International Journal on Advanced Science Engineering Information Technology

Vol.13 (2023) No. 1
ISSN: 2088-5334

Recognition of Agricultural Land-Use Change with Machine Learning-Based for Regional Food Security Assessment in Kulon Progo Plains Area

Zulfa Khoirun Nisa [a], Ansita Gupitakingkin Pradipta [a,*], Liana Ni'mathus Sholikah [a], Bangkit Fatwa Pratama [a], Akram Sripandam Prihanantya [b], Ngadisih [a], Sahid Susanto [a], Sigit Supadmo Arif [a]

[a] *Department of Agricultural and Biosystems Engineering, Universitas Gadjah Mada, Sleman, 55281, Indonesia*
[b] *Department of Geodetic Engineering, Universitas Gadjah Mada, Grafika Street No. 2, Sleman, 55281, Indonesia*
*Corresponding author: *ansita.pradipta@ugm.ac.id*

***Abstract*— High conversion of agricultural land in Kulon Progo Regency, as such the construction of the Yogyakarta International Airport (YIA) and the Bedah Menoreh road, has resulted in food production and impacted food security, including Kulon Progo plains area. This study aimed to calculate the conversion rate of agricultural land and analyze its impact on food security in the Kulon Progo plains area from 2005 to 2020. The primary materials needed are Kulon Progo administrative maps, Landsat 7 and 8 images, land productivity data, population data, and consumption per capita data. With tools used is Google Earth Engine (GEE), SPSS 25, Google Earth Pro, and ArcGIS 10.3. The method used is calculating the Normalized Difference Vegetation Index (NDVI) and machine learning-based classification through GEE to identify land-use change and analyze the state of food security. The study proved that between 2015 and 2020, there was a conversion of paddy fields, with an average rate of 126 ha/year. The existence of new paddy fields influenced this land increase. However, in 2020 there is still food insecurity in Pengasih District, thus caused by the new paddy fields not being optimally used for rice growth. The productivity of the land produced is not optimal. With the availability of agricultural land in 2020 (1382.85 ha), food self-sufficiency will be limited for the next 24.75 years if there is no effort to increase paddy fields.**

***Keywords*— Land-use change; agricultural; machine learning; GEE; food security.**

Manuscript received 27 Oct. 2021; revised 20 Jul. 2022; accepted 18 Sep. 2022. Date of publication 18 Feb. 2023.

I. INTRODUCTION

The use of land as a strategic and necessary asset to the economy and to keep a sustainable living, especially amid increasing food needs becoming increasingly vital [1]. As time goes by, the demand for land rises; due to the increasing human population, there is an increase in food demand and consumption by the whole population [2]. The rise of the population makes the development of civilization and the demands of human needs increase, accelerating regional development [3]. Thus, it requires additional land for various purposes such as settlements, industry, and various facilities and infrastructure. Despite its socio-economic significance, this has led to ecological depletion and ecosystem disruptions in ecologically critical areas [4].

Land-use change occurs in various regions in Indonesia, including in Kulon Progo Regency. Massive developments currently taking place in Kulon Progo are the construction of Yogyakarta International Airport (YIA) [5] and the Bedah Menoreh project, the road that connects YIA and Borobudur Temple [6]. Agricultural land is most vulnerable to land-use change [7]. Agricultural land is considered very potential for non-agricultural sector land conversion. Thus, caused by it is relatively more expansive than the other sector's land [8]. The high conversion rate of agricultural land to non-agricultural land can result in food supply and affect food security, especially rice [9]. Food security can be achieved if there is a surplus of rice supplies compared to the rice needs in a region, which indicates the fulfillment of food needs for everyone in the area [10].

