (S) or not suitable (N). These suitability classes can then be further sub-divided, as required. In practice, three classes (S1, S2 and S3) often used to distinguish land that is highly suitable, moderately suitable and marginally suitable for a particular use.

After the AHP and ANP process was completed, the criteria were reclassified into four classifications that were included in the weighted overlay. 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 the reclassified raster data were combined with weighted overlay tools. 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 and ANP application. Using the reclassification and weighted overlay method, a spatial analysis was conducted, and a suitability map for cassava production was created (Eckert & Sujata, 2011; Gatrell *et al.,* 2011).

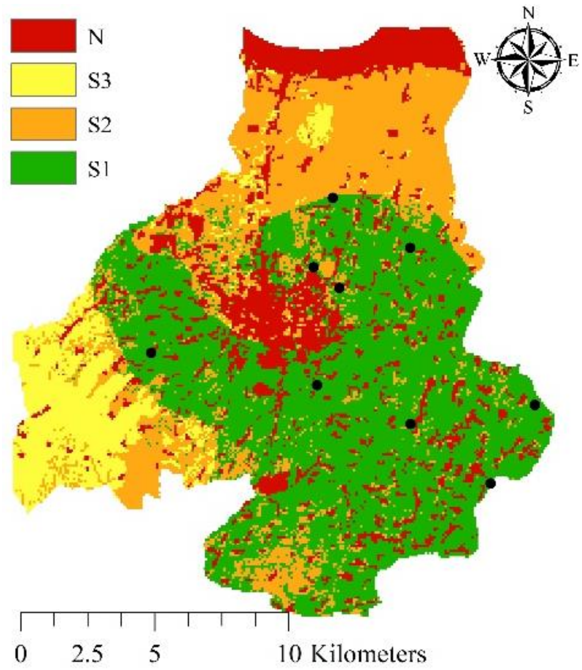
In the GIS analysis, the reclassified raster was used with AHP and ANP weights and ranked accordingly. The CR was the indicator of judgments to refer to the AHP weight, whether consistent or not. In the AHP analysis, a CR of 6.1% was found, which was less than 10%, referred the consistency of expert 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 4.7).** 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 4.7).**

Table 4.7. Priority criteria weights according to expert's opinions for selecting land suitability in cassava production

Criterion Names	Weights of Criterion											
	Expert A (11 years)		Expert B (10 years)		Expert C (20 years)		Expert D (21 years)		Expert E (15 years)		Mean	
	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



(a) ANP based weighted overlay

Figure 4.6. Land suitability distribution using weighted overlay

Table 4.8. Suitable area for cassava production

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	17.692	4718

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 **(Figure 4.6).** A suitability map for cassava production was created from a weighted overlay. Using AHP analysis, the 41.60% (11094 ha) are of the study area found as 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 **(Figure 4.6 and Table 4.8)**. 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 of fertility, a lack of water during dry seasons, soil erosion on steep slopes, and high levels of acidity in some areas.

4.5 Discussion

The 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. 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, the ANP also employed 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.

4.6 Summary

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, the priority criteria was found, 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. To complete the analysis of the regional suitability, the model can be further expanded spatially by adding the provincial scale of analysis. Moreover, to overcome the uncertainty in MCDM of the suitability model, application of the fuzzy can be used for further analysis.

CHAPTER 5

Land Suitability Model for Cassava Production using GIS and Fuzzy-MCDM (F-MCDM)

5.1. Background

The fundamental assessment process of land suitability for crop production is to measure the significance of each factor which affects the land suitability. The variable that influences land suitability to have different levels of significances as a result of various and multiple criteria, therefore the land suitability assessment become complicated (Elsheikh *et al*., 2013). The AHP is the widely approved modeling framework that has applied for Multi-Criteria Decision Method (MCDM) purposes and utilized for land suitability evaluation (Zabihi *et al*., 2015; Akıncı *et al*., 2013; Zolekar and Bhagat, 2015; Malczewski, 2004). These methods also have assessed by Malczewski (1999), who evaluated spatial models through several research experiments. The combination of GIS and AHP tools have been used in conjunction to solve land suitability problems (Akinci *et al*., 2013). However, the employment of this method can determine the uncertainties of outputs. The expert's opinion in AHP was observed in the previous chapter, specially, have the limitation in scoring. In the land suitability analysis, if the criteria need to express use continuous value then Fuzzy membership is more suitable. In this case, optimization tools based on mathematical models are essential to overcome the uncertainties in decision alternatives.

In order to accommodate the complexity in assigning the suitability classes, the fuzzy classification is used. In Multi-Criteria Evaluation, fuzzy set membership can be used in the reclassifying of the criteria and reduces the subjectivity of discrete scoring in AHP. Fuzzy set theory allows the continuous factors to be modelled for a suitability assessment within a Geographic Information System (GIS) analysis. In a standard approach, membership with a set, or class, is clearly and crisply defined as either in the class or not in the class (Bellman and Zadeh, 1970).

However, most of those studies either used MCDM technique or fuzzy set alone were resulting in a poorly handling weight of each factor or inappropriately calculating the suitability index when perform separately. Furthermore, MDCM with fuzzy set theory have the potential to reduce the subjectivity in the assessment of results. There have been few studies which assess land suitability for crop production by using the integrated approach of GIS, fuzzy set, and MDCM, which has a great potential to increase the effectiveness and accuracy of land suitability assessment for crop production.

5.2 Objectives

The MCDM process for continuous scoring of criteria is needed to develop for the geo-spatial land suitability model using Fuzzy Membership function. Furthermore, the model needs to scale up from city to provincial level integrating GIS, remote sensing and multi criteria analysis for recommendation in policy implications. Therefore, following specific objectives are taken in this part of the research.

1. To scaled up the geo-spatial land suitability model to provincial level integrating GIS, remote sensing and multi criteria analysis.
2. To extend the MCDM for continuous scoring of criteria to develop the geo-spatial land suitability model using Fuzzy Membership function.

5.3 Methodology

5.3.1 Study Area

The regional land suitability for cassava production was scaled to up for policy level implementation for 8 sub-districts in the Banten province. Banten Province is located between 5°7'50" - 7°1'1"S and 105°1'11" - 106°7'12"E and is identified as the most western point of Java and is about 90 km from Jakarta. Banten Province is strategically positioned as the connecting area of land between Java and Sumatra Islands. Since, the productivity of cassava is decreasing in Indonesia, the productivity of cassava in Banten province should be increased to support national food security **(Figure 5.1).**

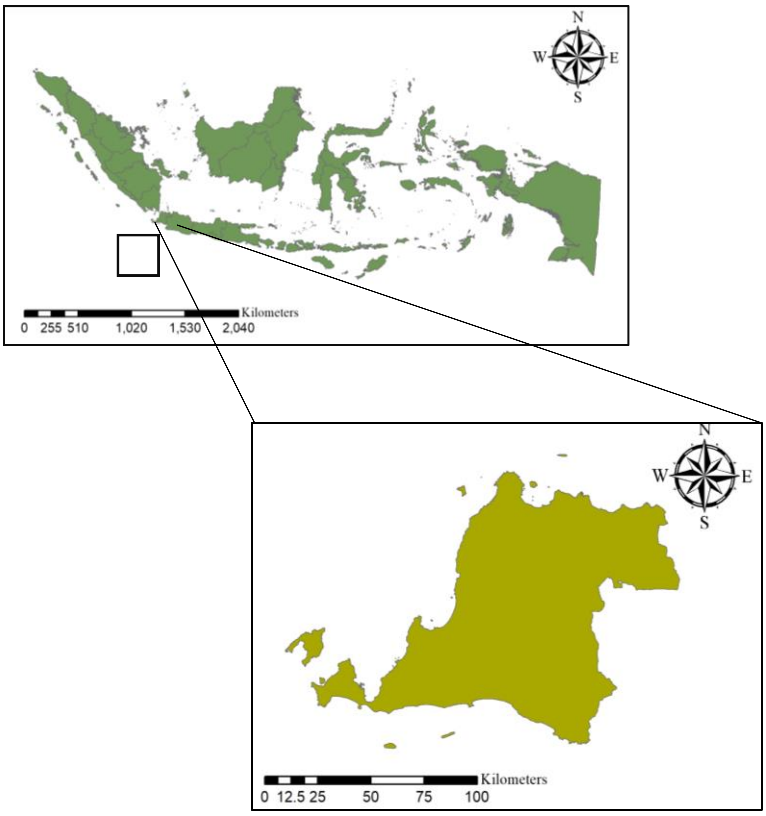


Figure 5.1. The extended study area of Banten province

5.3.2 Framework of Suitability Analysis

The model was built over three stages: first, the satellite digital images were processed and vector data layers as our database, where land cover types, topographical features, rainfall levels, distances from rivers, soil types, vegetation index data and distances from roads were used as criteria for suitability analysis. Second, the most suitable area for producing cassava was obtained using Geographical Information System (GIS) and Fuzzy-multi-criteria decision-method (F-MCDM). Then using fuzzy membership functions in ArcGIS 10, all map layers were standardized. In this study, the large and small fuzzy functions was used. The MCDM based on AHP model was used to determine weights using expert choice software. Finally, the weighted overlay method was performed to select the best location for cassava production **(Figure 5.2).**

5.3.3 Geographical Extent of Banten Province

5.3.3.1 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 Banten was 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

5.3.3.2 Slope

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

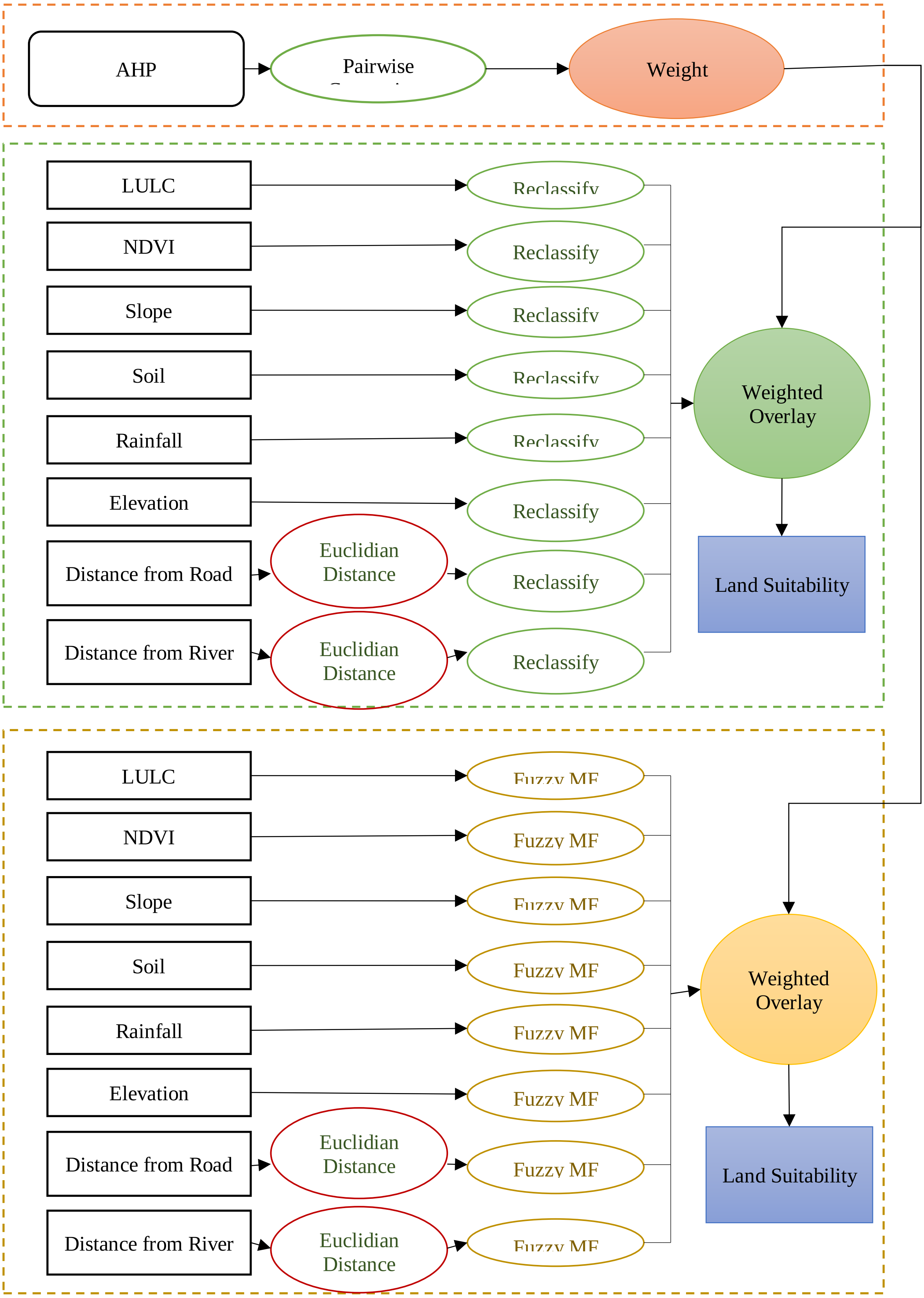


Figure 5.2. Framework of land suitability analysis

5.3.3.3 Distance from River

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.

5.3.3.4 Rainfall

Banten 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, 2017). 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.

5.3.3.5 Soil

The major soil types found in Banten 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.

5.3.3.6 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 Banten Province, elevation ranges from 0 to 700 m. Most of the area is suitable for cassava production, although the optimal elevation for cassava production is approximately 62.5–137.5 m.

5.3.3.7 Distance from Road

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.

5.3.3.8 Vegetation Index

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. In Indonesia, cassava production begins with planting at various times, but most field harvests occur during June or July.

5.3.4 Reclassification by Score

The reclassification is a analytical process to reclassify or change cell values to alternative values using a variety of methods. The process of taking input cell values and replacing them with new output cell values. Reclassification was used to simplify or change the interpretation of raster data by changing a single value to a new value **(Figure 5.3).** Each source map of the Serang city was reclassified into four classifications. The classification used the value group ranges of the class of suitability. There were Highly Suitable (S1), Moderately Suitable (S2), Marginally Suitable (S3), and Not Suitable (N). The range of suitability collected from Tienwong *et al.* (2009) as shown on the **Table 5.1**

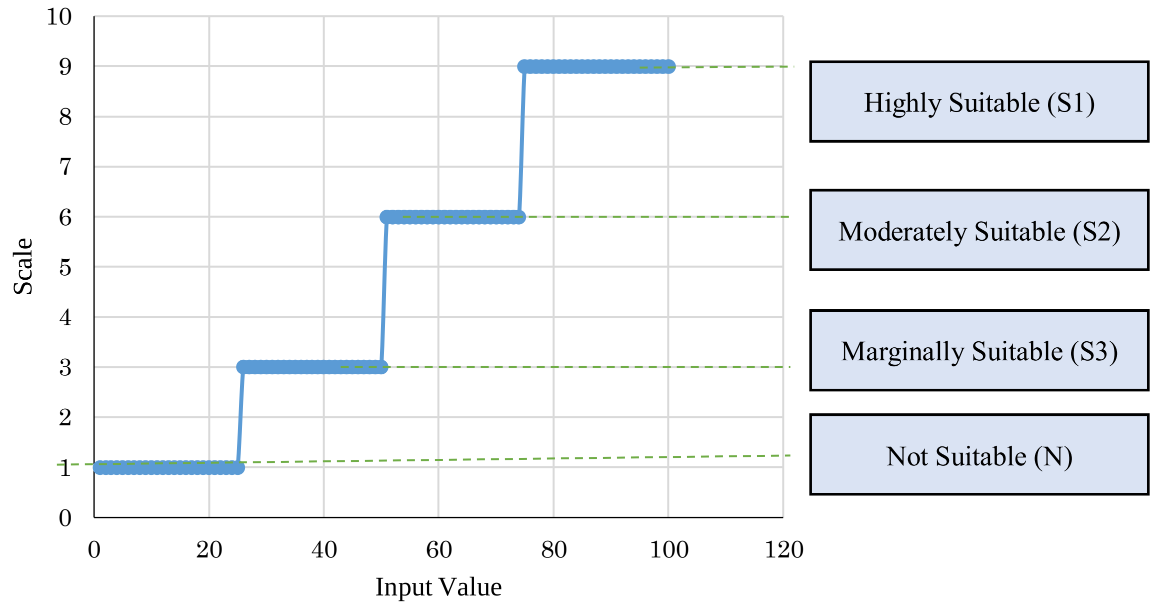


Figure 5.3 Reclassification by score

Table 5.1 Suitability Class by Score for Cassava Production

	Suitability Class							
Criteria	S1 (Highly Suitable)	Score	S2 (Moderately Suitable)	Score	S3 (Marginally Suitable)	Score	Not Suitable	Score
LULC	Class I	9	Class II	6	Class III	3	Class IV	1
Slope (%)	0-8%	9	8-15%	6	15-25%	3	> 25%	1
Rainfall (mm.)	1000-1500	9	1500-2000	6	-	-	>2000	1
Distance from roads (m)	<1000	9	1000—2000	6	2000—3000	3	>3000	1
Distance from rivers (m)	<500	9	500-1000	6	1000-1500	3	>1500	1
Elevation (meters)	0-100	9	100-300	6	300-700	3	>700	1
Soil Type	Class 1	9	Class II	6	Class III	3	Class IV	1
NDVI	1-0.7	9	0.7-0.5	6	0.5-0.3	3	0.3-0	1

5.3.5 Reclassification by Fuzzy Membership Function

Fuzzy set theory allows for the concept of these continuous factors to be modelled within a suitability assessment within a GIS or spatial domain **(Figure 5.4).** In a standard approach, membership with a set, or class, is clearly and crisply defined as either in the class or not in the class. In the present study the use of fuzzy membership classification is used to accommodate the above uncertainty in assigning the suitability classes. In this study, the fuzzy membership functions were used in ArcGIS 10 for standardization.

