

Article

Development of Spatial Model for Food Security Prediction Using Remote Sensing Data in West Java, Indonesia

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Abstract: The food crisis is a problem that the world will face. The availability of growing areas that continues to decrease with the increase in food demand will result in a food crisis in the future. Good planning is needed to deal with future food crises. The absence of studies on the development of spatial models in estimating an area's future food status has made planning for handling the food crisis suboptimal. This study aims to predict food security by integrating the availability of paddy fields with environmental factors to determine the food status in West Java Province. Food status modeling is done by integrating land cover, population, paddy fields productivity, and identifying the influence of environmental factors. The land cover prediction will be developed using the CA-Markov model. Meanwhile, to identify the influence of environmental factors, multivariable linear regression (MLR) was used with environmental factors from remote sensing observations. The data used are in the form of the NDDI (Normalized Difference Drought Index), NDVI (Normalized Difference Vegetation Index), land surface temperature (LST), soil moisture, precipitation, altitude, and slopes. The land cover prediction has an overall accuracy of up to 93%. From the food status in 2005, the flow of food energy in West Java was still able to cover the food needs and obtain an energy surplus of 6.103 Mcal. On the other hand, the prediction of the food energy flow from the food status in 2030 will not cover food needs and obtain an energy deficit of up to 13,996,292.42 Mcal. From the MLR results, seven environmental factors affect the productivity of paddy fields, with the determination coefficient reaching 50.6%. Thus, predicting the availability of paddy production will be more specific if it integrates environmental factors. With this study, it is hoped that it can be used as planning material for mitigating food crises in the future.

Keywords: food security; food crisis; spatial model; CA-Markov; MLR

1. Introduction

Food is the essential basic human need, because food contains nutrients used to maintain reproduction and carry out activities in daily life [1]. Everyone deserves access to decent food, because it is an aspect of human rights guaranteed by [2] as a fundamental component for realizing quality human resources. In addition, the food aspect is listed in the second point of the Sustainable Development Goals (SDGs)—namely, no poverty.

Its main goal is to end all forms of hunger for all people in the world by 2030. The availability of food and the ability of individuals to access that food is measured using the food security index. Food security is defined as the condition of fulfilling food for the state of individuals as reflected in the availability of sufficient food in quantity, quality, safety, diversity, nutrition, equity, and affordability. It also does not conflict with the beliefs and culture of the community to be able to live healthy, active, and productive in a sustainable manner. Food security can be measured by calories ingested per person per day, available by household budget [3]. Food security is viewed from three aspects, namely the aspects of food availability, aspects of food affordability, and aspects of food utilization. Various factors influence food security. According to [4], several factors cause the decline in food security in an area, especially in Indonesia. These factors include narrow land ownership and low incomes, extreme climatic phenomena, the disturbance of plant-invading organisms, and uncontrolled land conversion.

As one of the national rice granaries, West Java has an essential role in the food security sector. Over the past 30 years, about 22% of the national rice production volume has been contributed from West Java. More than 95% of rice production is produced from wetland agriculture, while the rest is from dry land agriculture. However, the rate of increase in rice production since 1973 has continued to decline. In the decades 1973–1983 and 1983–1993, the rise in production decreased from 5.5% per year to 2.69% per year. Furthermore, from 1993 to 2003, rice production increase only reached 0.83% per year of the total rice production from the previous year [5]. In Indonesia, since 2005, it has been estimated that there will be a conversion of 42.40% of irrigated paddy fields. The reduction in agricultural land area is due to the conversion of agricultural land (paddy fields) into built-up and industrial areas. This conversion of paddy fields from year to year continues to increase, and it is feared that it can threaten rice food security in the long term. The conversion of agricultural land is a serious threat to food security. In 2016, there was a decrease in the paddy fields area in West Java by 17.35%, from 1,189,728.85 hectares in 2006 to 983,342.77 hectares [6].

On the other hand, economic growth in West Java demands infrastructure development for transportation, industrial buildings, and settlements. Infrastructure development is thought to have resulted in increased land conversion. Thus, many agricultural lands, especially urban areas, have been converted to other uses, mainly built-up land. As a result, the attractiveness of the agricultural sector continues to decline, which makes farmers tend to give up their land ownership. This condition results in a decreased rice productivity in the West Java region, resulting in a reduced food security index.

In addition to decreasing paddy fields for built-up land, rapid population growth is also one factor that affects food security in the future. Currently, the population in various regions, especially urban areas, has increased significantly. Many factors cause this population growth. Population growth certainly has implications for future food needs. West Java is the province with the largest population in Indonesia. Based on the results of the 2020 population census conducted by the Indonesian Central Statistics Agency, the people in West Java are 48.27 million or more than 17% of the total population of 270.2 million people, with a population growth rate for the 2010–2020 period of 1.1% per year. The world's population is estimated to reach 8 billion in 2030, so food production is a crucial thing to achieve [7]. Climate change also plays an essential role in decreasing paddy field productivity and affecting the food security index. This condition is because paddy fields depend highly on water and soil moisture availability. In 2020, based on information from the Head of the West Java Agriculture and Horticultural Food Crops Service, 13,000 hectares of paddy fields in West Java were threatened with damage due to flooding. Meanwhile, the drought caused damage to fields covering an area of 29,913 hectares in West Java.

Considering that rice is the primary commodity, the government, as a policymaker, must guarantee food security for some time to come. The government must take the right policies related to areas that need attention regarding food security. Therefore, information on food security is essential to provide direction and recommendations for decision-makers

in preparing programs, policies, and the implementation of interventions at the central and regional levels. This study will predict food security using various geospatial data to determine the food status in an area using specific models. The prediction of food security is carried out for 2030 as the target year of the SDG policy. With the prediction of food security in 2030, incumbents can take appropriate food policies for each region that will experience a food deficit so that the second target of the SDGs can be achieved.

This paper consists of several parts; Section 1 explains the importance of calculating food security predictions in 2030 and its benefits for stakeholders in West Java. Section 3.3 describes spatial methods for predicting food security and its factors. Section 4 explain the results of the land cover predictions and paddy fields decline in West Java, food security predictions obtained from land cover predictions, and an analysis of the environmental factors that affect rice productivity.

2. Related Works

The Markov Chain (MC) concept describes a stochastic process involving discrete steps in time and space. The probability of transition from one form to another in the chain depends on the previous state [8]. The MC concept shows the nature of dependence that can predict future land cover. The MC process states that changes in a state in the future only depend on the state's current state and do not depend on previous conditions in obtaining the current state [9]. Cellular Automata (CA) can explore dynamic properties through modeling various phenomena [10,11]. A cellular automaton is a concept that can describe the transition (movement) of each element or object called an automaton. In simple terms, an automaton (singular automata) is a discrete processing mechanism. Research results [12] have used the CA-Markov model to simulate and predict changes in LULC. The steps taken are to analyze the Markov Chain on land change data from 2002 to 2018 to produce a transition area matrix. The next step is to build a map of the LULC transition area and evaluate the model's accuracy to simulate future changes based on the kappa index. The last one predicts the spatial distribution of LULC in 2050. This study used a near neighborhood filter with 5×5 pixels to assign the cell value, a land cover class, based on the surrounding cells. Each pixel's future land cover class depends on how close the center cell's pixel is to the surrounding pixels. This study attempts to simulate land use dynamics processes and the effects of physical, demographic, and socioeconomic driving forces on LULC in Thimpu, the capital city of Bhutan, using remote sensing and GIS technology.