For minimization, it is necessary to plan land use optimally so that sustainable land use can be carried out. Geospatial technology can make it easier to plan suitable land uses. Machine learning-based geospatial technology that works by conducting training and learning processes or training based on data collections to process data automatically has been developed. One machine learning-based geospatial technology is the Google Earth Engine (GEE) [11]. This study aims to calculate the conversion rate of agricultural land and analyze its impact on food security in the Kulon Progo plains area, which consists of the Nanggulan, Sentolo, Pengasih, and Lendah Districts, from 2005 to 2020.

II. MATERIALS AND METHOD

A. Study Area

Kulon Progo is one of five regencies located in the Special Region of Yogyakarta. Kulon Progo has topographic conditions between 0-1000 meters above sea level (masl), divided into three regions. The northern part is the highland area and the Menoreh Hills. In the middle is a plains area with a topography classified as choppy and wavy, a transition between lowlands and hills. The southern part of Kulon Progo is a lowland, a coastal area with a coast of 24.9 km. This research was conducted in the Kulon Progo plains area, consisting of Nanggulan, Sentolo, Pengasih, and Lendah Districts, as shown in Fig. 1.

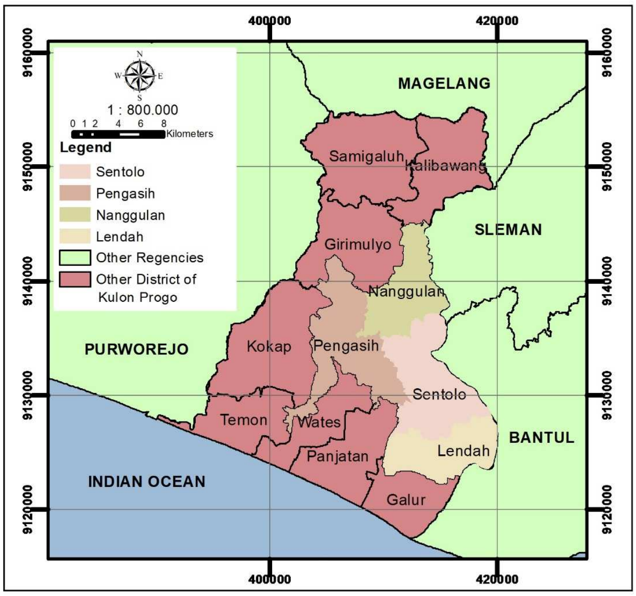


Fig. 1 Administrative map of Kulon Progo plain area

Kulon Progo plain area has C3 climate conditions according to the Oldeman classification [12]. This is adequate to plant crops three times a year, with a couple of periods for palawija crops on the first and second planting and paddy in November or December [13]. Kulon Progo plains area is dominated by grumosol soil types with regosol in some parts of Nanggulan and alluvial in Pengasih and Nanggulan [14]. Grumusol soils have base saturation, high absorption capacity, slow permeability, and erosion sensitivity [15]. A sand fraction dominates regosol. Therefore, it has good aeration and drainage. However, it has low plant available water, lousy soil chemical properties, and significantly fewer plant nutrients because they are accessible to leach [16]. Alluvial soils derived from sediment deposited in fluvial systems are usually fertile and underlie the most productive agricultural regions [17].

B. Data Collection

The framework of this study can be seen in Fig. 2. The primary analysis is land-use change and food security, beginning with data collection. Land-use change analysis was carried out using Landsat 7 for 2005 and 2010 and Landsat 8 for 2015 and 2020. From the results of this land-use change analysis, land area is differentiated based on each land cover class. The occurrence of this conversion of agricultural land use will impact food production, which affects food security. So analysis is carried out to determine the impact of changes in agricultural land use on food security in the Kulon Progo plains area. Data collection is required to carry out this analysis of the initial stages of research, as shown in Table 1.