The kind of fuzzy functions were determined by literature review and expert opinions. In ArcGIS 10 there are seven fuzzy functions explained as large and small function. The fuzzy linear transformation function applies a linear function between the user-specified minimum and maximum values. Anything below the minimum will be assigned a 0 (not a member) and anything above the maximum a 1 (a member).

In the fuzzy membership function, the control point has to decide including midpoint and spread **(Table 5.2).** Midpoint is a point that has 0.5 value in large and small functions and determined by user. The spread generally is assigned numbers lower than 1, with the larger the value results in a steeper distribution around the midpoint. The spread generally ranges from 1 to 10 for both small and large functions with the larger the value results in a steeper distribution from the midpoint **(Figure 5.5).** The equations for the fuzzy Large **(Eq. 5.1)** and Small **(Eq. 5.2)** functions are depended with the control point including midpoint and spread. Finally, the reclassification map was generated for scoring method and fuzzy membership method **(Figure 5.6).**

$$\mu(x) = \frac{1}{1+\left(\frac{x}{f_2}\right)^{-f_1}} \tag{5.1}$$

$$\mu(x) = \frac{1}{1+\left(\frac{x}{f_2}\right)^{f_1}} \tag{5.2}$$

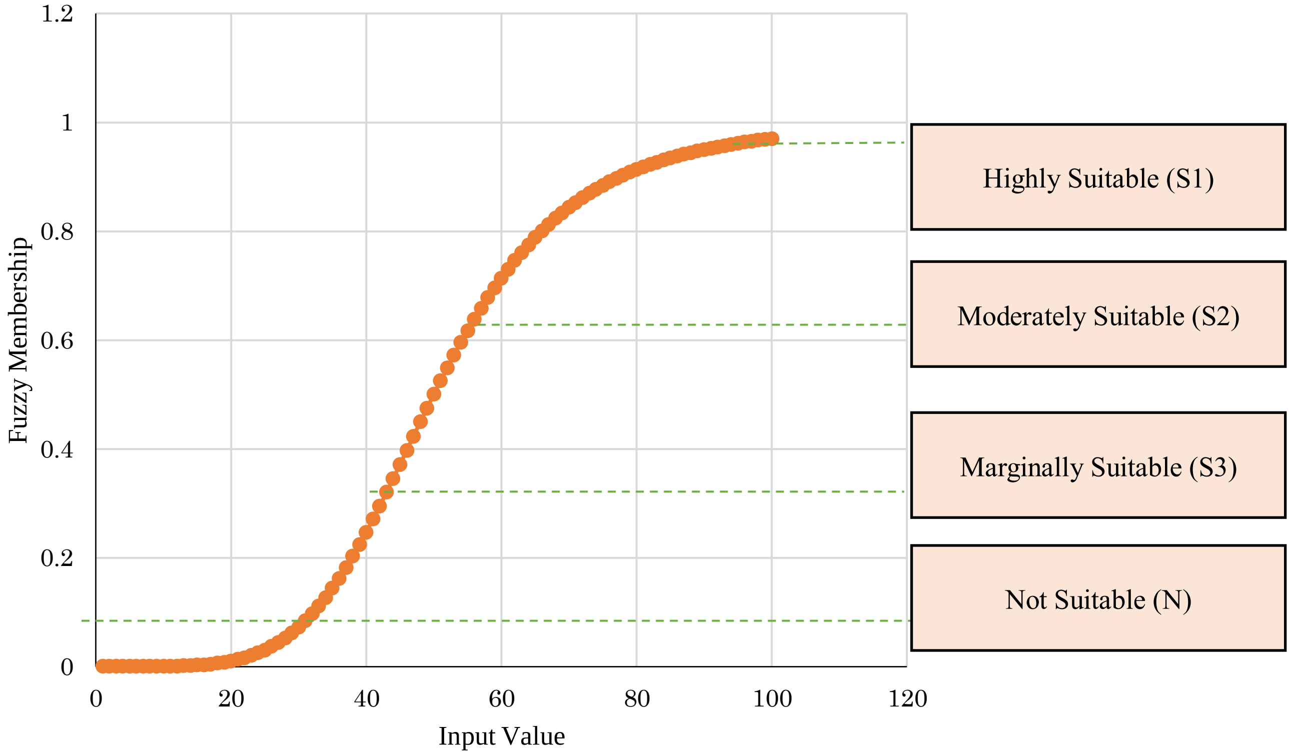
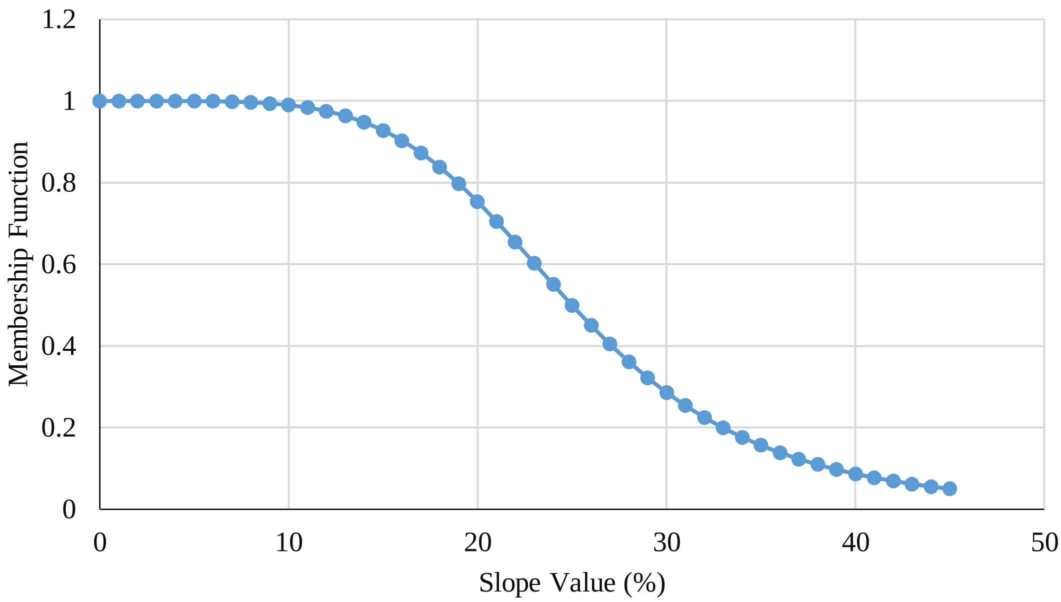


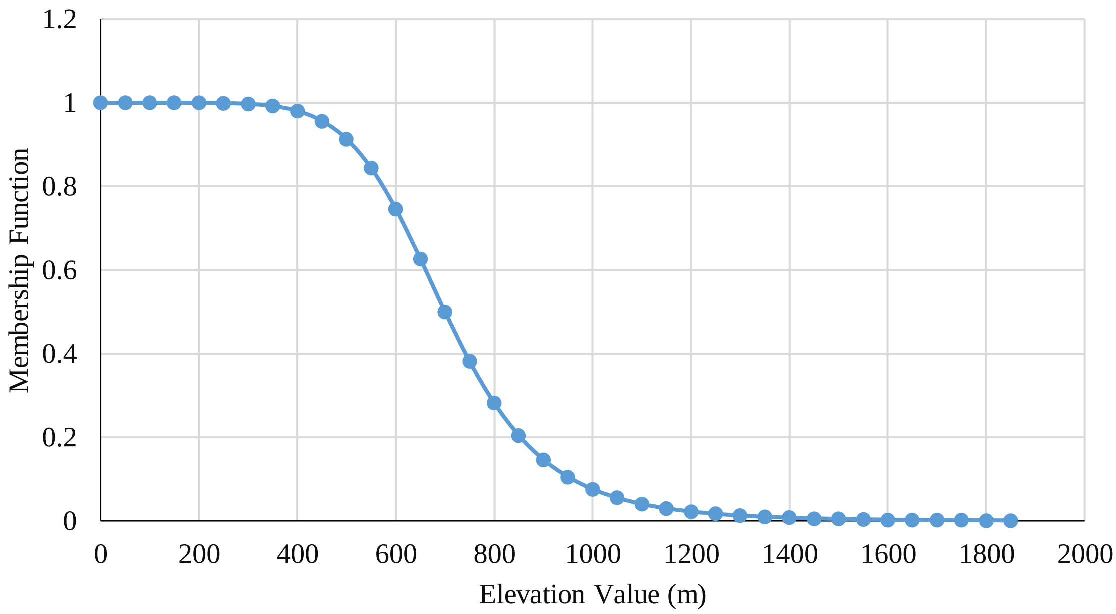
Figure 5.4 Reclassification by fuzzy membership function

Table 5.2 Suitability Class by Fuzzy Membership for Cassava Production

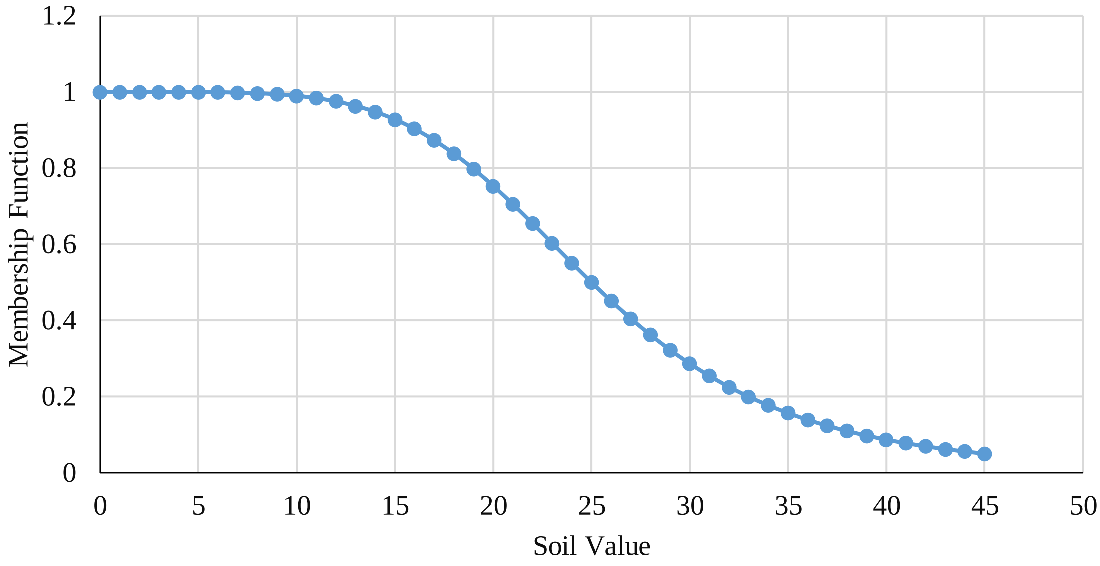
	Suitability Class				Fuzzy Membership Function		Equation
Criteria	S1	S2	S3	N	Midpoint	Spread	
LULC	Class I	Class II	Class III	Class IV	4	3	$\mu(x) = \frac{1}{1 + \left(\frac{x}{4}\right)^{-3}}$
Slope (%)	0-8%	8-15%	15-25%	> 25%	25	5	$\mu(x) = \frac{1}{1 + \left(\frac{x}{25}\right)^{5}}$
Rainfall (mm/year)	1500-2000	2000-2500	2500-3000	>3000	1500	3	$\mu(x) = \frac{1}{1 + \left(\frac{x}{1500}\right)^{3}}$
Distance from roads (m)	<1000	1000—2000	2000—3000	>3000	2000	5	$\mu(x) = \frac{1}{1 + \left(\frac{x}{2000}\right)^{5}}$
Distance from rivers (m)	<500	500-1000	1000-1500	>1500	1000	5	$\mu(x) = \frac{1}{1 + \left(\frac{x}{1000}\right)^{5}}$
Elevation (m)	0-100	100-300	300-700	>700	700	7	$\mu(x) = \frac{1}{1 + \left(\frac{x}{700}\right)^{7}}$
Soil Type	Class 1	Class II	Class III	Class IV	25	5	$\mu(x) = \frac{1}{1 + \left(\frac{x}{25}\right)^{5}}$
NDVI	1-0.7	0.7-0.5	0.5-0.3	0.3-0	0.53	5	$\mu(x) = \frac{1}{1 + \left(\frac{x}{0.53}\right)^{-5}}$