A previous study related to food security capacity modeling was conducted by [13], who reviewed food security from four aspects: availability, utilization, accessibility, and food stability. The availability considers food demand and supply, aid distribution, food and production subsidies, and food prices. Food accessibility considers food price stability, per capita income, gender, social level, season, and climate influences. Food utilization considers calorie needs per capita, nutritional status, macro- and micro-nutritional needs, and anthropometry. Meanwhile, food stability considers food stock, production, import ratio, and climate change variability. However, no spatial modeling of food security was carried out in this study to support the visualization. It is hoped that it will become a starting point in the dynamics of food security for reflection on vulnerabilities in methodological implications and policy decisions using this approach.

Rahman et al. (2017) conducted a study on the impact of temperature and rainfall on rice productivity in Bangladesh [14]. In their research, a multiple regression analysis was carried out, which obtained a significant correlation between the Rice Productivity Index (RPI), Standardized Precipitation Index (SPI), and Diurnal Temperature Range (DTR) with values of 41%, 45%, and 49%, respectively, of the variability of the results in dry, terrace, and coastal ecosystems. In addition, in monitoring and modeling rice field productivity, remote sensing technology can be used. The research by [15,16] conducted the monitoring and modeling of rice field productivity. In this case, one of the advantages of using remote sensing data is continuous monitoring. Another study on the environmental effects on rice production was conducted by [17], which analyzed terrain factors. In this research,

several results were obtained. Namely, terrain factors affect the distribution of paddy fields and rice development. However, terrain factors (except elevation) are not very visible compared to paddy fields and rice development distribution. The research conducted by [14] used dynamic data, which changes in value from time to time, while the study of [17] used relatively constant values from time to time. Dynamic and relatively stable environmental factors need to be combined to get a more comprehensive environmental influence in identifying paddy field productivity.

Based on previous research, no research has integrated environmental factors into predicting food availability mapping. Therefore, the estimation of paddy fields productivity in previous studies is still not optimal, because they do not involve the environmental factors. The integration of future paddy fields availability data with the environmental factors of the paddy fields will provide a more comprehensive predictive approach with remote sensing data. This study will be the first research to develop predictions of future food availability by integrating the future availability of paddy fields and environmental factors.

3. Data and Employed Methods

3.1. Study Area

The study area of this research is the Province of West Java, Indonesia, as shown in Figure 1. The location for West Java was chosen because West Java Province is the third national rice producer, with a contribution of 16.6% [18,19]. Furthermore, West Java is the largest rice consumer, with about 21.1% of the total national rice consumption [20].



Figure 1. West Java Province as the study area.

3.2. Data

The data used is divided into 9 areas, as seen in Table 1.

Table 1. Data used in the study.

No	Data	Product	Temporal Resolution	Spatial Resolution	References
1	Landsat-8	USGS Landsat 8 Level 2, Collection 2, Tier 1	16 Days	30 m (Raster Data)	[21]
2	Land Surface Temperature (LST) (Celsius)	MOD11A2.006 Terra Land Surface Temperature and Emissivity 8-Day Global 1 km	8 Days	1 km (Raster Data)	[22]
3	Precipitation (mm/day)	TerraClimate: Monthly Climate and Climatic Water Balance for Global Terrestrial Surfaces, University of Idaho	Monthly	4638.3 m (Raster Data)	[23]
4	Soil Moisture (%)	NASA-USDA Enhanced SMAP Global Soil Moisture Data	3 Days	10 km (Raster Data)	[24]
5	Normalized Difference Vegetation Index	MOD13Q1.006 Terra Vegetation Indices 16-Day Global 250 m	16 Days	250 m (Raster Data)	[25]
6	Administrative boundaries	West Java Regional Planning Agency	-	1:25,000 (Vector Data)	[26]
7	West Java Land Cover	West Java Regional Planning Agency	2005 2010	30 m	[26]
8	West Java Paddy fields Productivity (ton/km ²)	Ministry of Agriculture Republic of Indonesia	Yearly	City/ District level (Tabular Data)	[27]
9	West Java Population (person)	Indonesian Central Statistics Agency	Yearly	City/ District level (Tabular Data)	[28]
10	Digital Elevation Model (DEM) (meter)	NASA	-	30 m (Raster Data)	[29]

3.3. Methods

This paper focuses on explaining food security in 2005–2030, focusing on the aspects of availability and needs. It also discusses what factors influence it. In this study, there were two significant parts carried out. The first part is the calculation of the spatial model of food security, which was carried out in 2005 as a baseline condition and 2030 as a predictive model and associated with the meteorological disaster conditions, such as climate data, etc. The second part is to estimate the environmental factors that affect rice productivity.

The spatial model of forecasting food security was carried out under baseline conditions in 2005 and predictions in 2030. The spatial model of forecasting food security requires land cover data, so land cover data is required for the predictions in 2030. Land cover data for West Java Province in 2030 is obtained by making prediction models using the Cellular Automata-Markov Chain (CA-MC) method. Another factor that affects food security in an area is food consumption. The value of food needs is derived from data on the population of an administrative area. The population model for 2030 is obtained by modeling a linear regression method from population data from 2005 to 2020.

On the other hand, land cover prediction data obtained from the CA-MC method is also used to analyze the factors that affect rice productivity. Regression uses productivity as the dependent variable and the factors that affect productivity as the independent variables. The independent variables used included drought quantified by the Normalized Difference Drought Index value, humidity, surface temperature (LST), vegetation fertility level quantified by the Normalized Difference Vegetation Index (NDVI) value, precipitation, elevation, and slope. Overall, the flow of the research carried out can be seen in Figure 2.

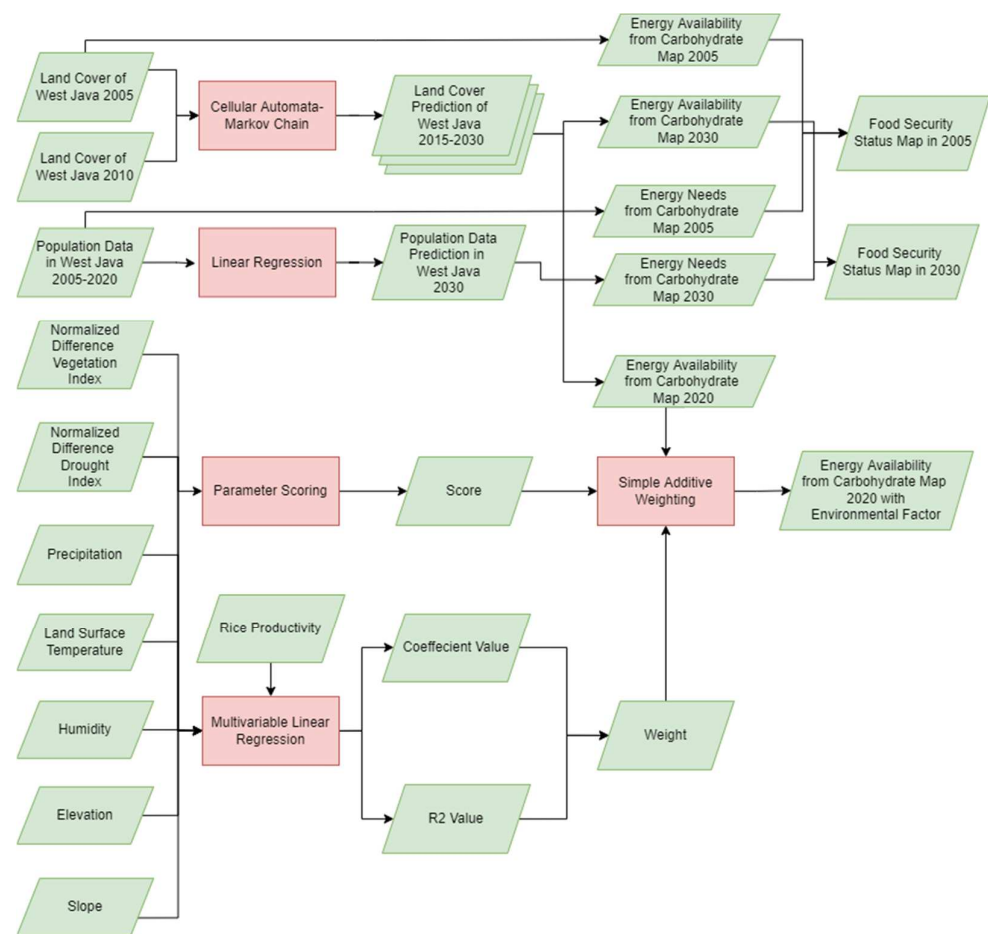


Figure 2. Flow chart of the methodology.