TABLE I
DATA COLLECTION

Data	Year	Source
Kulon Progo administrative boundary		Department of Public Works, Housing and Settlement Areas Kulon Progo
Central Java administrative boundary		http://tanahair.indonesia.go.id.
Landsat 7 image	2005, 2010	Google Earth Engine
Landsat 8 image	2015, 2020	Google Earth Engine
Paddy productivity	2005, 2010, 2015	Department of Agriculture and Food Kulon Progo
Total population	2005, 2010, 2015, 2021	Central Bureau of Statistics (BPS)
Paddy price	2005, 2010, 2015, 2020	Central Bureau of Statistics (BPS)
Consumption per capita	2005, 2010, 2015, 2020	Central Bureau of Statistics (BPS)

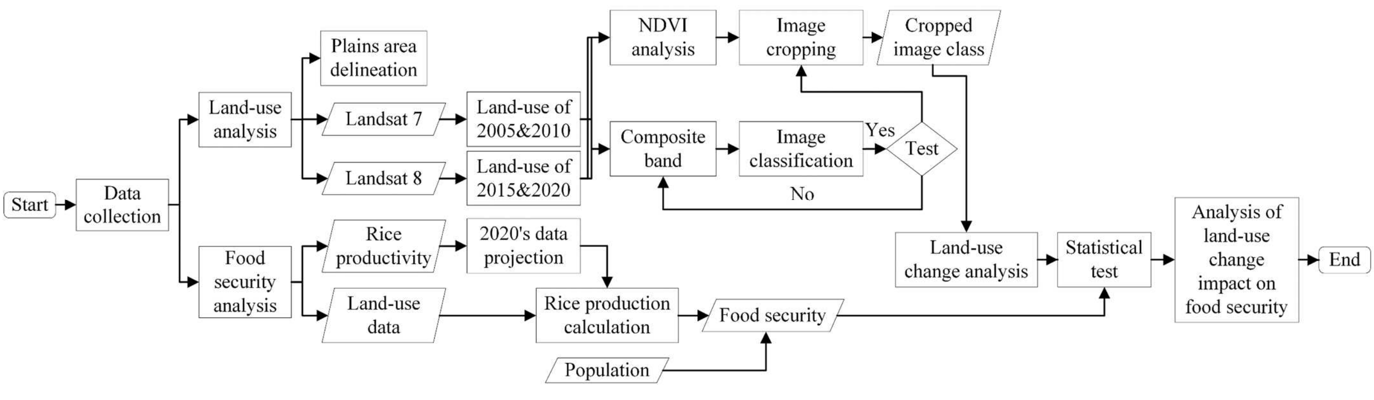


Fig. 2 Research framework

C. Analysis of Agricultural Land-Use Change

Land-use change is processed on the Google Earth Engine (GEE) platform, where data processing and validation suitability tests will be carried out at this stage.

1) Calling Up Landsat Image Data: Calling Landsat 7 and 8 aim to select the image data needed by selecting the best data for one year with the lowest cloud cover level.

2) Composite Image Data: Composites are carried out to determine each year's land cover condition. There are four composites to display: the original color, water bodies, paddy fields, and settlements. Composite image data can be obtained by defining the bands on each RGB channel that will be used and explaining the min and max visualization parameters [18].

3) Land Classification: Land classification is done by making training points in the classification that has been made; water bodies (blue), vegetation (dark green), paddy fields (light green), built-up land (red), and open land (yellow). This training point is used as an algorithm defined in the machine learning process.

4) Normalized Difference Vegetation Index: NDVI is a calculation analysis method used to identify vegetation density by observing the color displayed on the image. Calculations on NDVI using band 4 (Red) and band 5 (Near-infrared) are reflected by the leaves [19]. The value of the NDVI calculation can be read as the closer the value to -1, the lower the vegetation level, then the closer the value to +1, the higher the vegetation level. And if the resulting value is close to or less than 0, there is no vegetation in the area [20].

5) Classification Suitability Test: The classification suitability test attempts to determine the accuracy of classification results that have been carried out. This test aims to approximate the classification results to the actual data and determine the confidence level in using classification results for analysis and further purposes [21]. There are several ways to carry out a classification suitability test, particularly field validation and confusion matrix tests. The confusion matrix test calculates the presence or absence of errors in each form of land cover from the results of the image classification process [22]. A confusion matrix is a square matrix containing the number of pixels classified in overall accuracy, kappa accuracy, producer accuracy, and user accuracy. The land cover classification accuracy is more than 80% [23].