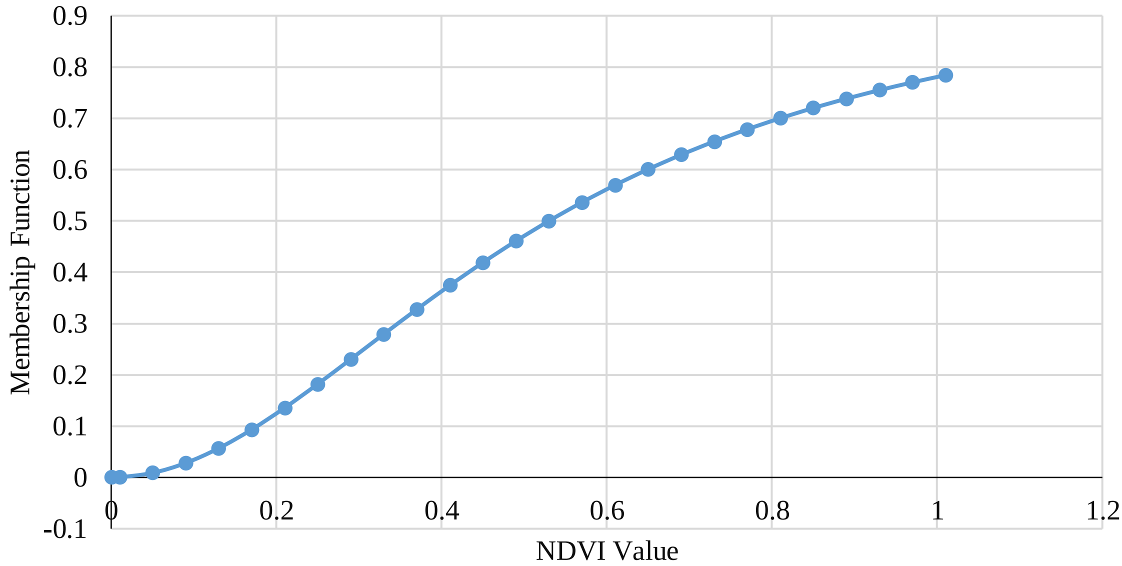
(a) Slope membership function



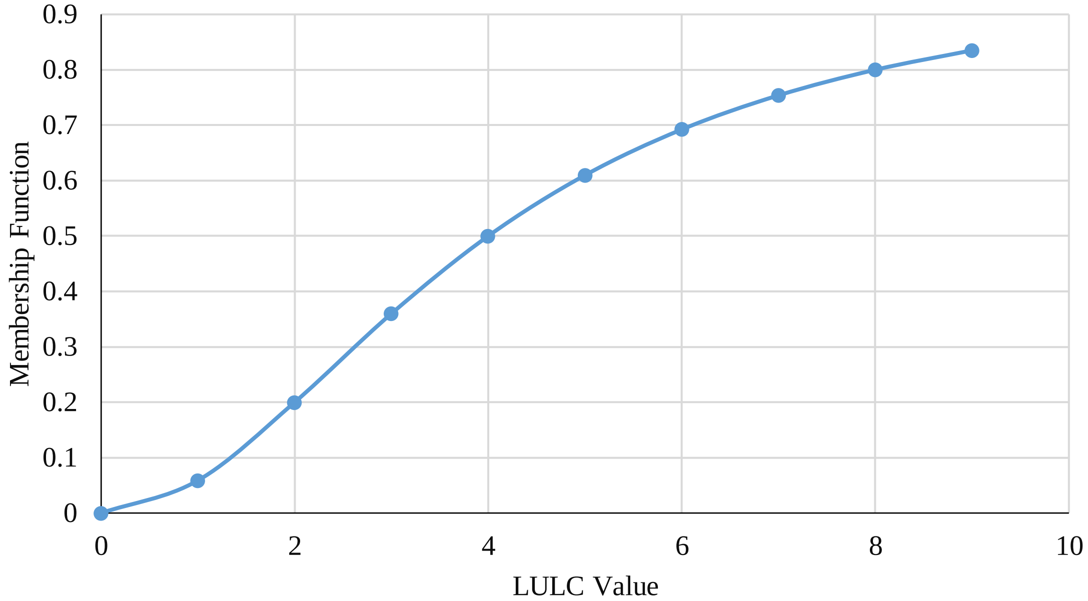
(b) Elevation membership function



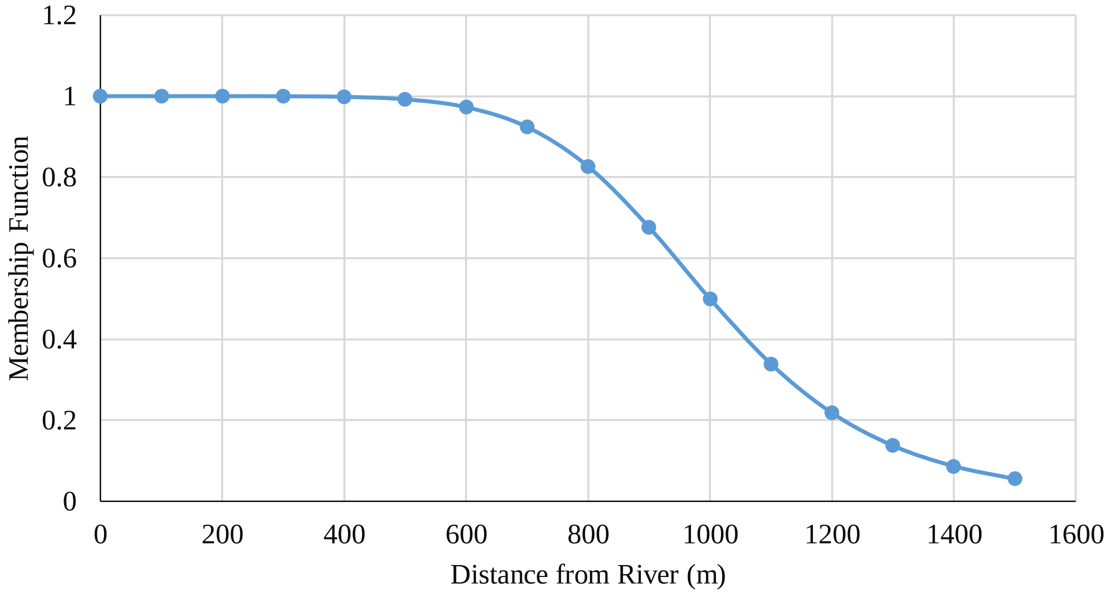
(c) Soil membership function



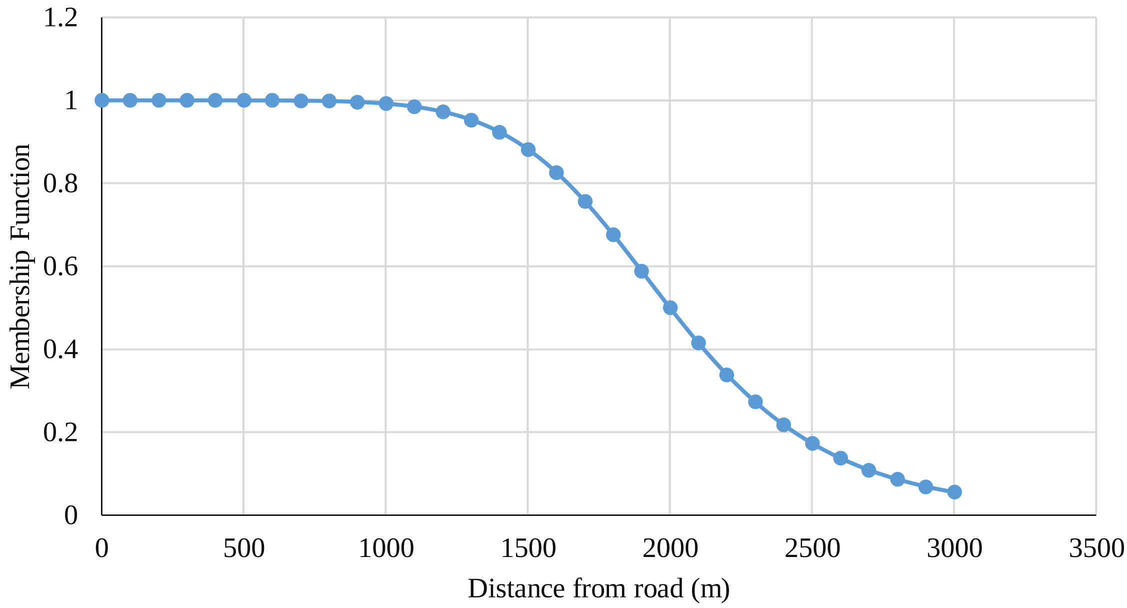
(d) NDVI membership function



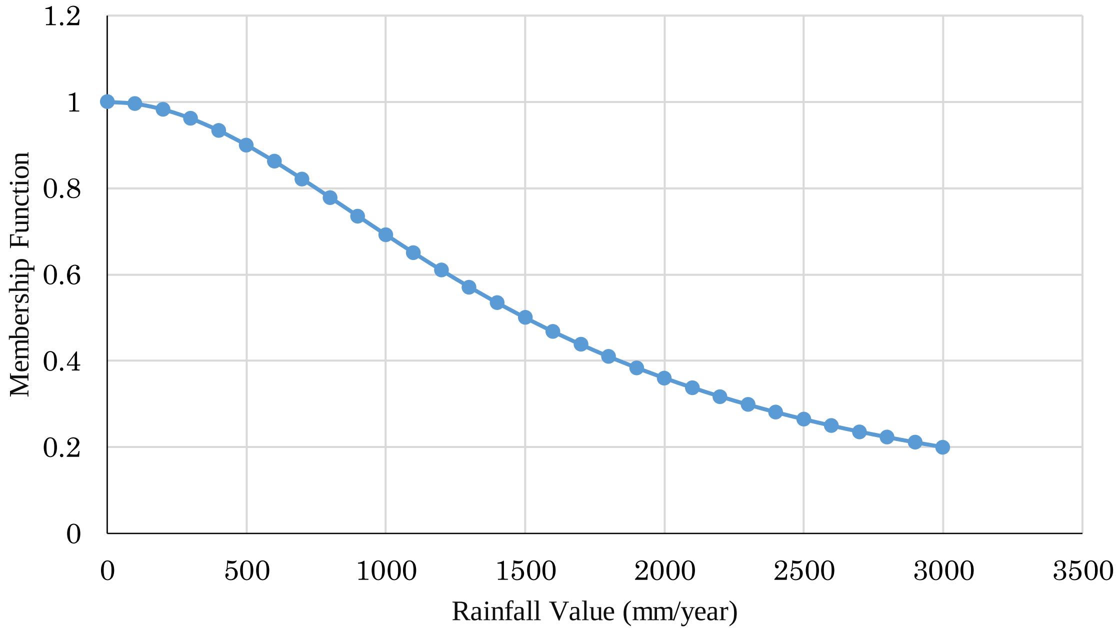
(e) LULC membership function



(f) Distance from river membership function

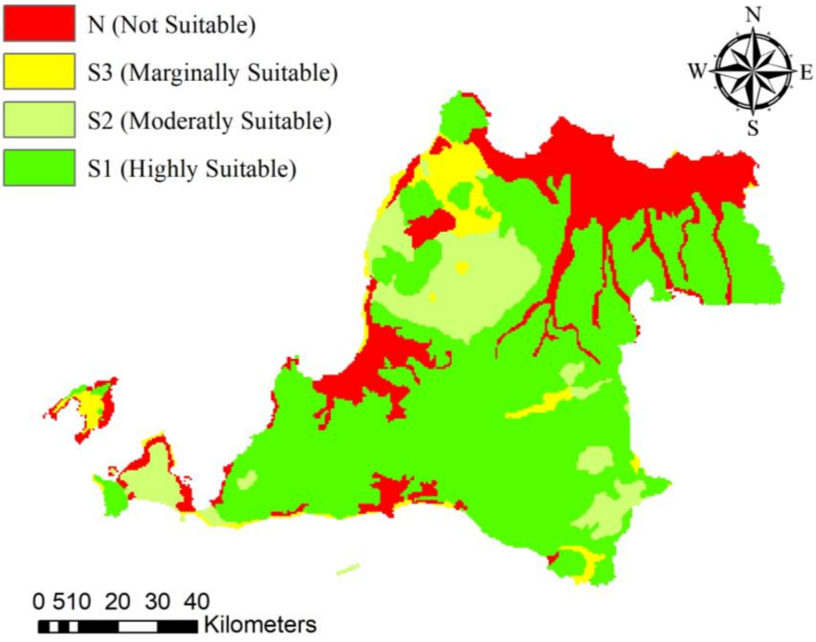


(g) Distance from road membership function

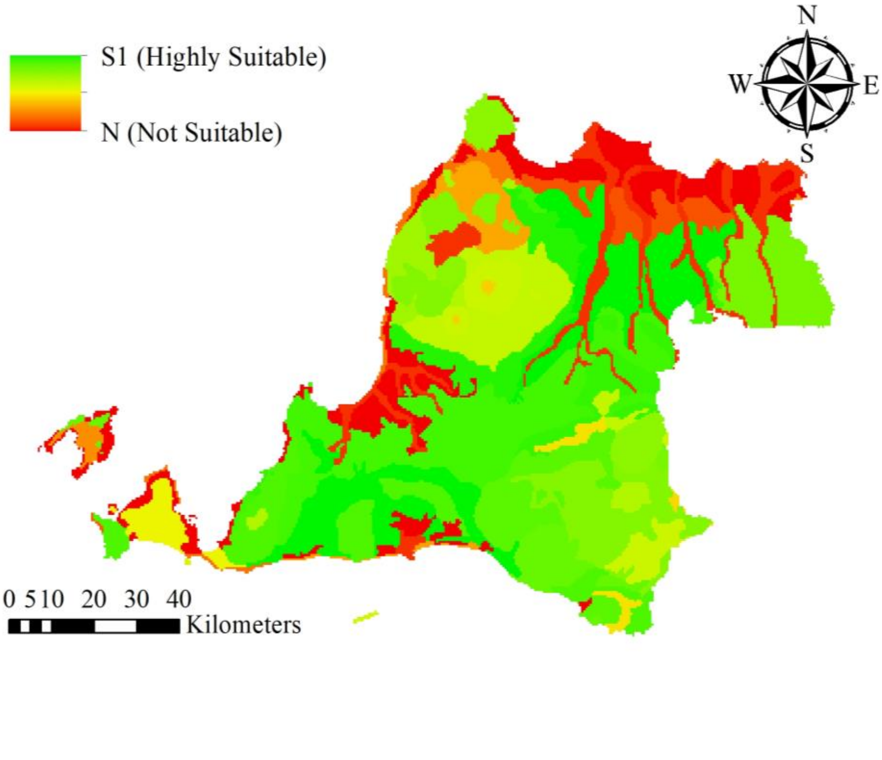


(h) Rainfall membership function

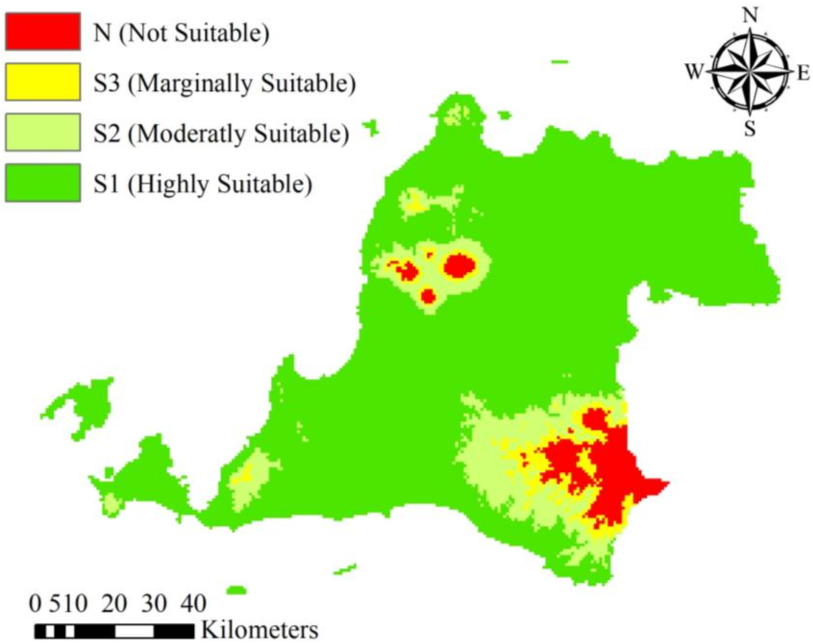
Figure 5.5 (a-h). Fuzzy membership function of criteria



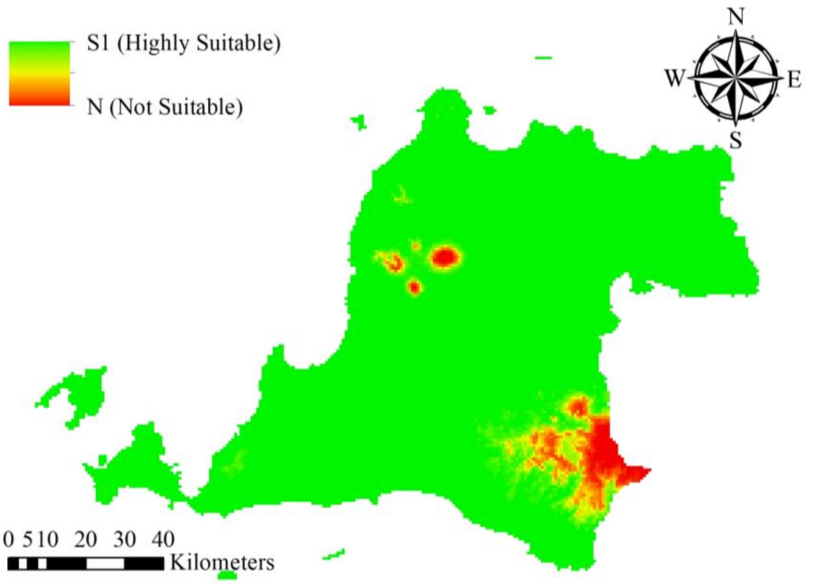
(a1) Soil map, reclassification by score



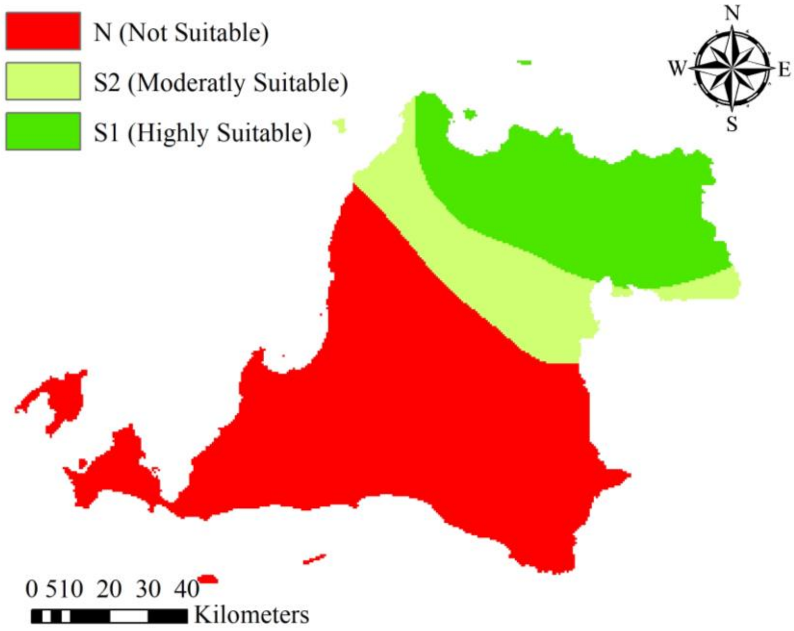
(a2) Soil map, reclassification by fuzzy membership function



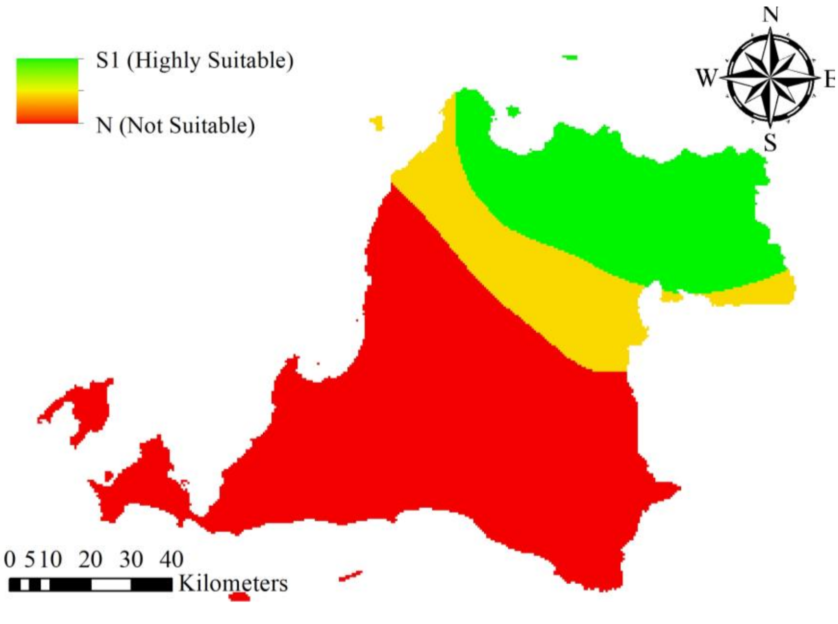
(b1) Elevation map, reclassification by score



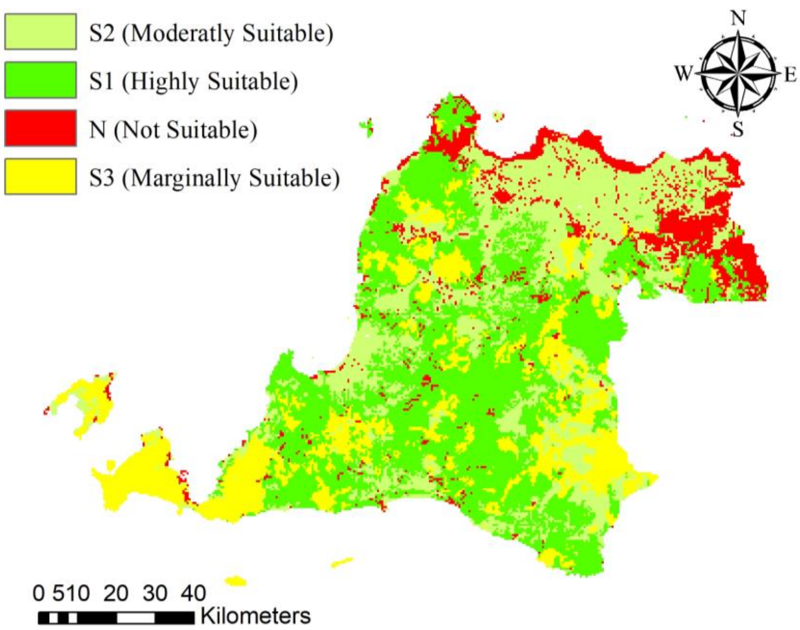
(b2) Elevation map, reclassification by fuzzy membership function