3.3.1. Land Cover Change Methodology

One of the methods used to predict land cover is the Markov Chain (MC). This method is a simple mechanism to determine future opportunities for land change based on opportunities that occurred in the past [30,31].

$$P\{Z(t_{n+1}) = E_j \mid Z(t_n), Z(t_{n-1}), \dots, Z(t_0) = E_i\} = P\{Z(t_{n+1}) = E_j \mid Z(t_n) = E_i\} \quad (1)$$

The magnitude of these changes can be obtained using satellite imagery data from two different periods [32]. Then, the opportunity is used to predict the allocation of each land classification for the next period based on the value of the land classification in the last year.

In addition to the MC method, there is a Cellular Automata (CA) concept that has been applied in GIS-based spatial modeling. Besides being easy to do, CA can develop dynamic properties in modeling the processes of changing various phenomena [33]. Cellular Automata is a concept that can describe the transition (movement) of each element or object called an automaton. In simple terms, an automaton (singular automata) is a discrete processing mechanism. The mechanism in question is the ability to change based on rules that are applied to itself (the object) and various inputs from outside [34].

In the context of geography, apart from input factors, there is one other factor that can affect the automaton. This factor is the condition of the neighbor (neighborhood). In this context, CA is a spatial system used to determine a set of automatons [33]. This understanding shows that an automaton will also depend on the surrounding conditions. The concept of the CA-MC can be seen in Figure 3.

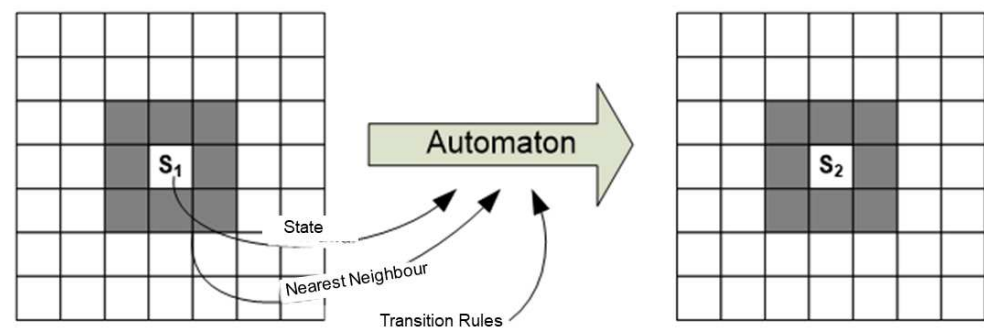


Figure 3. CA concept in determining the location of the automaton. An automaton is defined by the presence of the automaton state factor (class or value of the automaton) itself, the transition rule factor that will be imposed on the automaton, along with the neighboring factor of the automaton [35].

From the results of the land cover predictions generated from CA-MC, validation of the prediction model will be carried out, which is intended to determine the accuracy of the resulting land cover prediction model. Validation is done by using the confusion matrix/error matrix. The confusion matrix is defined as a table of class comparison results predicted through image classification analysis with reference data classification or field data [36–38]. The principle of the confusion matrix, which compares the mapped land classification with this reference data, can be collected through a sample-based approach. In research, the spatial unit in sampling is pixels, and the number of samples used is based on the Slovin formula, as seen in Equation (2):

$$Pn = \frac{N}{1 + ne^2} \quad (2)$$

where n is the number of samples, N is the number of populations, and e is error tolerance. The confusion matrix can provide information on the accuracy of the whole or each class related to land cover classification. The classification accuracy test can be done using Equation (3):

$$\text{Mapping Accuracy} = \frac{X_{cr}}{X_{cr} + X_o + X_{co}} \quad (3)$$

where X_{cr} is the correct number of pixels/sites of class X , X_o is the number of pixels/sites of class X that belong to another class (omission), and X_{co} is the number of pixels/sites of class X that are additional from other classes (commission).

The overall accuracy shows the overall proportions of areas that are classified correctly. This condition means that randomly selected areas on the map are classified correctly [39]. The overall accuracy can be calculated based on Equation (4):

$$\text{Overall Accuracy} = \frac{D}{N} \times 100\% \quad (4)$$

where D is the total value of the correct rows that have been added diagonally, and N is the total value of the correct rows in the error matrix.

While the kappa coefficient measures the overall alignment of a matrix that considers the nondiagonal elements of a matrix [40], the kappa coefficient has a maximum level of correspondence between the number of rows and columns of 1.00. The kappa coefficient formulation can be seen in Equation (5):

$$\hat{K} = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r X_{i+} X_{+i}}{N^2 - \sum_{i=1}^r X_{i+} X_{+i}} \quad (5)$$

where r is the number of rows and columns in the confusion matrix/error matrix, N is the total number of observations, X_{ii} is the observations in row i and column i , X_{i+} is the total marginal of row i , and X_{+i} is the total marginal of column i .

3.3.2. Mapping Food Status

Based on Reference [41], food security (Food Security and Vulnerability Atlas) can be viewed from three aspects: availability, access, utilization, and stability. However, this research will focus more on the aspect of food availability. The availability aspect is the aspect that considers the ratio of normative consumption per capita to food availability. In the modeling of food availability, only paddy fields are considered that are rice producers, namely the staple food in Indonesia.

The modeling of the food status is carried out using a grid system in its calculations. The grid system is a two-dimensional structure that divides an area into contiguous cells. Each cell has a unique identifier that is different for each cell that can be used for spatial indexing [42]. This system can store spatial data and is very good at representing geographical phenomena that are continuous and change gradually, such as altitude, soil type, soil moisture, vegetation, soil temperature, land use, air quality, etc.

In food demand modeling, briefly, the method used is to determine the population density of each grid (30'' × 30'') based on the weight of the land cover in a city/district area. The weight is represented in Table 2. The population data used is Indonesian Central Statistics Agency data, which is then predicted using a linear model to obtain the population in 2030 for each city/regency. Therefore, in this study, the population increase every year is assumed to have a linear trend. Next, the energy adequacy rate is calculated based on the distribution of the population. Based on Reference [43], the recommended nutritional adequacy rate for the people of Indonesia is 2100 calories, and 60% of it is met from carbohydrate sources. In this case, for the Indonesian people, the staple foods are dominated by rice. In addition, the energy demand and availability model are also predicted for 2030 using a land cover map that was predicted for 2030.

Table 2. Land cover weight for the population distribution [44].