D. Analysis of Food Security

Regional food security is achieved when there is a surplus of rice supply than the need for rice, which indicates food needs for everyone in the region [10]. Food security begins with calculating the area in each district in the Kulon Progo plains area obtained from the analysis of land changes. Paddy production can be calculated based on [24] by multiplying the land area and the existing paddy productivity as described in Equation 1.

$$Paddy\ production = land\ x\ paddy\ productivity \quad (1)$$

Later, we determined the calculation of the availability of rice. The measure of rice availability aims to convert changes from paddy to rice. This conversion is based on the value of paddy shrinkage when it is processed into rice because it is used as animal feed, the rice that is scattered during the milling process, and the rice as seed for subsequent planting [25]. Based on [24], the determination of rice availability is described in Equation 2.

$$Availability\ of\ rice = (p\ x\ (1 - (S + F + W))\ x\ C \quad (2)$$

The amount of rice expenditure per capita per month can determine the need for rice. The value of rice consumption expenditure per capita is then converted to the nominal price of rice that applies every year to the rice consumption per capita of the population. The consumption per capita will be multiplied by the total population to know the rice needed. This value of rice needs describes the amount of rice that must be met to support regional food security [24].

The rice needs of all people in the region and the availability of rice can determine regional food security. According to [24], the value of food security in an area can be formulated by Equation 3.

$$\text{Food security} = \text{Availability of rice} - \text{Need for rice} \quad (3)$$

Food security with a surplus value in an area indicates a higher level of regional food security. The higher the food deficit that occurs, the lower the level of food security. If the result shows a positive number (surplus), it indicates food security, and vice versa; if it shows a negative value (deficit), it indicates food insecurity [26].

E. Analysis of Self-sufficiency Limit

Rice self-sufficiency is an effort to fulfill local and national food needs. The limit of self-sufficiency in rice can be interpreted as a limit of an area that can still meet the rice needs of the population in its territory [27]. The analysis of the impact of land use on rice self-sufficiency can be calculated as Equation 4.

$$P = \frac{L\,x\,\mathrm{Pr}\,x\,Pl\,x\,R}{K} \quad (4)$$

The predicted value of paddy fields will be obtained from the equation above. The paddy field area number will be used to calculate the rice self-sufficiency limit. The rate of land-use change with the population growth rate can be described as mutually influencing each other to form the rice self-sufficiency limit, as described in Equation 5 [27].

$$F(x) = a1e^{bx} \quad (5)$$

Then, if it is known the value of the rate of population growth against the requirement for agricultural land, it will produce an equation due to the population growth rate in an exponential function such as Equation 6. This is because the population growth rate is an exponential function.

$$f\ (x) = a2e^{bx} \quad (6)$$

One cut point (x, y) will be generated as a result of applying Equations 5 and 6, and this point can be interpreted as the limit of rice's self-sufficiency. Imagine that there is a consistent shift in land usage while at the same time the pace of population growth contributes to an ever-increasing need for agricultural land. In that scenario, there will be a situation where there is no longer sufficient food security.

F. Multiple Linear Statistical Test

The indicators that this approach of ensuring food security is acceptable can be observed from the regional food security value, which is obtained by searching for the difference between the amount of food that is available and the amount of food that is required. There are three classifications of food security; food security occurs when the difference in rice availability and rice demand shows a positive value (+), and sufficient food occurs when the difference shows zero (0). Food insecurity occurs when the difference shows a negative value (-) [26].