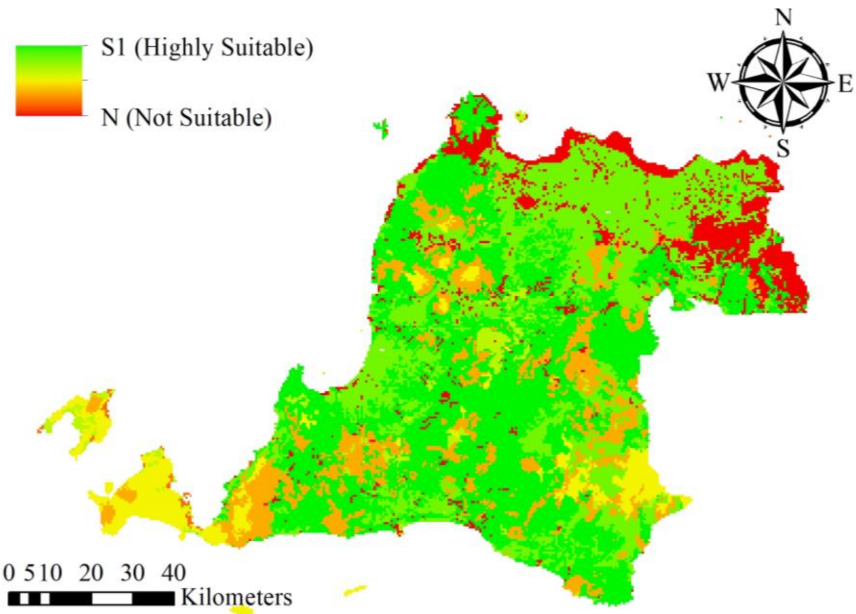
(c1) Rainfall map, reclassification by score



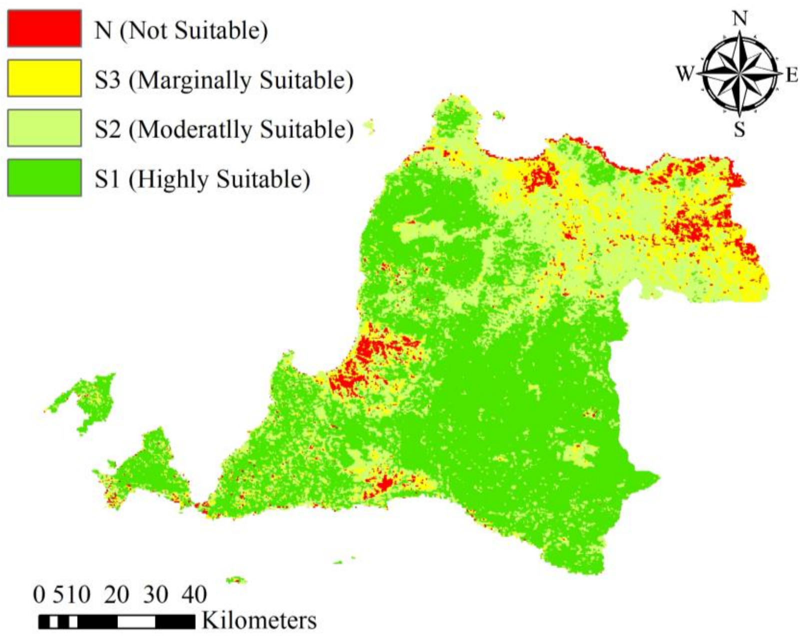
(c2) Rainfall map, reclassification by fuzzy membership function



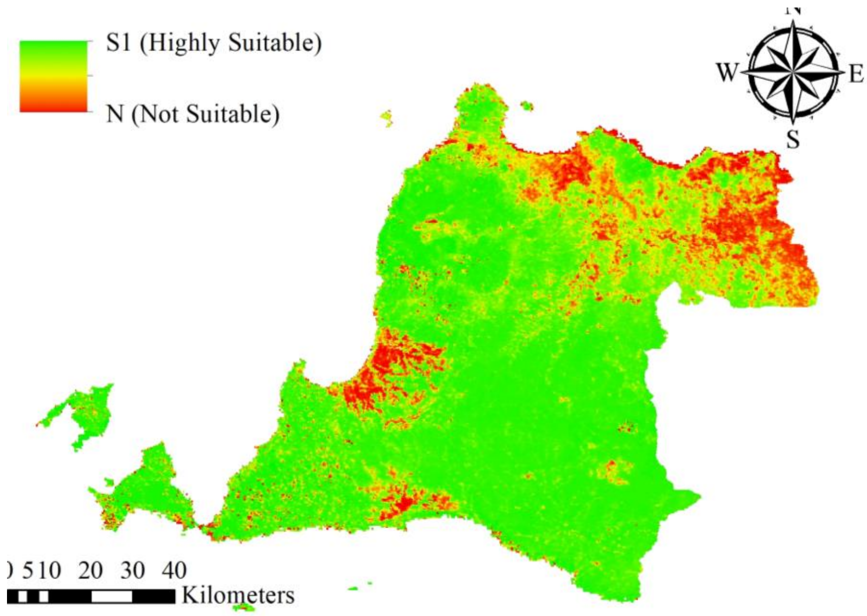
(d1) LULC map, reclassification by score



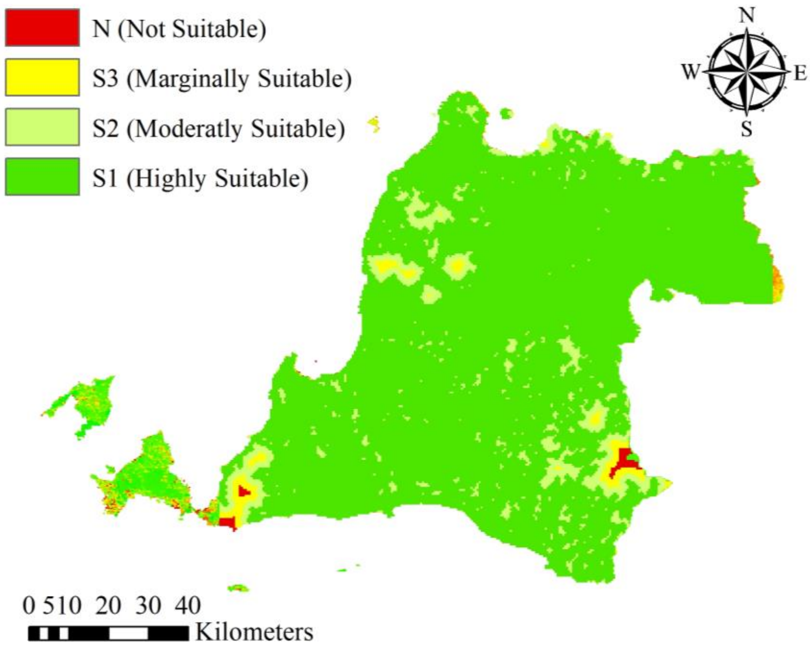
(d2) LULC map, reclassification by fuzzy membership function



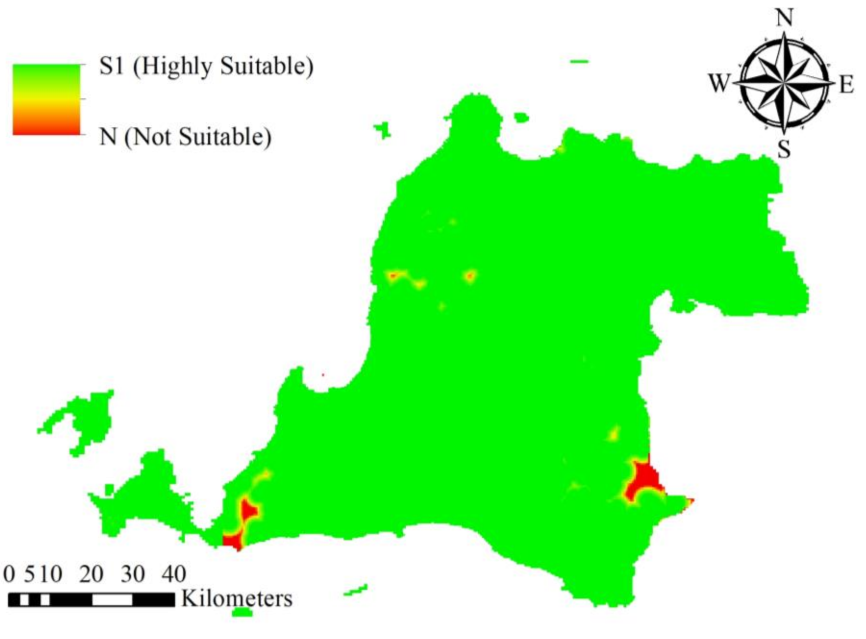
(e1) NDVI map, reclassification by score



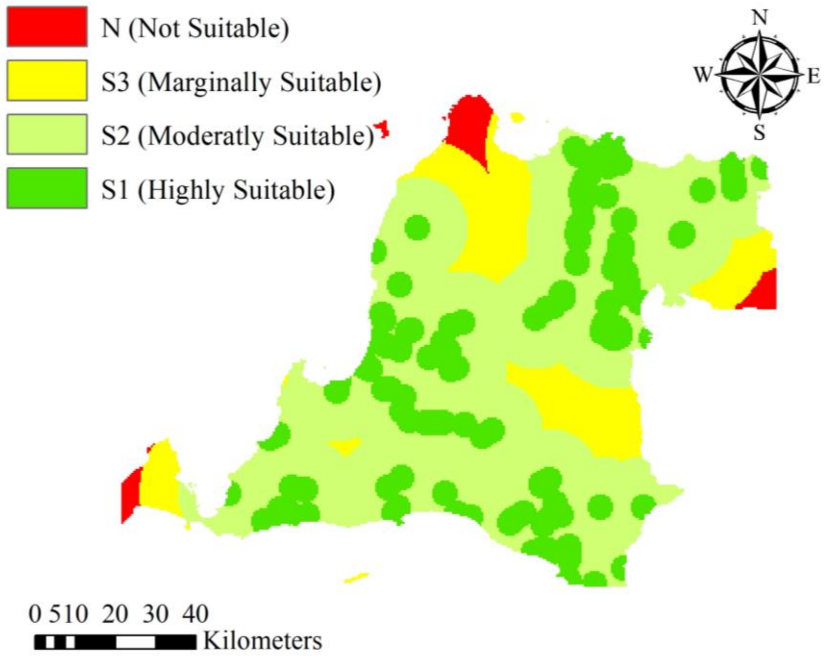
(e2) NDVI map, reclassification by fuzzy membership function



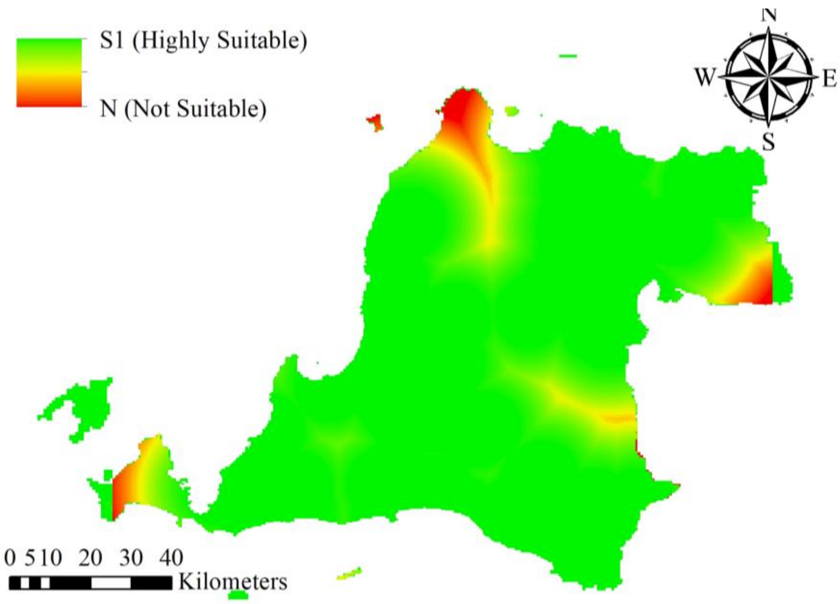
(f1) Distance from road map, reclassification by score



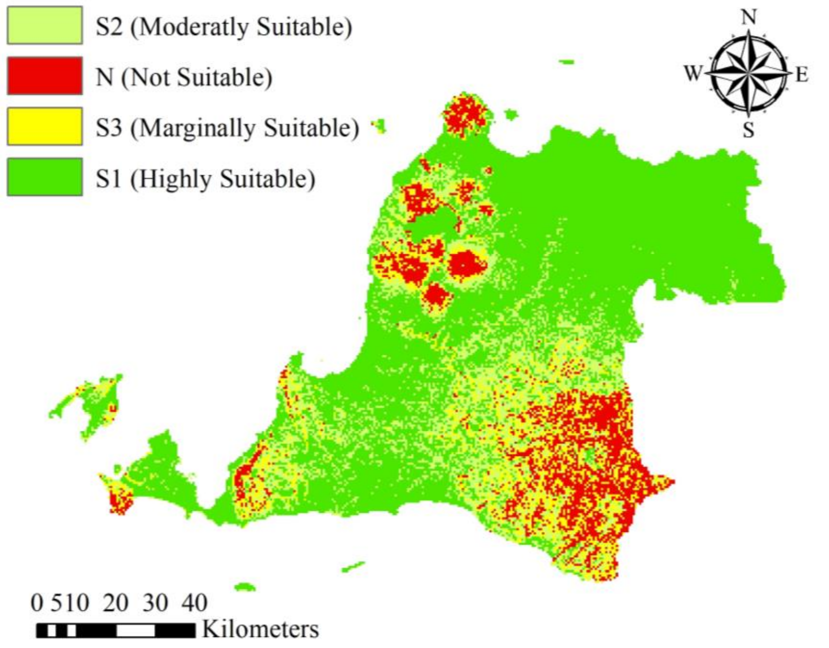
(f2) Distance from road map, reclassification by fuzzy membership function



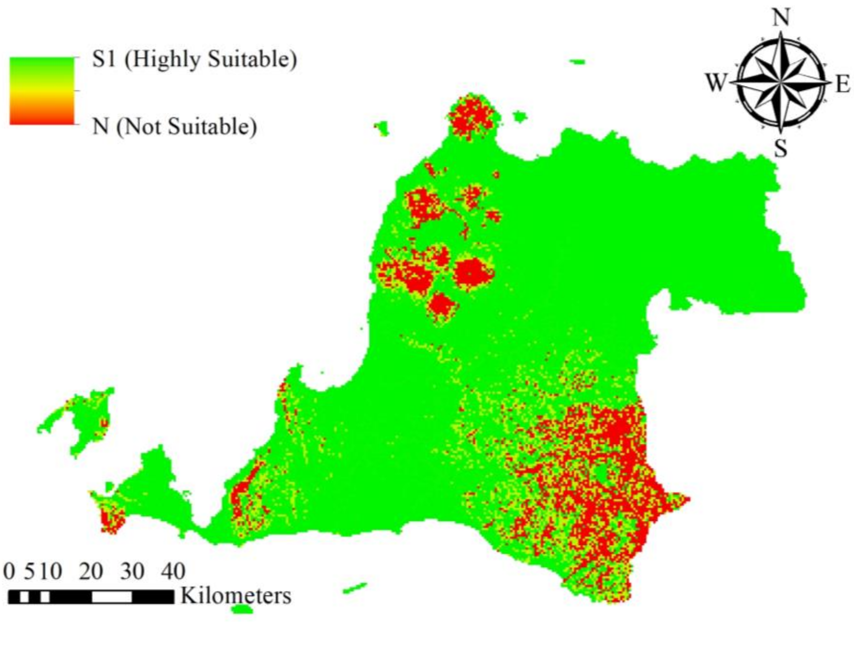
(g1) Distance from river map, reclassification by score



(g2) Distance from river map, reclassification by fuzzy membership function



(h1) Slope map, reclassification by score



(h2) Slope map, reclassification by fuzzy membership function

Figure 5.6 (a1-h2). Reclassification of the criteria

5.3.6 MCDM Application

In this study, MCDM based on AHP was applied for weighting. After preparation of questionnaire and using experts' opinions **(Appendix 2)** by formation of pair-wise comparison matrix, the criteria weights were determined using Super Decisions software®. Furthermore, the Super Decisions software® was used to calculate the consistency ratio (CR). CR and weights of the main and sub criteria are presented in **(Table 4.7, Chapter 4),** which indicates a good consistency of the judgments used for the comparison. According to the results of weighting, among the main criteria, soil type and LULC were the most and least important sub-criteria. Distance from road centers and distance from river were the most and least important criteria.

5.3.5.1 Suitability Assessments

In the FAO's framework for land evaluation, the land classification was designated as suitable (S) or not suitable (N). These suitability classes can then be further sub-divided as required. In practice, three classes (S1, S2 and S3) 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 from the GIS environment. AHP results were secured from experts of related fields and from literature reviews. Through this process, the consistency ratio (CR) was calculated and used in the suitability analysis as stated above. The AHP method was applied to determine the relative importance of all of the selected criteria and factors (Ahamed *et al*., 2013).