Skor	Land Cover	Skor	Land Cover
0.328	Built up area	0.018	Shrubs
0.048	Rice field	0.009	Forest
0.038	Mine/Pond/Swamp	0.002	Plantation
0.029	Field/Moor	0	River/Lake/Reservoir

For the calculation of food needs using Equations (6)–(8), Equations (6) and (7) are modified from the Nengsih (2015) [42] method. Meanwhile, Equation (8) is a calculation of the energy needs every year based on the daily energy needs of the community based on the Indonesian Ministry of Health [41].

$$D_i = A_i \times W_i \quad (6)$$

where D_i is the weight density, A_i is the area of land cover, and W_i is the land cover weight.

$$P_{ij} = \frac{D_i}{\sum_{i=1}^n D_i} P_j \quad (7)$$

where P_{ij} is the population density weight per grid, $\sum_{i=1}^n D_i$ is the total weight of the population density, and P_j is the total population of each city/district.

$$KB_{ij} = P_{ij} \times AKE \times 365 \quad (8)$$

where KB_{ij} are the basic energy needs in one year, and AKE is the daily energy adequacy rate of 2100 calories [43] (carbohydrate AKE is 60% AKE).

Since it only focuses on calculating staple food (rice) availability in food availability, the only land cover considered is paddy fields. The method used is to calculate the

energy produced from paddy fields based on agricultural productivity data for each grid (30" × 30"). Based on the data from [45], the energy produced per 100 g of rice is around 357 calories.

3.3.3. Identification of Environmental Factors Influence on Paddy Fields Productivity

The productivity of paddy fields is not only influenced by the availability of paddy fields but also influenced by the surrounding environment. This study will use several environmental factors that affect the productivity of paddy fields based on [46]. The environmental factors used are dynamic and environmental factors that are relatively constant over time. The combined effect of dynamic and relatively constant factors can be seen in paddy fields' productivity. This study will show how much these factors affect the productivity in West Java. The environmental factors used to identify agricultural productivity are the NDVI [47], NDDI [48,49], LST [50], soil moisture [51], precipitation [52], elevation [17], and slope [17].

In processing some data, some require processing before they can be used to analyze paddy fields' productivity. In determining the NDVI value, a red band and a NIR (near-infrared) band are needed. The NDVI calculations can use Equation (9):

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (9)$$

Furthermore, in performing NDDI calculations, NDVI and NDWI values are needed. In determining the NDWI, NIR and SWIR (short-wave infrared) bands are needed. The NDWI calculations can use Equation (10). After getting the NDVI and NDWI values, the NDDI value can be calculated using Equation (11).

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \quad (10)$$

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \quad (11)$$

In addition to the NDVI and NDDI, already available data will be used. The data used is sourced from remote sensing satellites with different temporal resolutions. In this study, the average data for each parameter in a year will be used to equalize the rice productivity data, which is the annual data. The average for each data pixel will be calculated in determining the average. In calculating the average data, Equation (12) will be used. Different temporal resolutions will impact the amount of data used.

$$\bar{x} = \sum_{i=1}^n \frac{x_i}{n} \quad (12)$$

where $\bar{x}$ is the average pixel value per year, n is the amount of data per year, and x_i is the i th data value.

After getting the average value, the difference between the two timescales for the data will be calculated between the two timescales of the paddy field productivity. In addition to using dynamic data, where the data changes from time to time, we will also use data whose changes take a long time to be considered constant, namely data on height and slope. In determining the effect of environmental factors on paddy field productivity, the correlation value (R) and coefficient of determination (R^2) on paddy field productivity will be calculated for each data. The calculations show the correlation of the data with the productivity and its percentage representing the correlation coefficient. Furthermore, after getting the effect of each data, the constant value of each data will be calculated using multivariable linear regression on paddy field productivity. Multivariable linear regression was chosen, because it can accommodate the estimation of the changes in rice field productivity using several natural factors [53,54]. The multivariable linear regression

equation that will be used is similar to Equation (13). This constant calculation is intended to calculate the productivity predictions using the productivity factor data.

$$\Delta P = a\Delta t + b\Delta u + c\Delta v + d\Delta w + e\Delta x + fy + gz \quad (13)$$

where

ΔP = Changes in Paddy Productivity (tons/km²);

a = NDVI constant;

b = NDDI constant;

c = LST constant;

d = Soil moisture constant;

e = Precipitation constant;

f = Elevation constant;

g = Slope constant;

Δt = NDVI value change;

Δu = NDDI value change;

Δv = LST value change (Celsius);

Δw = Soil moisture value change (%);

Δx = Precipitation value change (mm/hari);

y = Elevation (m);

z = Slope (%).

3.3.4. Prediction of Food Availability by Integrating Paddy Fields Area and Environmental Factors Methods

During the prediction of food availability by considering environmental factors using land cover prediction data in 2020 and the results of the statistical calculations on the effect of environmental factors on productivity, merging each parameter is done using the Simple Additive Weighting (SAW) method. SAW is a method that is often used to solve multi-attribute decision-making according to Equation (14) [55], which calculates the weight of each pixel.

$$Weight_i = \sum (Score \times Weight) \quad (14)$$

The *Score* and *Weight* values are calculated based on the correlation value (productivity and environmental factors). The score is calculated by dividing the value of each parameter into five classes using the Natural Breaks method [56]. After that, each class of parameters is graded 1–5 by adjusting the positive or negative value on the correlation value. If it has a positive correlation value, then the provisions of the weight value are as follows: the value $0 \leq r \leq 0.3$ has a weight of 1, $0.3 < r \leq 0.7$ has a weight of 2, and $0.7 \leq r \leq 1$ has a weight of 3 [57].

The paddy production of each city/regency (P) is calculated using Equation (15). Next, to identify the value of paddy production in each pixel of each city/regency, (P_i) is calculated using Equation (16) with $\Sigma Weight_i$ as the total weight in each city/regency.

$$P = Productivity \times Paddy Field Area \quad (15)$$

$$P_i = \frac{Weight_i}{\Sigma Weight_i} \times P \quad (16)$$

4. Results and Discussion

4.1. Land Change Model

The first product is a land cover prediction based on the land cover in 2005 and 2010. Land cover predictions are carried out over five time periods, namely 2015, 2020, 2025, and 2030. The land cover predictions for every five years can be seen in Figure 4.

The first product produced is a land cover prediction based on the land cover in 2005 and 2010. Land cover prediction is carried out over five periods, namely 2015, 2020, 2025,

and 2030. Based on these land cover predictions, there is a decrease in the area of paddy fields from year to year. In 2030, the decrease in the paddy fields area was 31% from 2005. This condition impacts the decline in rice productivity in the West Java Province. This conclusion is directly proportional to the statement from [58], which stated that the land cover area in Indonesia continuously decreases by 650,000 ha per year. The paddy fields area decline in West Java has also been proven by [6]; there was an area decrease of 17.35%, from 1,189,728.85 ha in 2006 to 983,342.77 ha in 2016 [6]. The graph of the decline in paddy fields can be seen in Figure 5 and Table 3.