Then multiple linear statistical tests were conducted to determine the relationship between land conversion and food security. This is performed to obtain the coefficient of determination or *R*. The *R*-value is the independent variable (*x*) effect on the dependent variable (*y*). The independent variable (*x*) was tested in paddy fields, and population growth conversion, and the related variable (*y*) was in rice production. In addition, the coefficient of determination can be used to predict and check how much influence the variable *x* simultaneously contributes to the y variable [28]. Based on scostatistical testing can be done using SPSS (Statistical Package for Social Science), consisting of several stages such as the F test and T-test.

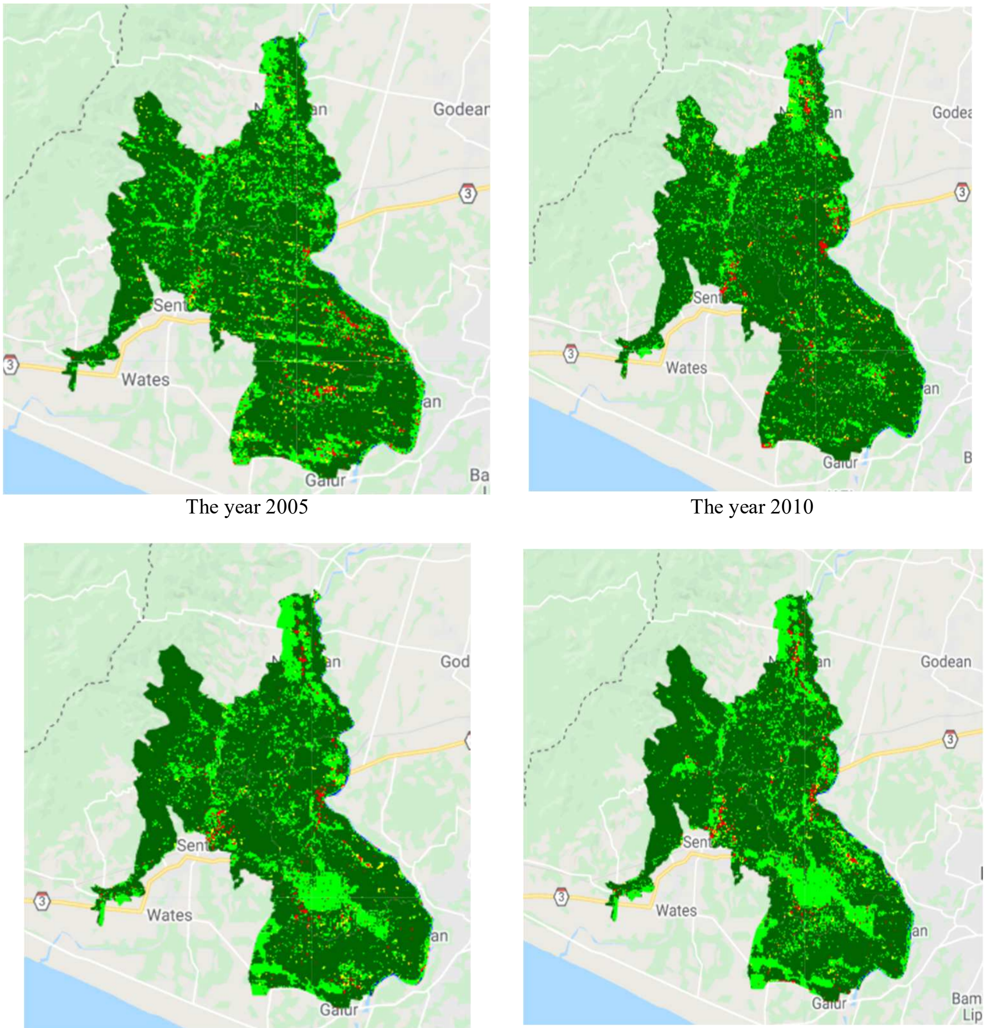
F-test is carried out to determine the effect of the independent variables simultaneously on the dependent variable. If the probability of the value of F significance <0.05, it can be said that there is an influence between the independent variables on the dependent variable simultaneously and the other way around. A T-test was carried out to test each variable partially. If the significance of the T value < 0.05, it can be said that there is an influence between the independent variables on the dependent variable partly and the other way around.