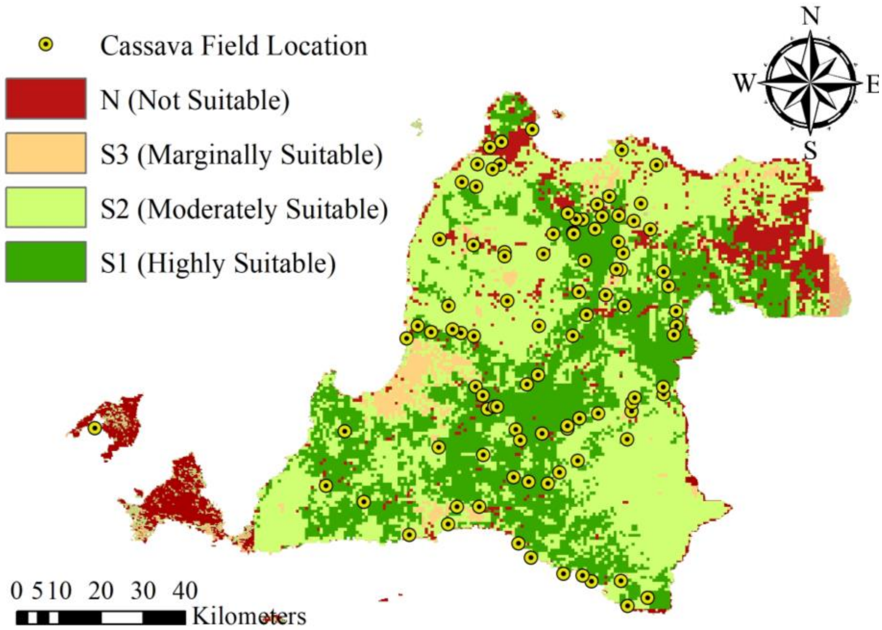
5.3.5.2 Weight Linear Combination (WLC)

WLC method was used to calculate for the suitability index (S) for area, Wi is the relative importance weight of criterion, Ri is the standardized value of the area under criterion i and n is the total number of criteria. The suitability score for each of the land unit was calculated using the following expression:

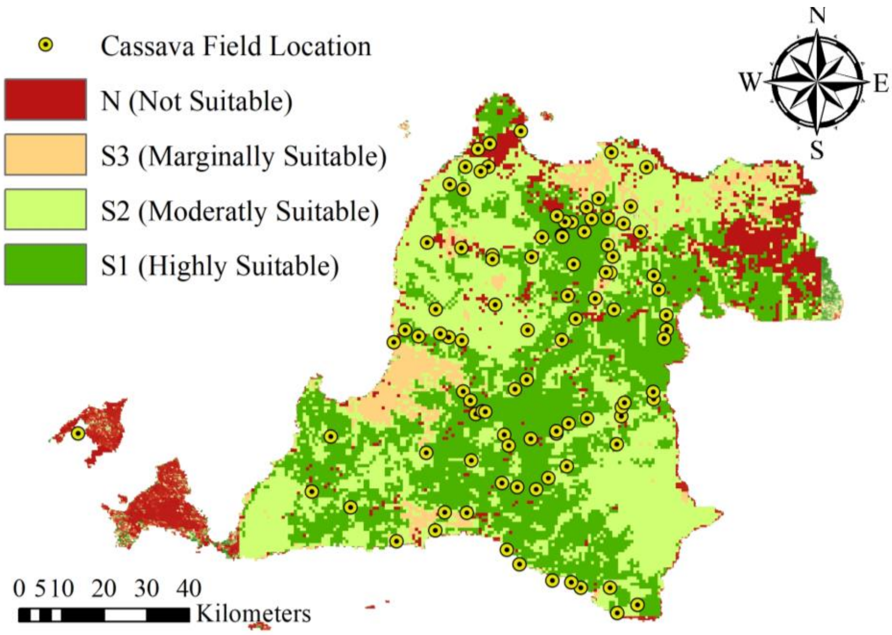
$$S = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{Wi} \times \mathrm{Ri} \tag{5.3}$$

5.4 Results

The suitability classification aimed to show the suitability of each land unit for cassava production. The suitability classes can then be further sub-divided, as required. In this section, three classes (S1, S2 and S3) was used to distinguish land that is highly suitable, moderately suitable and marginally suitable for cassava production.



(a) Suitable area of cassava production based on MCDM



(b) Suitable area of cassava production based on F-MCDM

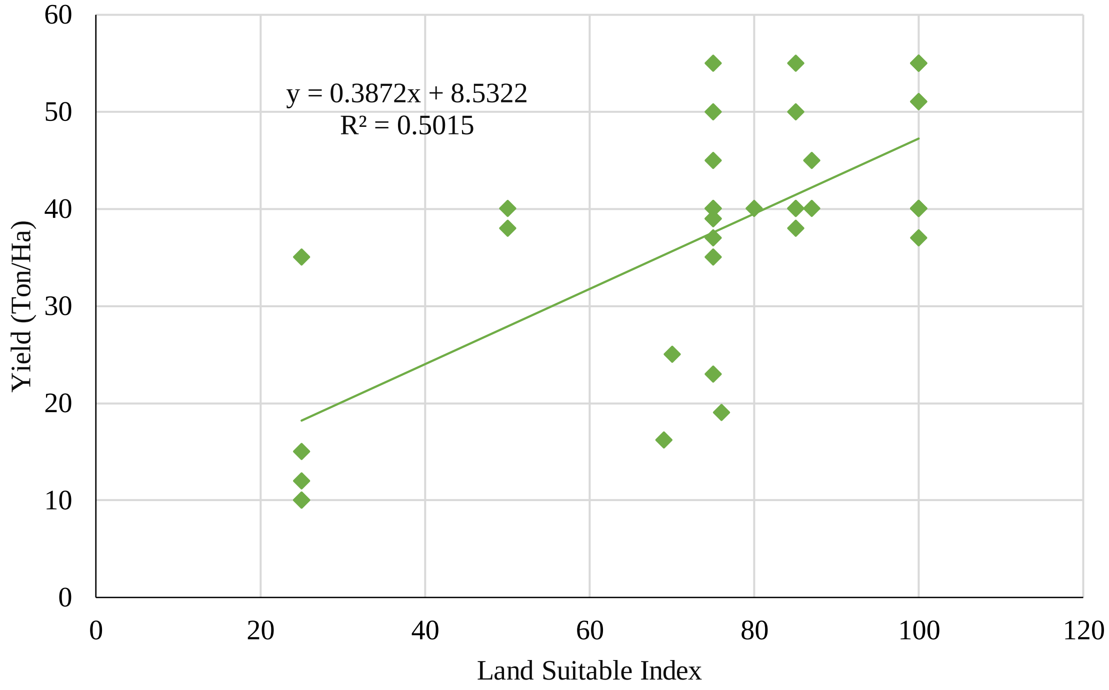
Figure 5.7 (a-b). Suitable area of cassava production

Several models were built to assess the suitability evaluation. In this research, the multi criteria analysis based on AHP with is referred as Fuzzy MCDM (F-MCDM) and only AHP is refereed as MCDM. A quantitative comparison of the differences in suitability is summarized in **Table 5.3.** The result was showed that 42.17% was found as highly suitable for F-MCDM model while 35.92% in MCDM Model **(Figure 5.7).** For the verification of the model, further the regression analysis was carried out using ground truth data collected from the cassava yield in the Banten Province. The correlation of the Land suitability index with actual yield is depicted **(Figure 5.8).**

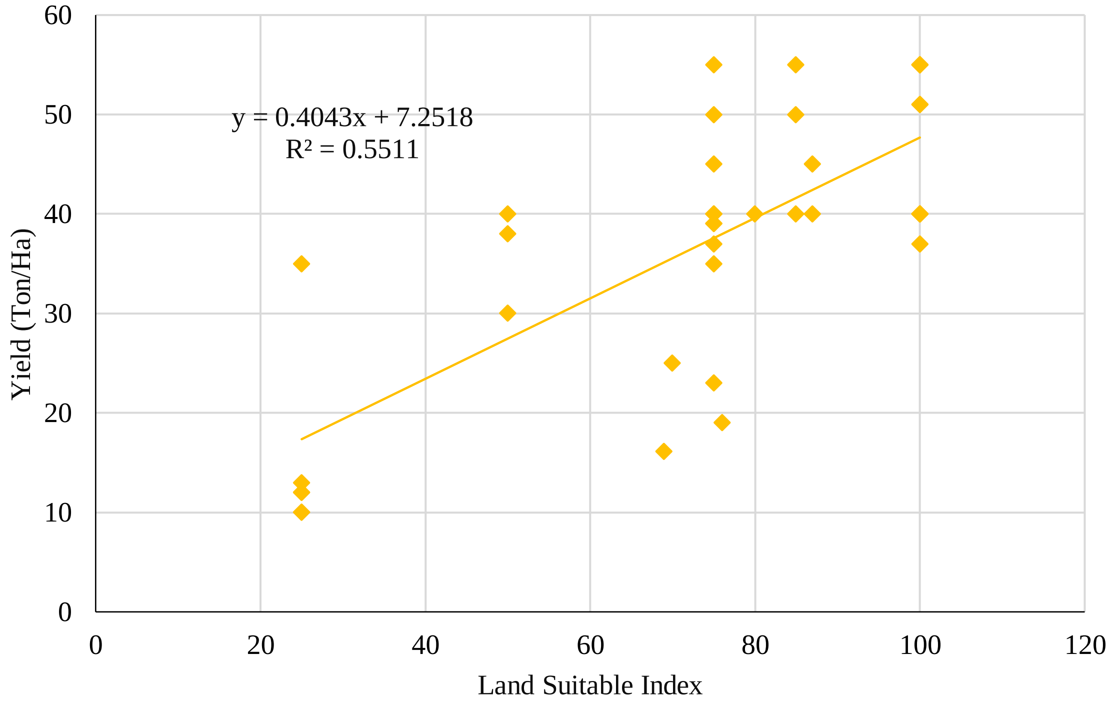
The result shows that F-MCDM land suitability maps had interaction between the fuzzy membership function values and their weights. The area of the land suitability analysis using F-MCDM method had approximately similar result compare to the land suitability analysis using scoring-MCDM. This is because the both method used the same weight from the same experts. To evaluate the accuracy of the methods, the correlation between land suitability index and yield of cassava was obtained. The higher land suitability index should be correlated with the higher yield. The R^2 of the F-MCDM method show higher than MCDM method. This was indicated that the F-MCDM method can explained more about the correlation of cassava yield with the suitability of land. Around 55% cassava field was located in the right suitable location.

Table 5.3. Suitable areas for cassava production

Suitability Class	MCDM	Fuzzy-MCDM
	Percentage area (%)	Percentage area (%)
Highly Suitable	35.92	42.17
Moderately Suitable	51.84	43.10
Marginally Suitable	3.75	6.25
Not Suitable	8.47	8.47



(a) MCDM model



(b) F-MCDM model

Figure 5.8 Verification of the land suitability model

5.5 Discussion

In this chapter, the study area was scaled up to provincial scale. The scaled-up phase is important to apply the policy to the others sub-district in Banten province. The suitable areas mostly located in the southern part of the Banten Province. In this area, farmers growing cassava as intercropped with or in rotation with other crops to prevent soil nutrient erosion. From the reference survey at the Banten province, many of cassava fields were not located in the suitable areas. Therefore, farmers in the Banten province required to cultivate cassava in the highly suitable land. Moreover, to obtain highly accurate validation results, future studies should integrate with application from remote sensing data. Over the past decade, remotely sensed data from satellite-based sensors have proven useful for evaluating large-area LULC characterizations and changes overtime.

5.6 Summary

In this chapter, the method was presented to select the best suitable land for cassava production using combination of fuzzy and MCDM based on AHP. AHP was used to assess importance of the criteria for decision making involving multiple and contradictory parameters. The MCDM-based AHP method enhanced with fuzzy membership function. Fuzzy set methodologies have proposed as a method for overcoming biased of AHP. The biased in MCDM based on AHP was occured in the scoring stage which used the discrete value. When, the criteria were more complex and need the continuous value, the fuzzy standardization using membership functions was needed. The F-MCDM shows the better suitability map than MCDM. The F-MCDM method can explained that around 55% cassava field was located in the right suitable location. In the further assessment, the highly suitable areas were determined for predicting yield for the sustainability of cassava production.

CHAPTER 6

Yield Prediction of Cassava for Regional Inventory Planning to Ensure Food Security using GIS and Satellite Imagery

6.1 Background

Cassava is the root crops and maximum growth of tubers cannot observe without harvesting. For estimation of yield in cassava, detection of changes in vegetation improvement are essential. Especially, the monitoring method to observe health and productivity through optical reflection of vegetation. Environmental factors significantly affect cassava production through vegetation development, biophysical condition, and crop growth. The development of crops growth from sowing state to harvest is a function of various driving variables, such as temperature, sunlight, precipitation, soil, slope and water.

Since the early development of spectral reflectance and remote sensing technologies, scholars have used various models to estimate the crop yield using remote sensing application (Sakamoto *et al.*, 2013; Lobell *et al.*, 2015; Zabihi *et al*., 2015). Satellite images have been used to monitor canopy optical properties, crop condition and forecast yield as well as production in many countries of the world. For example, healthy crops and stress conditions distinguished by absorption of red energy and reflectance of NIR energy. This combination of the red and near-infrared reflectance defined as vegetation indices (Tucker, 1979). The optical reflectance from the satellite play a role in providing information about crop conditions and crop yield from the field level to extended geographic areas like countries or continents.

The method to get crop conditions and crop yield is using ground truth data measurement which takes the sample from vegetations. This method needs much cost and more times to obtain the sample. Satellite-derived VIs provide another possible way to get the biophysical parameters of vegetation over large areas. Furthermore, the low cost and robust measurements of crop condition for smallholder cassava farms are important to understand the yield prediction due to variability soil. Moreover, yield mapping for smallholder cassava farms is challenging because small field sizes and heterogeneous land cover. Remote sensing methods have been demonstrated to identify the crop field using various sensors. Recent high-resolution satellite sensors offer promise to monitor the production and condition of the field crops. In this study, the utility of publicly accessible Sentinel-2 satellite was investigated to predict the yield of cassava from smallholder farm area.

Sentinel-2 has high-resolution up to 10m, and unique spectral capabilities including three bands in red-edge with a frequency revisit time around 5-days. This satellite provides beneficial information for the monitoring of vegetation and disturbances for agricultural and forest practices. Sentinel-2 provides three red-edge bands 705nm, 740nm, 783nm, which are important for vegetation attribute reflectance. This uniqueness made the investigations of applications based on Sentinel-2 images are valuable in precision agriculture.

Over recent years, exploring research activities have focused to understand the relationships between vegetation optical properties and photosynthetic pigments such as: chlorophyll-a, chlorophyll-b, and carotenoids from leaf tissue to canopy level. The well-known and widely used vegetation index to estimate greenness of vegetations in remote sensing is the normalized difference vegetation index (NDVI) proposed by Rouse *et. al* 1973. NDVI highlighted the absorption of red energy and reflectance of NIR energy. Many research use NDVI to perform the crops growing stages and detect the chlorophyll concentration of vegetation canopy (Hill and Donald 2003, Wardlow and Egbert 2008). In some cases, the calculation of vegetation indices is influenced by soil background conditions. To reduce soil background effect, Huete (1988) recommended in the soil-adjusted vegetation index (SAVI) to use a soil adjustment factor L to account for first-order soil background variations and proposed a constant adjustment factor ($L = 0.5$). Besides the visible red band, the red-edge band has often been used as an estimate for chlorophyll content. A measure of red-edge position contains the narrow bands in the 680-750 nm. Current method and algorithm presented the Inverted Red Edge Chlorophyll Index (IRECI) uses all RE bands that Sentinel-2 provided. The IRECI is the optimal red edge index for evaluating the grassland health status using Sentinel-2A imagery.

The other factor that influences the production of cassava were biophysical properties such as leaf area index (LAI) and the fraction of absorbed photosynthetically active radiation (fAPAR). Leaf area index (LAI) is a critical parameter in many land-surface vegetation and climate models that simulate the carbon and water cycles. Ren *et al*. (2008) calculated yield estimation using retrieved LAI from Remote Sensing. Measurements of APAR (total amount of photosynthetically active radiation) represent another source for yield estimates. In some research, fAPAR incorporated into a simple model based on crop light-use efficiency. This model was used to predict yield (Lobell *et al.*, 2003). The effectiveness of each factor from vegetation indices and biophysical properties will be tested for accurate yield estimates. Furthermore, the combination formula of cassava prediction model will be evaluated.

6.2 Objective

To increase sustainable cassava production, it is required to know the estimation yield crop information (Heumann *et.al*., 2011). Many empirical models have been tried to develop the estimation yield before harvesting. Previously, crop models have shown by regression of static measurements, but this model has limit to describe the reasons for yield variability related with spatial and temporal aspect (Basso *et al*., 2007). The spatial technologies such as Global Positioning Systems (GPS), Geographic Information Systems (GIS) and remote sensing have promising possibility to assess the spatial variability that occur in the geographical extension. Therefore, the objective of this part research is to develop a model from various vegetation indices and biophysical properties derived from satellite datasets to predict the yield of cassava for regional food inventory planning.

6.3 Methodology

6.3.1 Study Area

The study area was located in Banten Province, Indonesia. Banten Province is located between 5°7'50" - 7°1'1"S and 105°1'11" - 106°7'12"E and is identified as the most western point of Java and is about 90 km from Jakarta. Banten Province is strategically positioned as the connecting area of land between Java and Sumatra Islands. Cassava serves as an important alternative source of food, and especially for traditional cuisine prepared for traditional events. In the Banten province, cassava has historically been grown by poor farmers with minimal inputs and poorly managed land **(Figure 6.1)**.