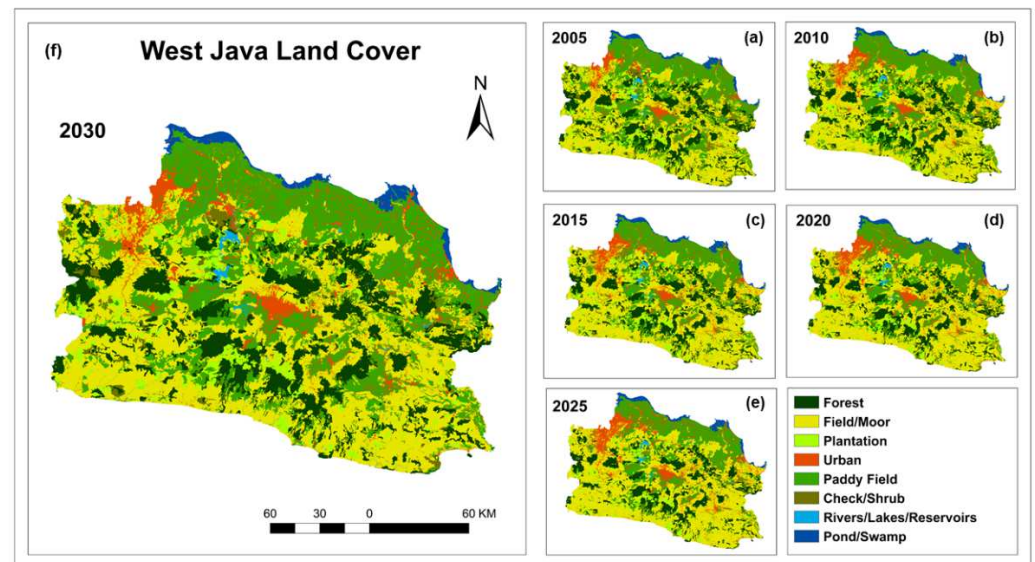


Figure 4. Land cover predictions in (a) 2005, (b) 2010, (c) 2015, (d) 2020, (e) 2025, and (f) 2030.

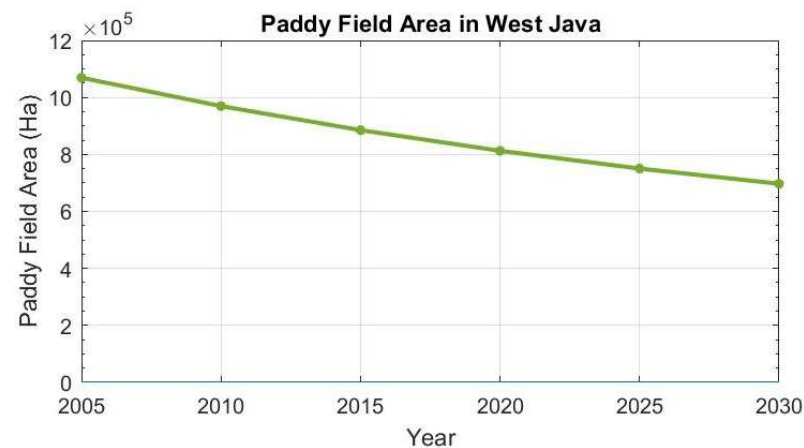


Figure 5. Graph of the decreasing paddy field area from year to year.

Table 3. Decrease in the paddy fields area from year to year.

Years	Area (Ha)
2005	1,069,095.78
2010	969,582.87
2015	885,170.05
2020	812,641.31
2025	750,275.99
2030	697,064.57

The crosstabulation table for land cover predictions in West Java in 2030 can be seen in Table 4. Based on the prediction results, many changes occur in vacant lands and urban areas for paddy fields. The change of paddy fields into vacant land is 340.095 km sq, and the change of paddy fields to built-up areas is 55.58 km². Paddy field changes into settlements imply rapid population growth in urban areas.

Table 4. The crosstabulation table for land cover predictions in West Java in 2030.

Cross Tabulation 2005 and 2030								
Unit (km sq)	Forest	Field/Moor	Plantation	Urban	Paddy Fields	Check/Shrub	Rivers/Lakes/Reservoirs	Pond/Swamp
Forest	508.54491	4.70952	0.61047	0.00414	0.2106	2.29113	0	0
Field/Moor	114.94971	1276.56603	52.35633	5.05107	340.09515	48.49614	0.43515	0
Plantation	1.19673	5.81022	121.44402	0.01989	0.40959	6.65658	0.02052	0
Urban	3.93597	83.34171	6.48693	265.81608	55.58004	1.79244	0.02061	0.28854
Paddy Fields	8.68122	11.21238	2.44422	2.30094	672.36723	0.56376	0.05535	0.08199
Check/Shrub	1.0701	0.12555	0.00018	0	0.03213	7.22286	0.15219	0
Rivers/Lakes/Reservoirs	0.01323	0.01125	0	0.00945	0.00639	0.01764	24.91749	0.00198
Pond/Swamp	0.06417	0.24057	0	0	0.39465	0	0.01035	69.49602

The 2015 land cover prediction results were then validated to obtain the accuracy of the prediction model made. Validation was carried out using the confusion matrix/error matrix by comparing the predicted land cover with 2015 satellite imagery data obtained from Google Earth Pro. In determining the number of samples representing the research data population, the Slovin formula is used, with a significance value of 0.1 or at a confidence interval of 90%. From the results of the calculation of the Slovin formula, the required sample points are 100 sample points. The distribution of the sample points was determined using the stratified random sampling method. In this method, the population is divided into several subgroups/strata, and then, samples from each stratum will be taken so that it will produce a sample from each of these strata. The strata in this study are divided into four strata, namely paddy fields, urban, vegetation, and water bodies. Thus, 100 sample points will be divided into these four strata, so that, for each stratum, 25 samples are taken. Then, the sample is validated with the existing cover of paddy fields, urban areas, vegetation, and water bodies from Google Earth Pro. Almost all of the samples were classified. Accordingly, 7 points from the sample of water bodies were classified into another land cover, namely 5 points classified as paddy fields and 2 points as urban areas. There are similar pixel values between wet paddy fields and water bodies, so there is a misclassification between paddy fields and water bodies. The validation results can be seen in Table 5.

Table 5. The validation results of the land cover predictions.

Reference										
	Unit (km sq)	Water Bodies	Paddy Fields	Urban	Vegetation	Total	Commission Error	Mapping Accuracy	Overall Accuracy	Kappa
Classification	Water Bodies	18	5	2	0	25	28%	0.72000	93%	0.9067
	Paddy Fields	0	25	0	0	25	0%	0.83333		
	Urban	0	0	25	0	25	0%	0.92593		
	Vegetation	0	0	0	25	25	0%	1.00000		
	Total	18	30	27	0	100				
Omission Error		0%	16.67%	7.41%	0%					

The overall accuracy value obtained is 93% based on the validation results. This value indicates that the resulting map has good quality, because the classification map has 93% suitability for field conditions. From the table above, it can also be seen that the resulting kappa coefficient value is 0.9067. According to [59], a kappa coefficient value of between 0.8 and 1 is included in the excellent and reliable category. This value means that the accuracy test on the classification results that have been carried out show that the results obtained are of good accuracy, which is very reliable.

In this study, the land cover will focus on paddy fields, because it will be used to calculate rice productivity, which impacts food security in an area. The mapping accuracy value of paddy fields cover is 0.83 or 83.33%. This value indicates that the paddy fields cover value obtained in the prediction is valid for use.

4.2. Food Status Model

The food status model on food availability produces two products: food availability and food needs. The food needs (carbohydrates) in West Java can be seen in Figure 6. Based on the results of the food needs, densely populated urban areas have a higher need than other areas, with the energy needs reaching 4765 Mcal per capita in 2005. The urban areas with higher energy needs are Bandung City, Bekasi City, Depok City, and Bogor City, which are indicated by yellow to red colors. The suburban area also has moderate food (carbohydrate) needs due to the expansion of food needs in urban areas, which is indicated by the color yellow. In order to view the food status in the future, this study tries to predict the food status in 2030. Based on the results, the need for food (carbohydrates) in 2030 is projected to experience a significant increase compared to 2005—namely the need for food (carbohydrates) is expected to reach 7230 Mcal per capita in 2030. This result is also in line with [27], which shows an increase in the population every year. Areas with the highest demand are located in urban areas and their surroundings, such as Bandung, City of Cirebon, City of Sukabumi, City of Bekasi, City of Cimahi, City of Depok, City of Tasikmalaya, and the City of Banjar.