6.3.2 Framework of Yield Prediction

As depicted in **Figure 6.2**, the Sentinel-2 satellite datasets were obtained to analyze for vegetation indices (VI) and biophysical properties. Before analyzing, the image pre-processing was done to prepare the cloud-free image based on the TOA reflectance. The 27 field-collected cassava yield data points chose within the highly suitable area for cassava production. These points were correlated to the corresponding VIs and biophysical properties to generate a formula for the early prediction of cassava yield for the given fields.

6.3.3 Sentinel-2 Imagery

All 24-available satellite images from of Sentinel-2A over Banten province between March 2017 until February 2018 were downloaded from the USGS earth explorer resources. The cloud masking and buffering were performed using idepix toolbox using Sentinel Application Platform (SNAP) 5.0. For calculating the vegetation indices, several bands in 10-meter resolution was used. The bands included in this analysis Band 4 (red), Band 8 (NIR) and three new bands in the red-edge region, Band 5, Band 6 and were Band 7 which are centered at 705, 740 and 783 nm.

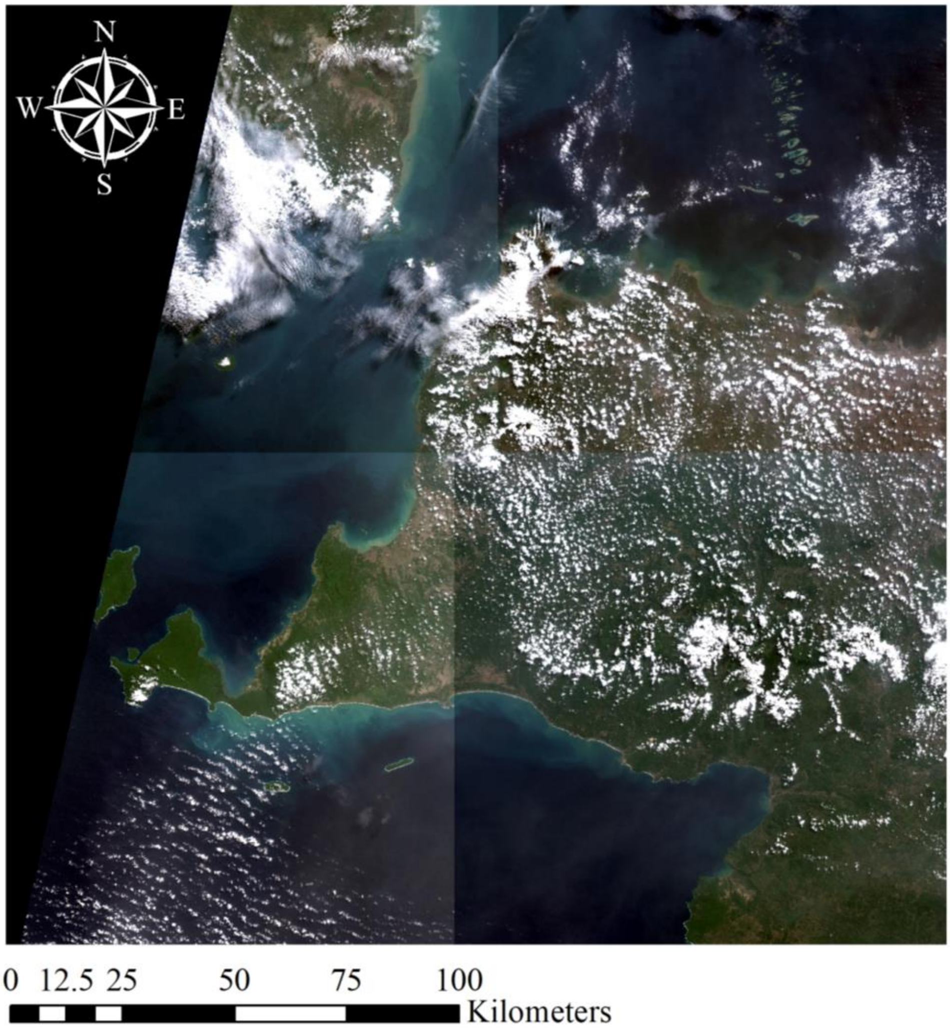


Figure 6.1 Sentinel-2 image for Banten province

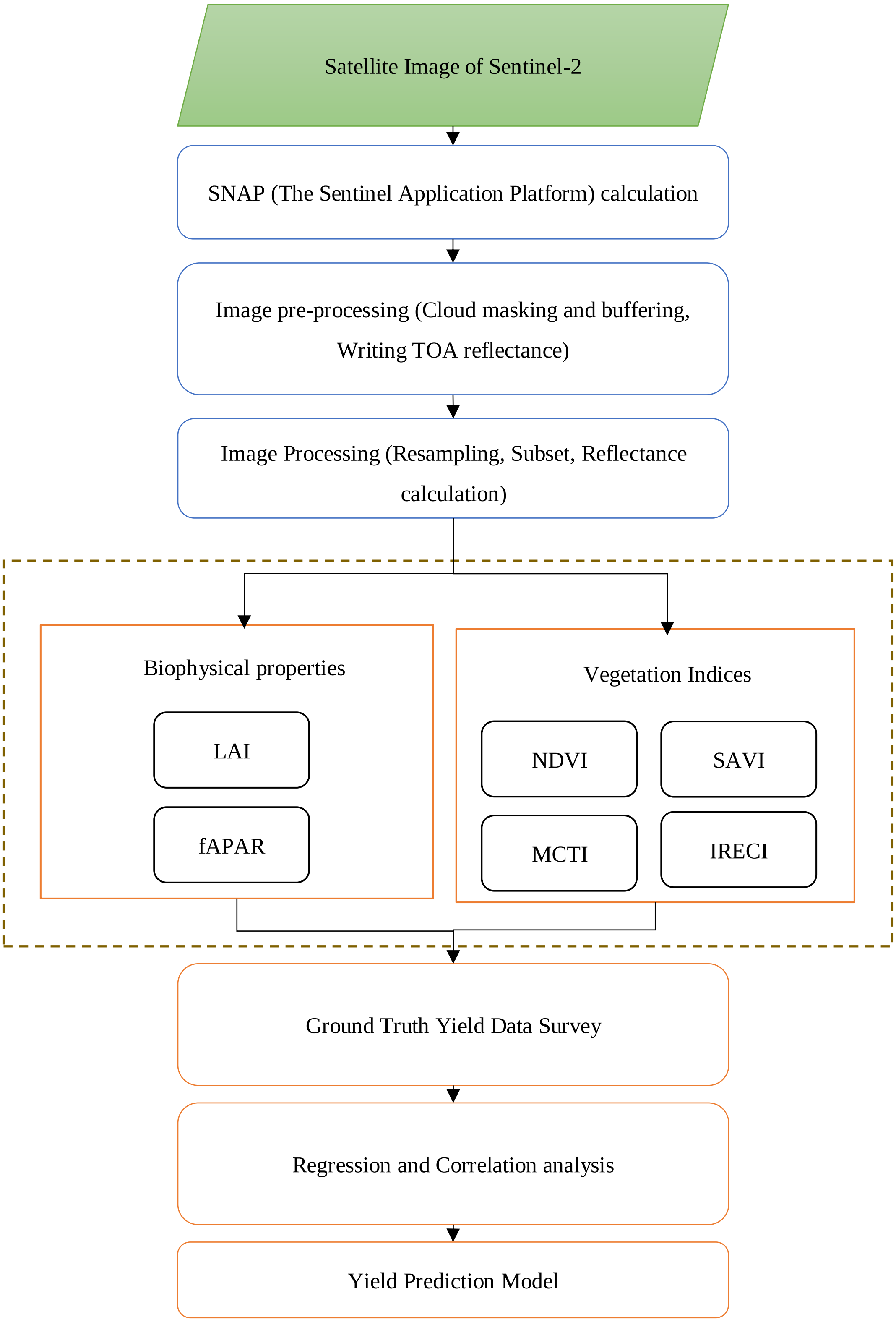


Figure 6.2 Framework of the yield prediction

6.3.4 Vegetation Indices

6.3.4.1 NDVI

The NDVI was proposed by Rouse et al. 1973, and it has become the most widely used indicator for studying vegetation canopy, crop production, green biomass, chlorophyll content, and canopy water stress. The NDVI utilized two essential wave bands: the red and near-infrared (NIR) bands. Band combinations corresponding to the red and NIR reflections using Band 4 and Band 8. The relationship between NDVI and yield has known from various experiments (Rasmussen, 1992). The NDVI was calculated as:

$$NDVI = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}} \tag{6.1}$$

6.3.4.2 SAVI

The calculation of vegetation indices is influenced by soil background conditions in some cases (Huete, 1988; Gilabert *et al*., 2002). Huete (1988) used a soil adjustment factor L to reduce soil background effect. The proposed a constant adjustment factor (L = 0.5) and referred as soil-adjusted vegetation index (SAVI):

$$SAVI = (1 + L)x\ \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}} \tag{6.2}$$

6.3.4.3 IRECI

IRECI (Inverted Red Edge Chlorophyll Index) utilized all red-edge bands that Sentinel-2 provided. The combined bands have substantial effects on chlorophyll absorption and internal leaf scattering. The IRECI is the optimal red edge index for evaluating the grassland health status using Sentinel-2A imagery.

$$IRECI = \frac{(R_{NIR} - R_{Red})}{\frac{R_{RE2}}{R_{RE1}}} \tag{6.3}$$

6.3.5 Biophysical Properties

6.3.5.1 LAI

The monitoring of essential plants biophysical and biochemical variables such as chlorophyll, nitrogen, LAI, leaf water content and crop health are very important. Leaf area index (LAI) is an important biophysical variable for agricultural land monitoring and modeling studies. Since it plays a crucial role in ecological processes, LAI retrieval maps from satellite have used in many land observation studies. LAI retrieval from sentinel-2 was calculated using an algorithm provided by SNAP biophysical operations toolbox.

6.3.5.2 fAPAR

Some research found that total biomass production is closely related to the fraction of photosynthetically active radiation (fAPAR). fAPAR absorbed the canopy over the growing season (Monteith, 1977). Estimations of fAPAR are often derived from VIs (Lobell, 2013). In the SNAP software, the calculation of fAPAR is also using biophysical operations toolbox.

6.3.6 Ground Collection Data

The location point of cassava field collected by GPS Garmin eTrex around Banten Province in 2017. Yield estimates were evaluated using the ground data yield based on the farmer survey in the cassava field location. The harvested time was recorded for each cassava field. The collection data of field location and yield listed in **Table 6.1**. In the Banten province, the farmer has a different time to start to grow cassava. The variability of the field within the various growing season showed in **Figure 6.3**.

6.3.7 Cassava Yield, Vegetation Indices and Biophysical Properties

The analyses of model relationship completed in several procedures. The yield estimation calculation procedure follows this process:

i. Establish the statistical relationship between crop yield and NDVI in every growing stage in the days after planting (DAP).
ii. Establish the statistical relationship between crop yield and SAVI in every growing stage in the days after planting (DAP).
iii. Establish the statistical relationship between crop yield and IRECI in every growing stage in the days after planting (DAP).
iv. Establish the statistical relationship between crop yield and LAI in every growing stage in the days after planting (DAP).
v. Establish the statistical relationship between crop yield and fAPAR in every growing stage in the days after planting (DAP).
vi. Establish the statistical relationship between crop yield, LAI, fAPAR and all Vis in the optimum accuracy time.

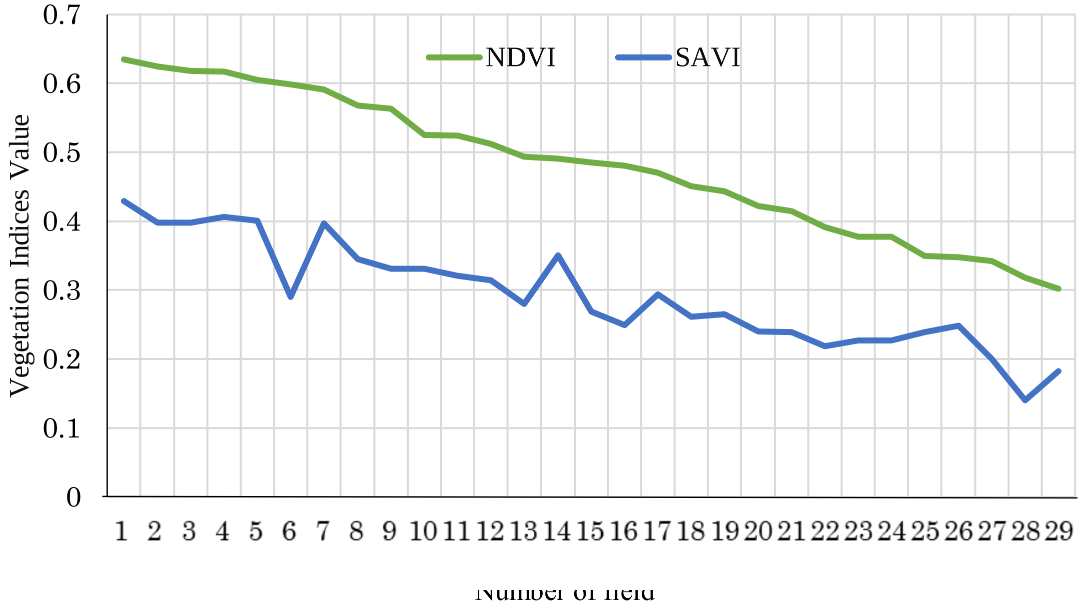
At each step, the coefficient of determination was calculated though linear correlation to estimate the amount of yield variability that can be accounted for the vegetation indices or biophysical properties.

Table 6.1 Ground reference collection for cassava yield within highly suitable area

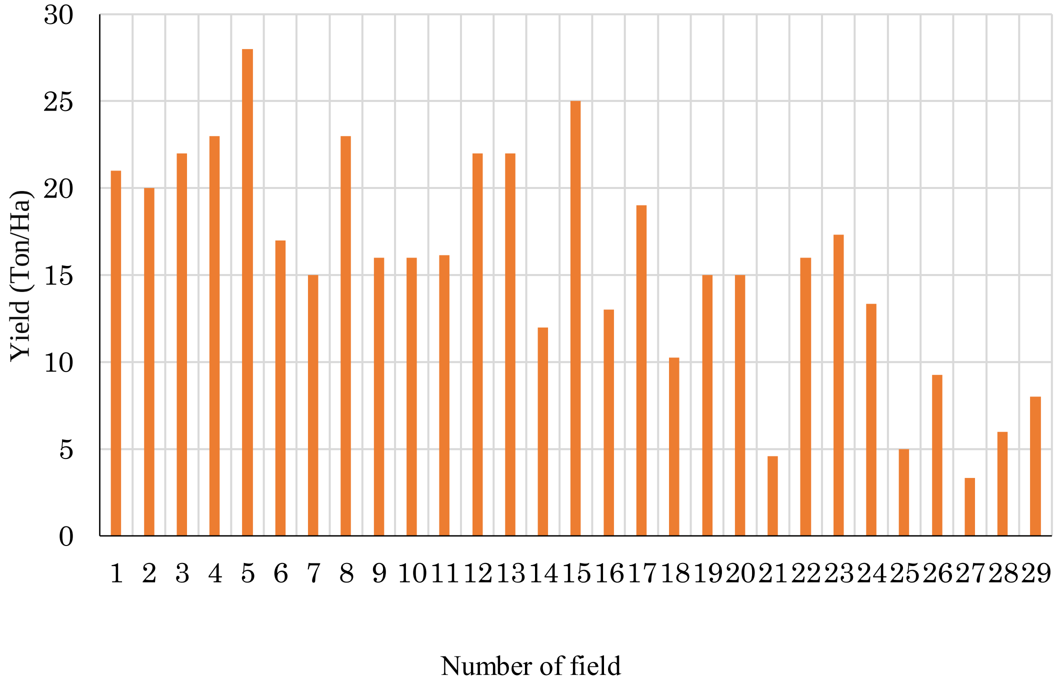
Field ID	Village	Latitude	Longitude	Yield (Ton/Ha)
31	Cililitan	-6.509367	105.975719	15
32	Sodong	-6.401745	105.972278	5
33	Pasireurih	-6.395216	105.944765	15
57	Bojongjuruh	-6.6550937	105.992709	23
58	Bojongjuruh	-6.528362	105.99105	23
61	Bejod	-6.764609	105.936332	21
63	Ciginggang	-6.5514399	106.016398	10.27
64	G. Kencana	-6.552202	106.02169	22
66	Kramat Jaya	-6.6236799	106.071154	9.25
69	Cigeulis	-6.6918084	106.155297	17
70	Lebak Tipar	-6.9588283	106.342997	17.33
71	Peucang Pari	-6.7152968	106.129852	15
72	Cirinten	-6.6669549	106.194429	16.15
75	Cihara	-6.8732454	106.094178	3.33
76	Panggarangan	-6.9235395	106.223654	8
79	Sawarna	-6.9765649	106.300831	4.6
83	Cimayang	-6.5980356	106.172184	25
84	Bojong	-6.5930714	106.172219	22
86	Cisimet Raya	-6.5659956	106.237359	28
87	Ciminyak	-6.5612666	106.309104	20
89	Sobang	-6.6209599	106.29969	13
91	Gajrug	-6.5102631	106.377055	22
92	Sukamarga	-6.5331168	106.316075	19
98	Maja	-6.3482881	106.404399	12
99	Sangiang	-6.3792799	106.405102	16
101	Cikulur	-6.4009125	106.183285	16
103	Cileles	-6.504683	106.085237	16

6.3.8 Cassava Growing Season

For both the optimum growing period, the vegetation indices and biophysical condition were extracted from average value of each cassava field in Banten province. The optimum growing season also analyzed by the vegetation indices and biophysical properties value from Sentinel-2 images **(Figure 6.4)**.