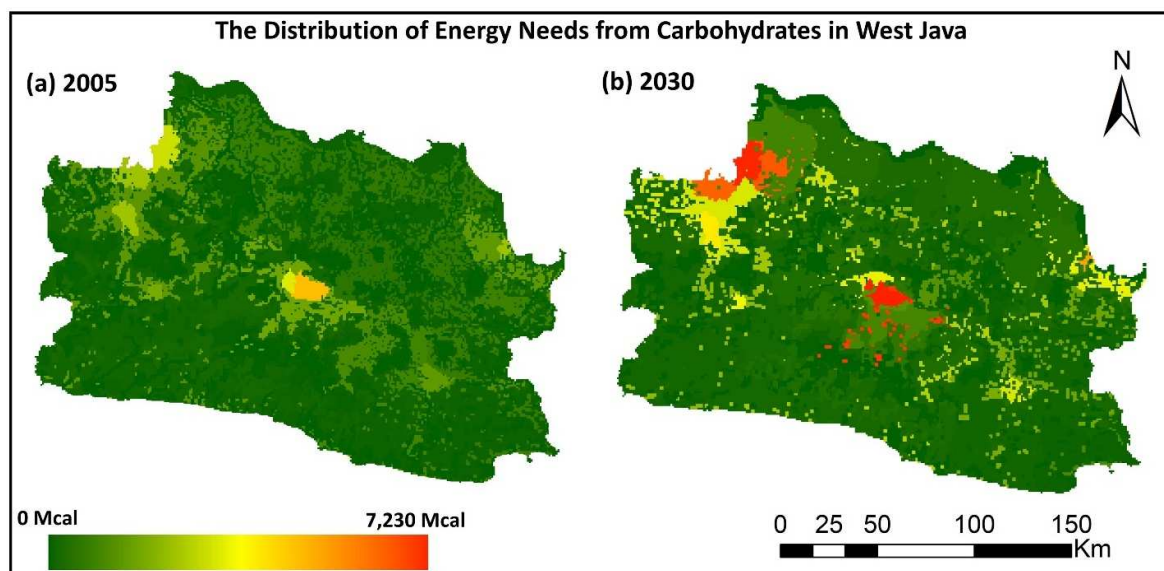


Figure 6. Energy needs (carbohydrates) in West Java in (a) 2005 and (b) predictions in 2030.

The availability of food (carbohydrates) in 2005 in West Java reached 1975.995 Mcal per capita. The distribution of food availability in West Java in 2005 was dominated in the northern areas of West Java, namely Bekasi Regency, Karawang Regency, Subang Regency, Indramayu Regency, and Cirebon Regency, with the color index tending to be light green (medium). The prediction in food availability data (carbohydrates) in 2030 shows a decrease in availability compared to 2005. However, in terms of the productivity per capita, it has

increased compared to 2005, which reached 2212.33 Mcal/capita. This result means that, although the land availability of food (carbohydrates) is reduced significantly, the paddy fields' productivity level will have increased significantly in 2030. This condition can be due to several supporting factors, such as natural factors and agricultural technology, supporting productivity. The flow of food energy in West Java in 2005 was still able to cover food needs and obtain an energy surplus of 6.103 Mcal overall in West Java.

Based on food needs (carbohydrates) and food availability (carbohydrates), it can be concluded that the status of food (carbohydrates) in West Java is as shown in Figure 7. The food surplus status means that the food availability is greater than the amount needed. This condition means that food availability in the region can still meet the current needs. On the other hand, a region experiencing a deficit means that the availability in that area cannot meet the current needs. Based on the results, most regions in West Java had a surplus status in 2005. Urban areas with a reasonably high demand, such as Bekasi City, Depok City, Bogor City, Bandung City, Sukabumi City, Tasikmalaya City, and Cirebon City, have a deficit food status. The regencies such as Bandung Regency, Sukabumi Regency, and Bogor Regency also have a deficit food status. This status is because the food availability is relatively high and cannot meet the population's needs.

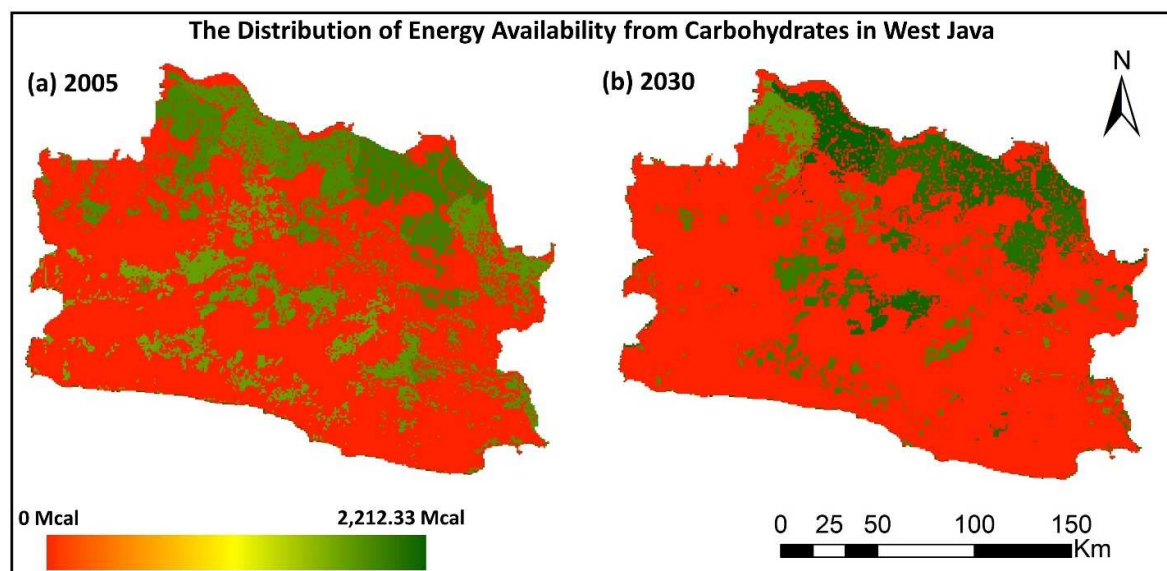


Figure 7. Food availability (carbohydrates) in West Java (a) in 2005 and (b) the predictions in 2030.

Based on the results of the food status (carbohydrates) prediction in 2030 above, as shown in Figure 8, in 2030, the food status in West Java will be dominated by the deficit status. Only six (six) regions have a surplus food status, namely Karawang Regency, Indramayu Regency, Subang Regency, Majalengka Regency, Purwakarta Regency, and Cianjur Regency. It is also quite clear that these six areas have the highest availability compared to the other areas. Although there is an increase in productivity in 2030, it still cannot meet the high energy needs as a result of the increase in the population every year. This increase means that reducing the paddy fields' area every year is a significant threat to food security. The surplus food status is expected to contribute to the food availability in deficit areas (flowing energy from surplus to deficit areas). The flow of food energy in West Java in 2005 was still able to cover the food needs and obtain an energy surplus of 6.103 Mcal. On the other hand, the prediction of the food energy flow in West Java in 2030 will not cover the food needs and will obtain an energy deficit of up to 13,996,292.42 Mcal.