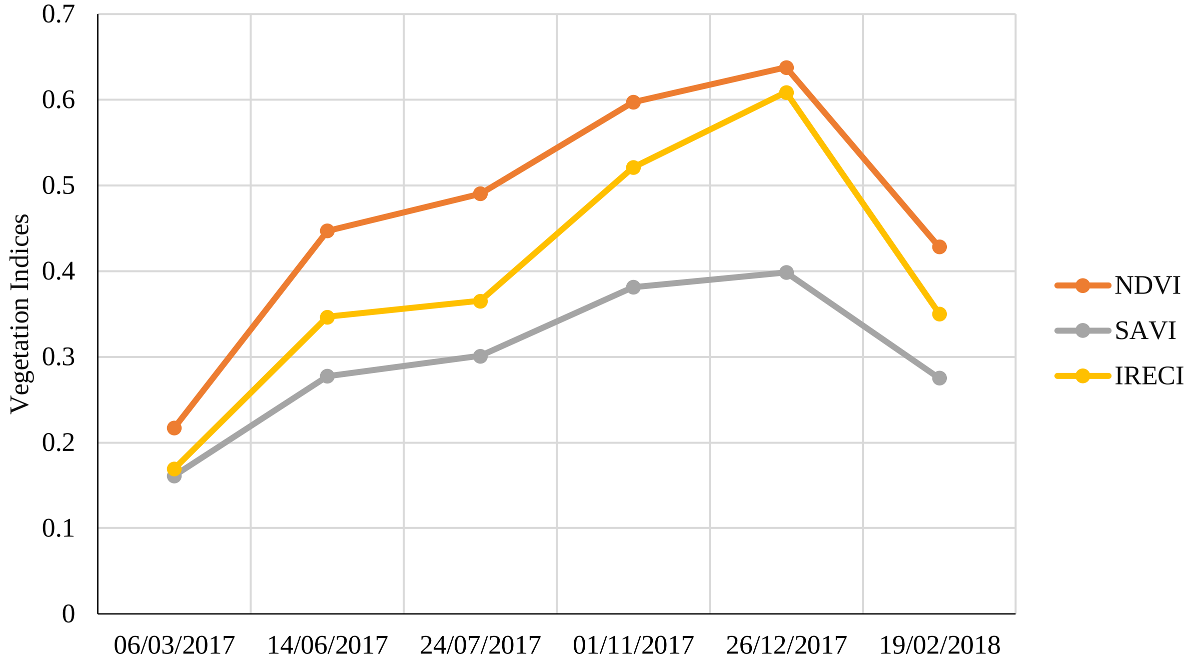


(a) Variability of NDVI and SAVI in Banten province

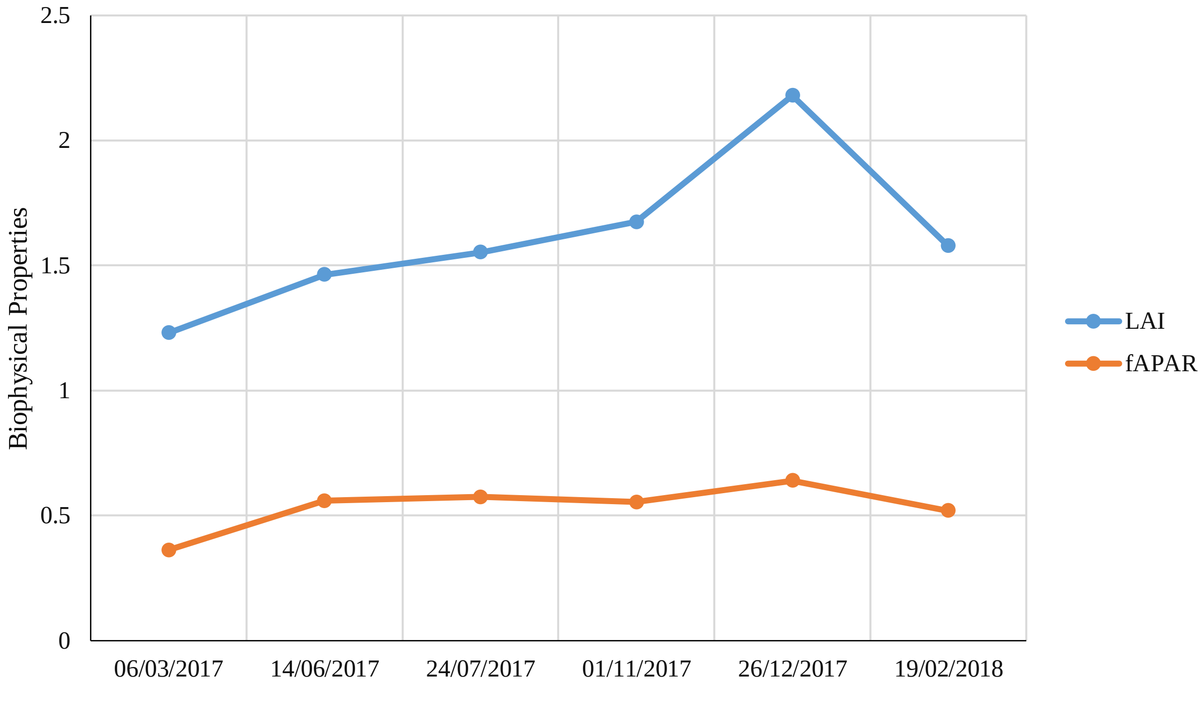


(b) Variability of yield of cassava in Banten province

Figure 6.3 Variability of cassava field in the same growing season



(a) Vegetation Indices value for cassava growing season



(b) Biophysical properties value for cassava growing season

Figure 6.4 (a-b). The optimum growing season based on VIs (a) and Biophysical properties (b)

6.4 Results

6.4.1 Estimation of Cassava Yield using Vegetation Indices and Biophysical Properties

The yield data from the field compared with data retrieved from Sentinel-2. The analysis was conducted to find the relationship between yield, VIs, and biophysical value at each growing stage. The correlation of the regression method showed in **Table 6.2 and Figure 6.5**.

This study investigates the use of VIs and biophysical properties at more detailed field area that located in a highly suitable location based on ground truth data survey. Results of the study shows that NDVI in 24 July 2017 growing season had slightly stronger correlations than other VIs and biophysical properties **(Figure 6.6 and Table 6.3)**. The relationship between the observed yield and NDVI reported the higher correlation. The linear regression was used for yield prediction. Finally, the yield map was generated to show the variability of the cassava yield in the Banten province **(Figure 6.7).**

Table 6.2. Accuracy assessment of cassava yield prediction

Date of growing season	R^2				
	NDVI	SAVI	IRECI	LAI	fAPAR
06/03/2017	0.1346	0.1525	0.1254	0.0206	0.2417
14/06/2017	0.005	0.0002	0.0088	0.0882	0.021
24/07/2017	0.5176	0.416	0.3973	0.4505	0.4187
01/11/2017	0.0311	0.0263	0.0476	0.0716	0.1125
26/12/2017	0.1717	0.1725	0.2237	0.083	0.2219
19/02/2018	0.1226	0.1966	0.2297	0.162	0.1403

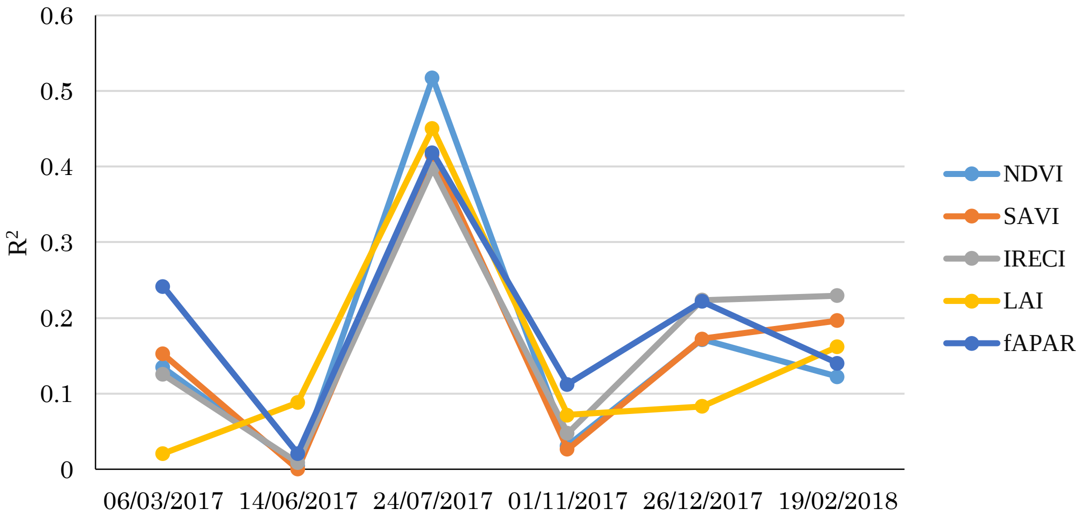
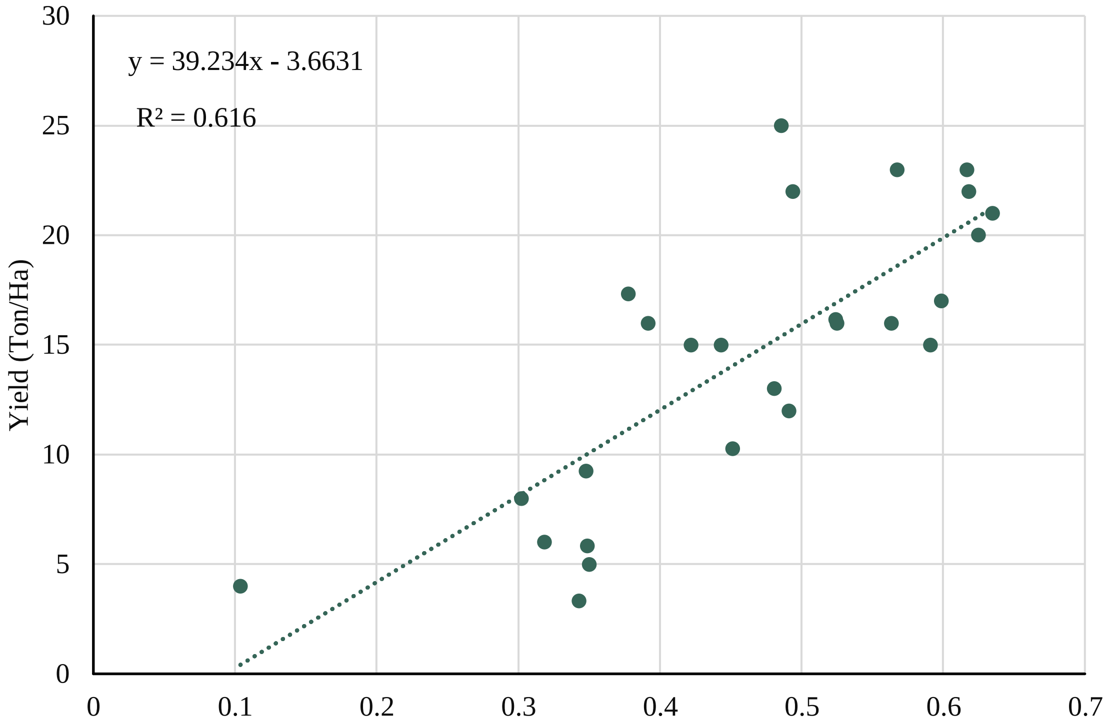
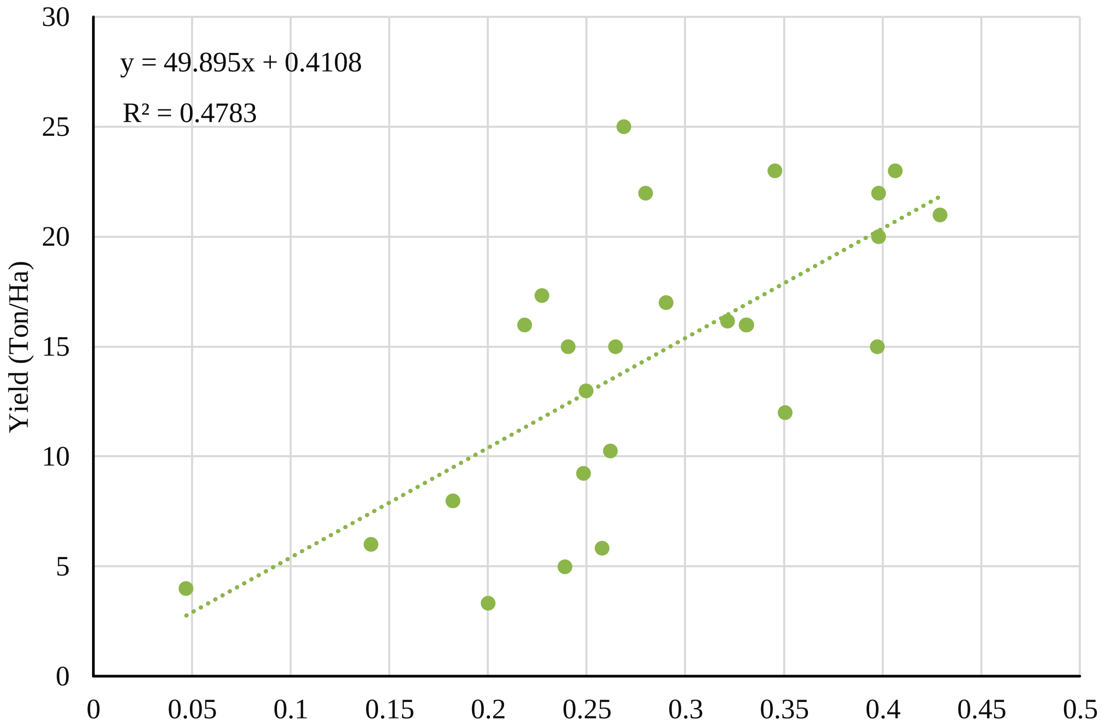


Figure 6.5 The accuracy of yield prediction during cassava growing season



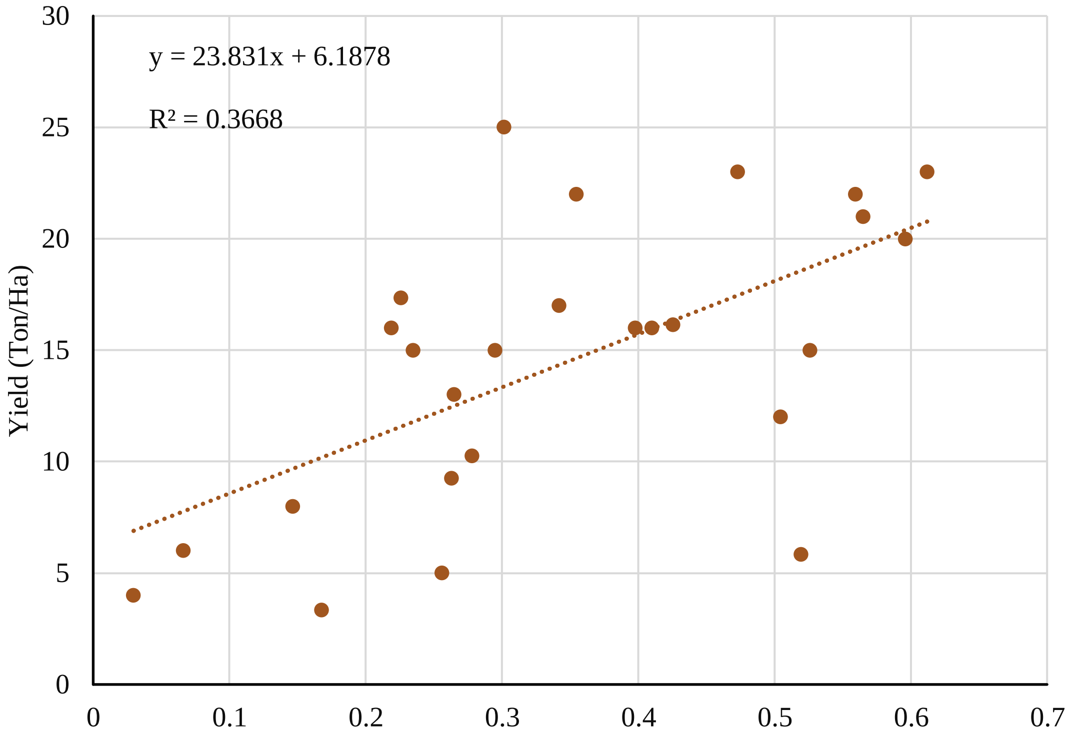
y = 39.234x - 3.6631
R² = 0.616
Yield (Ton/Ha)
30
25
20
15
10
5
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

(a) NDVI



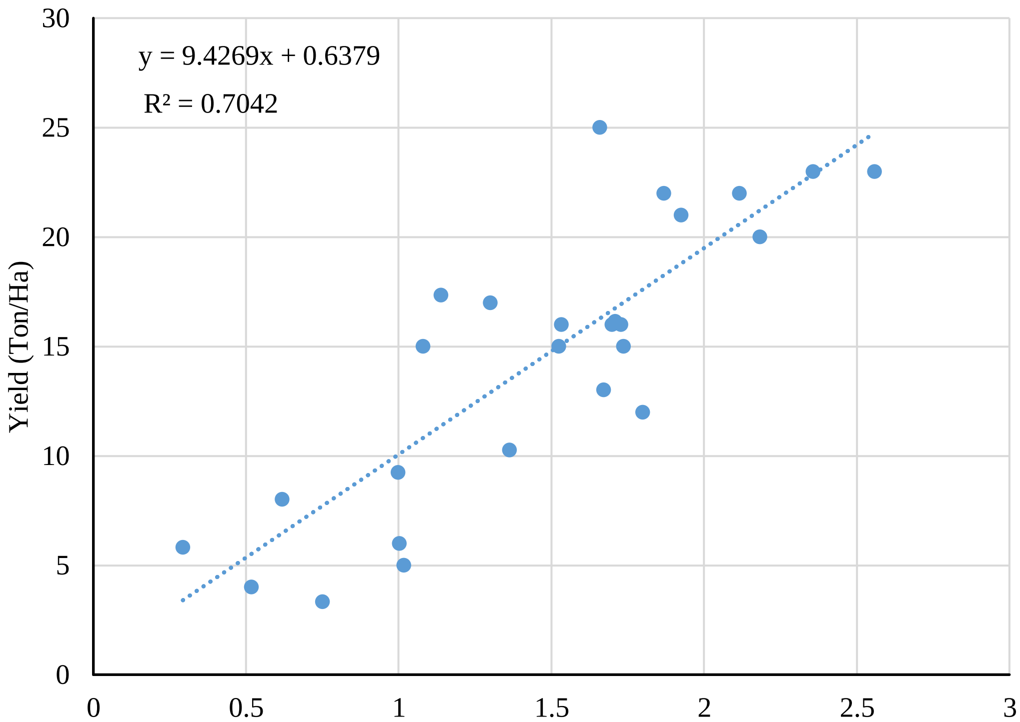
y = 49.895x + 0.4108
R² = 0.4783
Yield (Ton/Ha)
30
25
20
15
10
5
0
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5

(b) SAVI



y = 23.831x + 6.1878
R² = 0.3668
Yield (Ton/Ha)
30
25
20
15
10
5
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

(c) IRECI



y = 9.4269x + 0.6379
R² = 0.7042
Yield (Ton/Ha)
30
25
20
15
10
5
0
0
0.5
1
1.5
2
2.5
3

(d) LAI

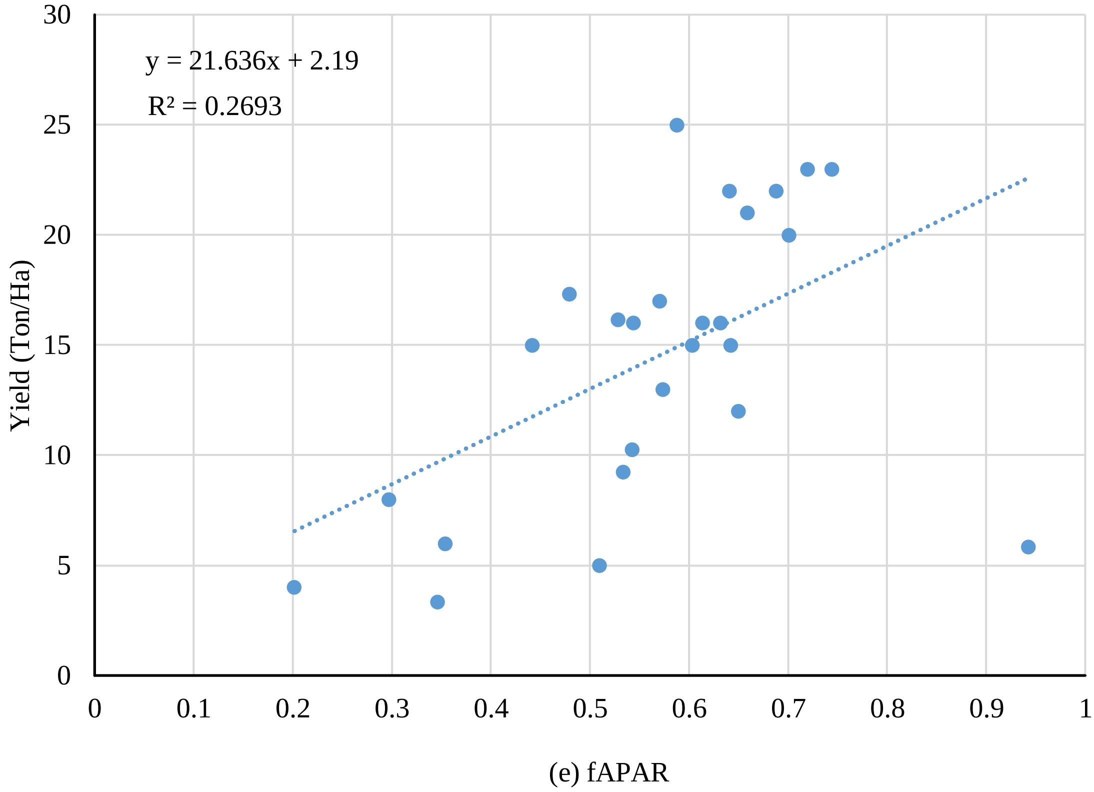


Figure 6.6 Relationship between VIs, biophysical properties and actual yield of cassava

Table 6.3 The formula of yield prediction model

Vegetation Indices	R^2	Formula
NDVI	0.62	Yield = 39.234*NDVI - 3.6631
SAVI	0.48	Yield = 49.895*SAVI + 0.4108
IRECI	0.37	Yield = 23.831*IRECI + 6.1878
Biophysical Properties	R^2	Formula
LAI	0.70	Yield = 9.4269*LAI + 0.6379
fAPAR	0.27	Yield = 21.636*fAPAR + 2.19
All Combination	0.77	Yield = 33*NDVI – 54*SAVI + 8*IRECI + 2.2*LAI + 4.8*fAPAR

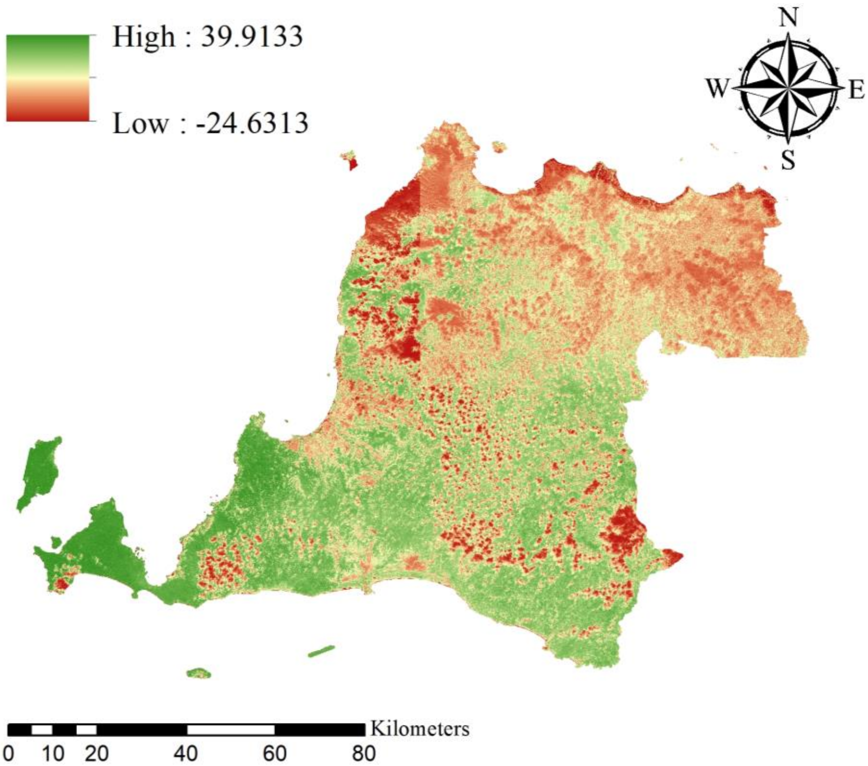


Figure 6.7 Cassava yield map prediction (Ton/Ha)

6.5 Discussion

The value of VIs and biophysical properties was calculated. In general, all indicators explain the vegetation canopy coverage. The higher accuracy was observed between yield and vegetation indices at a green up stage around July 2017. This result indicated that cassava yield can be predicted on July, or four months before harvest in November. The good prediction model was obtained from the combination of vegetation indices and biophysical properties. The value of VIs and biophysical properties which calculated from satellite images were used to develop the yield prediction model.

6.6 Summary

The yields prediction model was developed using the vegetation index retrieved from Sentinel II datasets (10 m resolution). The vegetation indices were used to predict cassava growth, biophysical condition, and phenology status over the growing seasons. The NDVI, SAVI, IRECI, LAI, and fAPAR were used to develop the model of prediction for cassava growth. The generated models were validated using regression analysis to estimate the variations among the observed and predicted yields. NDVI showed the higher accuracy in the yield prediction model (R^2=0.62) compared to SAVI and IRECI. The biophysical properties had higher prediction accuracy (R^2=0.70). The combined model using NDVI, SAVI, IRECI, LAI and fAPAR reported the highest accuracy (R^2=0.77). The combination model was used to generate the yield prediction map. The ground truth data were referred for evaluation of satellite remote sensing data between the observed and predicted yields.

CHAPTER 7
Conclusions and Recommendations

The inappropriate decision on land selection limits the productivity of cassava and increases associated cost to farmers for production. The research was conducted to develop a land suitability model extended from a city scale to the provincial scale to find the best suitable areas for cassava production. The sustainability analysis indicated the land use was decreased for cassava production. The determination of criteria for the identification of sustainability assessment which were divided into 4 main criteria: availability, accessibility, affordability, and profitability were reported. There were four criteria and eight factors in the form of sustainable evaluation for cassava production. The analysis was done using statistical database for 5 years within regional context. For the further assessment, by using the national or regional land resources database and crop suitability assessment approach, it is possible to improve the impact of sustainable intensification on various environmental parameters.

The second stage of research was 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, the priority criteria were found, 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 the criteria. To cut on the bias of AHP, the results also confirmed with the ANP. To complete the analysis of the regional suitability, the model was expanded spatially by adding the provincial scale of analysis. Moreover, to overcome the uncertainty in MCDM of the suitability model, application of the fuzzy was used to overcome the discreate scoring of criteria for suitability analysis.

In third stage, the method was presented to select the best suitable land for cassava production using combination of fuzzy and MCDM based on AHP method. AHP was used to assess importance of the criteria for decision making involving multiple and contradictory parameters. Fuzzy set theory had the advantaged for standardization of criteria using fuzzy membership functions. In ArcGIS10® there were 7 fuzzy functions classified into large and small functions. In other words, this research tried to demonstrate the sufficiency of fuzzy functions in ArcGIS10® for cassava production area selection which were based on midpoint and spread for large and small functions. After this stage, the final suitability maps were determined using weighted overlay method. The fuzzy based MCDM shows the better suitability map than MCDM. In the further assessment, the highly suitable areas were determined for predicting yield for the sustainability of cassava production.

In the last stage, the spectral bands of Sentinel-2 satellite imagery, vegetation indices and biophysical properties was used as input parameters to generate cassava yield prediction models. The study was carried out in the cassava field that located at highly suitable locations for cassava production in the Banten province in Indonesia. The regression models were generated using the vegetative indices. The generated models were empirical models for the cassava at the 7 months after the planting of the crop. The generated models were validated using two statistical tests: regression analysis and standard error of estimate between reported yield and predicted yield. The result was showed that 42.17% of land was highly suitable using F-MCDM model, while 35.92% using MCDM Model. In the ground truth data from harvested yield, it was observed that F-MCDM model showed higher accuracy (R^2=0.56) compare to the MCDM (R^2=0.50). Finally, the yield prediction model was developed using the vegetation index from Sentinel II datasets of 10 m resolution. The vegetation indices were used to predict cassava growth, biophysical condition, and phenology status over the growing seasons. The NDVI, SAVI, IRECI, LAI, and fAPAR were used to develop the model of prediction for cassava growth. The generated models were validated using regression analysis of estimate between observed and predicted yield. NDVI showed the higher accuracy in the yield prediction model (R^2=0.62) compared to SAVI and IRECI. The biophysical properties had the accuracy higher prediction accuracy (R^2=0.70). The combined model using NDVI, SAVI, IRECI, LAI and fAPAR reported the highest accuracy (R^2=0.77). The combination model was used to generate the yield prediction map. The ground truth data were referred for evaluation of satellite remote sensing data between the observed and predicted yields.

The developed decision support system was integrated with expert system, GIS, and Sentinel II satellite datasets to evaluate land suitability and prediction of Cassava yield from canopy biomass and soil adjusted indices. The developed model can be used for the regional and country levels in land suitability assessment and yield estimation of cassava to maximize production. In the further research, machine learning will be added to validate the yield prediction model. The developed integrated DSS model can be recommended to the policy planer in Indonesia to increase practices of producing cassava in the most suitable areas. Furthermore, the developed model can be employed for yield perdition for the inventory planning to ensure the regional food security.

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Sincerely,
Author

Appendix 1

1. List of expert's profiles

Experts Initial.	Education Level	Years of Experience	Affiliations	Signature Research Areas
A.	Doctoral	11	Department of Agronomy and Horticulture, Bogor Agricultural University, Indonesia	1. Changes in Chlorophyll, Specific Leaf Area, and Efficiency of Light in Cassava inter-cropping with Corn. 2. Growth and Production of Three Cassava Varieties (Manihot esculenta Crantz.) On Several Ground Water Levels 3. Production of Organic Materials on Cassava Planting
B	Doctoral	10	Department of Agronomy and Horticulture, Bogor Agricultural University, Indonesia	1. Cassava (Manihot esculenta Crantz.) improvement through gamma irradiation 2. The leaf color performance on several lines of cassava and its relationship with tuber yield as early reference 3. Influence of Agro-ecology on Growth and Performance of Several Potential Mutants of Cassava
C	Doctoral	20	Department of Soil Science and Land Resources, Bogor Agricultural University, Indonesia	1. Land Evaluation and Land Use Planning 2. Spatial landuse planning using land evaluation and dynamic system to define sustainable area of paddy field: Case study in Karawang Regency, West Java 3. Spatial Multi-Criteria Decision Making for Delineating Agricultural Land In Jakarta Metropolitan Area's Hinterland: Case Study Of Bogor Regency, West Java
D	Doctoral	21	Dept. of Agro-industrial Technology Faculty of Agriculture, University of Lampung, Indonesia	1. Sustainability assessment of biomass utilization for bioenergy case study in Lampung Indonesia 2. Mitigation of Green House Gases Emission in Cassava Mill: Case Study in Lampung, Indonesia 3. Reduction of greenhouse gas emissions by biogas utilization in a tapioca starch factory
E	Doctoral	15	Ministry of Agriculture of Indonesia	1. Strategy of achieving self-sufficiency of soybean through expansion of planting area on acid dry land 2. Opportunity of Soybean Development at Cassava Plantation Areas on Dry Dried Land

Appendix 2

2. AHP Questionnaire

SURVEY QUESTIONNAIRE

“Land Suitability Assessment for Cassava Production using GIS, Remote Sensing and Multi-Criteria Analysis in Indonesia”

The aim of the study is to evaluate the land suitability for cassava production in Indonesia, especially in Banten Province. A part of the research is required to incorporate expert’s judgement for ranking the criteria, influencing the land suitability area. Based on the baseline survey and review of literatures eight criteria have selected. A pairwise matrix, supported the Analytical Hierarchy Process (AHP) for the eight criteria has presented here for the expert’s opinion.

Instructions:

1. Compare one criterion (from row) to another (from column) by the following scale

1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1	2	3	4	5	6	7	8	9

Extreme Strong Moderate Weak or Slight Equal Weak or Slight Moderate Strong Extreme

LEAST IMPORTANT **MORE IMPORTANT**

2. For example, if you are comparing **Soil Type (cell no. A24)** with **Elevation (cell no. E23)** and you think **Soil Type is "extremely more important" than Elevation**, then you put **"9"** on **cell no E24**. But if you think **Soil Type is "extremely least important" than Elevation** then you put **"1/9"**, the reciprocal value of 9. However, if the **both criteria** have the **same importance** then put **"1"** i.e **Equal**.

3. The **CR value** is an important aspect of the analysis to determine whether the expert’s judgement is consistence. That’s why the CR value should be **less than 0.1**. If it is **more than 0.1** it will be **invalid (will be RED)** and you need to **reconsider** your judgement.

Note: You only need to complete the **Green cells** of the matrix

Criteria	**Soil Type**	**LULC**	**NDVI**	**Elevation**	**Slope**	**Rainfall**	**Distance from Road**	**Distance from River**
Soil Type	**1**							
LULC		**1**						
NDVI			**1**					
Elevation				**1**				
Slope					**1**			
Rainfall						**1**		
Distance from Road							**1**	
Distance from River								**1**
Sum								

CI	0
RI	1.41
CR	0

……………………………..

Signature

Appendix 3

3. The weighted Supermatrix for ANP analysis

Alternatives		Criteria											
		N	S1	S2	S3	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
	S1	0.000	0.000	0.000	0.000	0.565	0.565	0.565	0.565	0.565	0.565	0.565	0.565
	S2	0.000	0.000	0.000	0.000	0.262	0.262	0.262	0.262	0.262	0.262	0.262	0.262
	S3	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
	Soil	0.361	0.361	0.361	0.361	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Appendix 4

4. The limited supermatrix for ANP analysis

		Alternatives				Criteria							
		N	S1	S2	S3	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
	S1	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283
	S2	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131
	S3	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