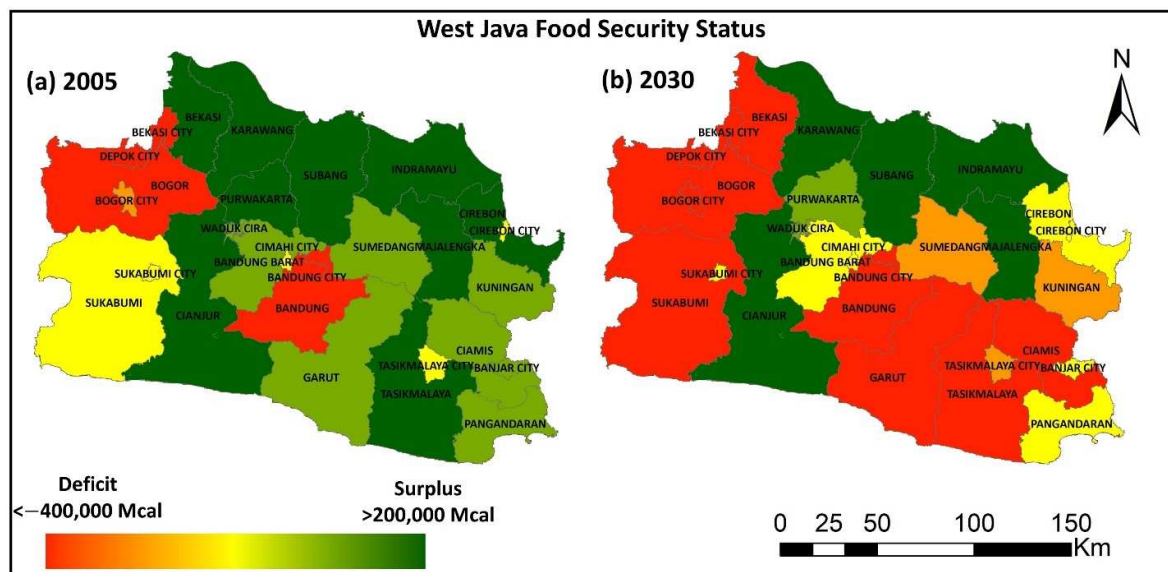


Figure 8. Food (carbohydrate) status in West Java (a) in 2005 and (b) the predictions in 2030.

4.3. Identification of Factors Influencing Rice Productivity in West Java

Many factors affect the environmental conditions, one of which is caused by climate change, which, in this study, is represented by the land surface temperature and precipitation [60]. In this study, a correlation of the factor changes with data on changes in the paddy fields' productivity was carried out. In Figure 9, the correlation of the NDDI change is negative, which means that the decrease in the drought index of an area will increase the productivity of the area's paddy fields. This statement is in line with the higher increase in crop drought, which will make the paddy fields' productivity decrease. The coefficient of determination (R^2) of the NDDI is 0.006, so only 0.6% of the effect of NDDI change on paddy fields productivity change. Figure 9 shows that precipitation change has a negative correlation with productivity change. The decrease in rainfall change will increase the paddy fields' productivity. This condition is because the paddy fields have an optimum value of precipitation so that if there is an excess or lack of water, the productivity will be reduced. The coefficient of determination shows that precipitation change affects 4.3% of the paddy fields' productivity change.

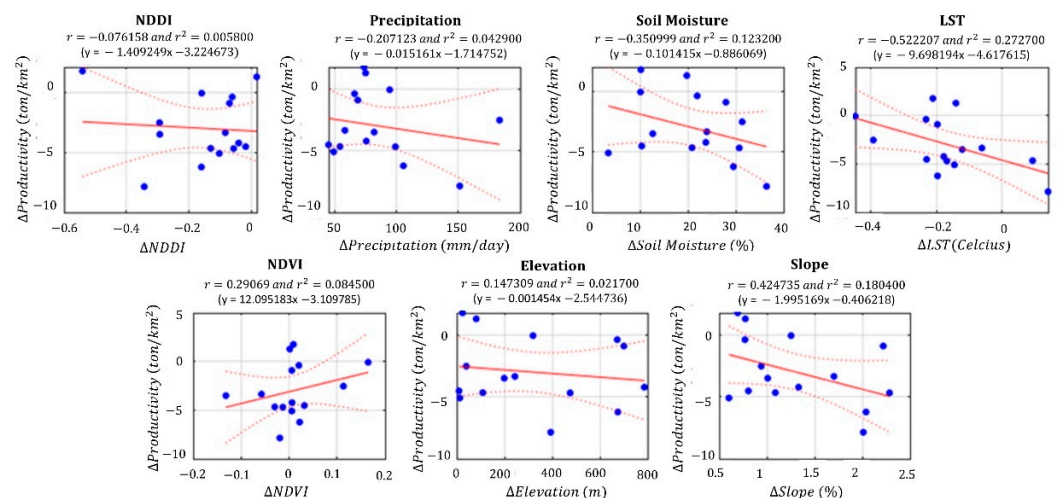


Figure 9. Linear regression between the productivity and environment factors.

Furthermore, the correlation between soil moisture changes and paddy field productivity change is negative, where the decrease in soil moisture changes will increase the paddy

fields' productivity change. This condition is because the soil moisture has an optimum value in paddy fields productivity, so it will affect the productivity if it is more humid or less humid. Soil moisture change has a coefficient of determination of 12.3% of the paddy fields' productivity change.

Furthermore, the LST change negatively correlates with the paddy fields' productivity change. The decrease in temperature changes increases the productivity change. This condition is because LST has an optimum value in paddy fields productivity, so it will affect the productivity if it is a higher temperature or less temperature. The LST change has the highest coefficient of determination, reaching 27.3%. Furthermore, the NDVI change has a positive correlation with the productivity change. Increasing the NDVI change increases the productivity of the paddy fields change. The NDVI indicates paddy health, so the high NDVI indicates a healthier paddy and is linear with the productivity of the rice field. The coefficient of determination of NDVI change reaches 8.4%. The altitude data has a negative correlation with land productivity change. It can be seen that the higher the area, the lower the productivity change. This condition is because the altitude has an optimum value in paddy fields productivity, so it will only be the optimum at several altitudes. The effect of altitude on productivity change is 2.1%. The value of the dependency coefficient of determination will be local in West Java only, and different regions will have different values.

Furthermore, the last data is the slope, which negatively correlates with paddy fields productivity. The steeper the slope, the lower the productivity change. This condition is because the slope has an optimum value in paddy fields productivity, increasing the optimum productivity in the optimum slope. The slope affects 18.04% of the paddy fields' productivity changes.

Of all the natural factors investigated, LST has the most significant relationship; this indicates that temperature increases in agricultural areas can harm paddy fields' productivity. Using this information, various efforts need to be made so that temperature increases around agricultural areas do not occur, such as switching to renewable energy, designing good regional development, and reducing CO₂ gas.

Equation (17) shows the results of multivariable linear regression using all data that affect paddy fields' productivity. From these results, the coefficient of determination value is 0.5066, or it can be concluded that seven factors affect the productivity of paddy fields, reaching 50.6% of all the factors that influence it. Other factors can come from technological advances and local or random factors. If the residual value is calculated from the linear regression that has been carried out, the result is 1,894 tons/km². Furthermore, the RMSE value is calculated for the equation made using four cities/districts of West Java, and a value of 7012 tons/km² is obtained.

$$\Delta P = 9.976\Delta t - 7.940\Delta u - 9.849\Delta v + 0.238\Delta w - 0.078\Delta x - 0.001y - 2.855z \quad (17)$$

where

ΔP = Changes in Paddy Productivity (ton/km²);

Δt = NDVI value change;

Δu = NDDI value change;

Δv = LST value change (Celsius);

Δw = Soil moisture value change (%);

Δx = Precipitation value change (mm/hari);

y = Elevation (m);

z = Slope (%).

In food security, the distribution of the food supply is essential. Using predictions of changes in paddy fields productivity based on environmental factors shows the value of paddy fields productivity in a year in a particular city. The results of this prediction can be used as a reference in distributing paddy fields products to other areas in West Java that experience a food deficit status. In this way, it is hoped that there will be no delay in

the delivery of rice supplies from areas with a positive food status to areas with a food deficit status.

4.4. Prediction of Food Availability by Integrating Paddy Fields Area and Environmental Factors

In predicting the availability of an area, it will be more specific if it integrates environmental factors. The distribution of productivity in a city will be known by integrating environmental factors. It can be seen in Figure 10a, where the food availability only considers the paddy fields area, whereas the distribution of productivity in the area cannot be known. While Figure 10b, which considers environmental factors, can be seen in the distribution of food availability in each area. The average food availability per paddy fields area of $30'' \times 30''$ ($\sim 1 \text{ km} \times 1 \text{ km}$) in West Java Province is around 2042.012 Mcal, with the highest availability being 183,516.201 Mcal.

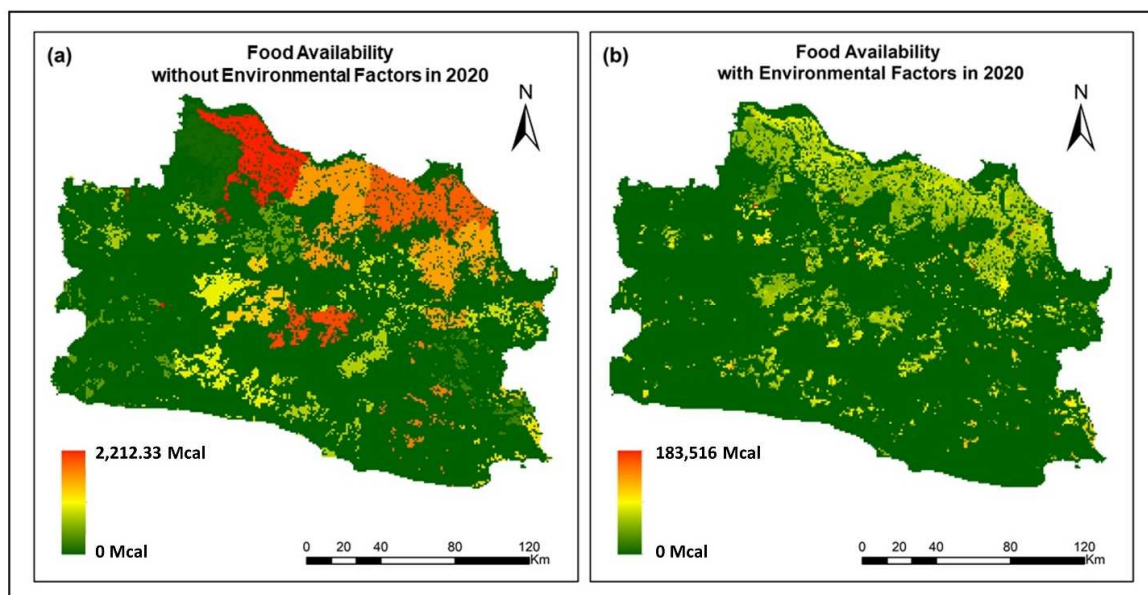


Figure 10. Food availability (a) without environmental factors and (b) with environmental factors.

With the availability of information on the distribution of food availability in an area, it will be possible to increase productivity in areas that experience low availability. Handling areas with low productivity can increase the value of food availability in a city. In addition, knowing areas with high availability can be used for regional planning to determine areas that focus on food production.

4.5. Limitation and Future Possible Direction

This research has several limitations that need to be considered. First, in this study, the prediction of food security only looks at the availability pillar, which includes aspects of food needs and food availability, so that, in the context of food security related to the socioeconomic aspects, it only considers the social aspect in terms of the population and does not consider the economic aspect. The land cover prediction modeling does not consider the driving factors, so it only considers changes from two different data. Prediction modeling of the food supply and demand also has limitations. In mapping, food availability predictions only consider paddy fields (agricultural sector) without considering food yields in other sectors such as plantations, fisheries, and livestock. Besides that, the population projection is approached linearly by assuming constant changes occur. At the same time, the predictive modeling of food needs does not consider the calorie needs of everyone based on age and gender. The last limitation calculates environmental factors using a linear regression model to find the relationship between each environmental factor

and productivity, because not every parameter of productivity has a high match with linear regression.

This research can be improved in the future by involving four pillars in predicting food security that includes the first pillar, namely food availability such as types of crops grown, land management, and aspects of food distribution [61,62]. The second pillar is food accessibility, which is everyone's access to adequate food based on their ability to buy, so one of the things that limit accessibility to food is the socioeconomic aspect of each individual [61,63]. The third pillar is the utilization, which, in this pillar, considers aspects of food quality, so things that need to be considered are the availability of clean water, sanitation, the level of public health, etc. [61]. The fourth pillar is stability, where everyone must always have access to food at all times to achieve resilience; in this pillar, one must consider all things related to crop failures, such as natural disasters, disease outbreaks, and the climate [64,65]. The four pillars can be included and analyzed in the calculation of food security. Of course, combining the four pillars during the calculation of the food security index will be a challenge in the future, because it will certainly require a lot of data integration [66]. Then, the driving factors related to land cover prediction, such as road distance, river distance, land slope, altitude, population density, etc., can be used [67]. Other land covers can be added for analyzing food availability, especially in farm areas, forests, fields, reservoirs, and others. Population projections can be increased by using other equations such as exponential, logarithmic, and power to facilitate external factors in population growth [68]. In addition, age and gender data [69] can be used because the energy needs of every human being depend on age and gender. In conducting a review of the environmental factors, it can still be improved to show the productivity of paddy fields by adding other environmental factors to complete 49.4% of the other influences, such as soil type [70]), aspect [71], etc. Finally, models such as polynomial models and others can be used in reviewing the environmental factors. In addition, the development of a spatial modeling approach can also be used to estimate future energy security [72,73], the mitigation of future geohazards [74–76], and water pollution management for paddy fields [77].

5. Conclusions

As one of the national rice barns, West Java has a vital role in national food security. Due to rapid population growth and a significant decrease in paddy fields in several areas, food security continues to decline. The government as the stakeholder must be able to create policies regarding food to avoid a food security deficit in regions in West Java. Food security predictions were made for 2030 in West Java using geospatial data and remote sensing to anticipate this condition. The first step was to predict the land cover for 2030. The results showed that paddy fields cover decreases yearly, calculated for every five years. The decrease in the paddy fields area in 2030 was 31% compared to the paddy fields in 2005. The predicted land cover was validated using the confusion matrix method and resulted in an accuracy of 93%. The paddy fields, which is the focus of the research, have a mapping accuracy value of 83%.

The land cover obtained from the prediction results is then used to calculate the food security in 2030. In 2030, the food status in West Java will be dominated by a deficit status. Only six regions will have a surplus food status, namely Karawang Regency, Indramayu Regency, Subang Regency, Majalengka Regency, Purwakarta Regency, and Cianjur Regency. It is also quite clear that these six areas have the highest availability compared to other areas. The environmental factors that influence food security were analyzed using the multivariable linear regression method. The variables used are NDDI, precipitation, humidity, LST, elevation, and slope. From these results, the coefficient of determination value was 0.5066, or it could be concluded that the seven factors affected the productivity of paddy fields, reaching 50.6% of all the factors that influenced it. The integration of the area of rice fields with environmental factors was carried out to determine the distribution of the rice

field productivity in a city. The average $30'' \times 30''$ ($\sim 1 \text{ km} \times \sim 1 \text{ km}$) paddy field has an availability of 2,042.012 Mcal, with the largest availability value being 183,516.201 Mcal.

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