III. Results and Discussion

A. Agricultural Land-Use Change

1) Normalized Difference Vegetation Index: The vegetation level changes every year. The denser the level of green in an area indicates, the thicker the vegetation in the area.

2) Land Classification: The classification process is carried out using GEE with the CART method, a decision tree-based algorithm [29]. The classification of land cover classes can be seen in Fig. 3.



The year 2005 The year 2010

The year 2015 The year 2020

Fig. 3 Visualization of land cover class

3) Classification Suitability Test: The confusion matrix test calculates the errors of land cover from image classification results. The confusion matrix is a square matrix containing a number of pixels classified in overall accuracy, kappa accuracy, producer accuracy, and user accuracy. Allowed classification accuracy is more than 80% [30]. Six different spots are selected at random and used to create a confusion matrix. The findings indicate that the kappa accuracy and ground checking in 2005, 2010, 2015, and 2020 are exhibiting more than 80 percent per year from the two methods used to test the accuracy: the Google Earth Engine and ground check. According to this result, the accuracy acquired is pretty accurate, with the land cover classification findings mirroring the scenario observed in the field.

B. Land Conversion Rate

Land cover in the Kulon Progo plains area can be divided into five classes: water bodies, vegetation, paddy fields, built-up land, and open land. After classifying each land cover, the area of each land cover class can be known. The analysis obtained shows that the water body cover area tends to increase every year, except in 2020, which decreases. In 2015 the increase was influenced by the construction of the Bogor reservoir. Then the decrease in 2020 is caused by sedimentation or siltation due to waste disposal. The land cover change of vegetation, paddy field, built-up land, and open land was significant from 2005 to 2010, which increased and then decreased in 2015. Holes in the Landsat 7 image might cause this fluctuation in the area because the Scan Line Corrector (SLC), the instrument to compensate for forwarding satellite movement, encountered a permanent failure. So then, the resulting pattern is zig-zag, which causes gaps to be generated in the image data [31]. It causes the resulting interpretation to be less accurate, and there is still a lot of cloud cover that confuses image reading. Also, a new paddy fields printing program in 2015 influenced the increase in the paddy fields area.

C. Food Security Condition

Data on the productivity of paddy fields in the Kulon Progo plains area in 2005, 2010, and 2015 were obtained from the Central Bureau of Statistics (BPS) of Kulon Progo. Data for the productivity of paddy fields in 2020 were obtained from linear extrapolation calculations (shown in Fig. 4).

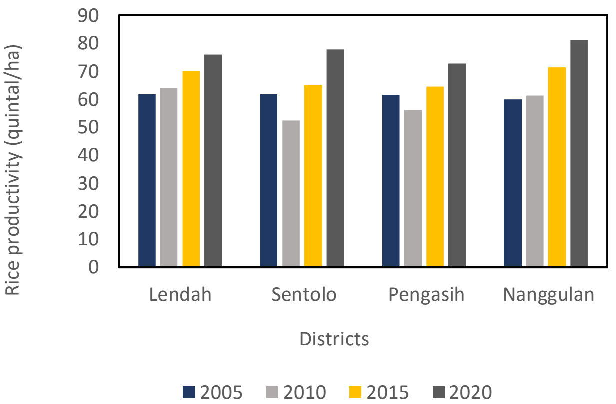


Fig. 4 Land productivity

Paddy production can be calculated by multiplying the existing land area and paddy productivity as described in Equation 1, which obtains paddy production data, as shown in Table 2.

TABLE II
CALCULATION FOOD NEEDS

D	p	R	A	N
Year 2005				
Lendah	51469.41	30154.07	29149.94	28571.48
Sentolo	66003.39	38669.01	37381.33	35105.99
Pengasih	71758.13	42040.5	40640.55	36757.17
Nanggulan	52931.65	31010.75	29978.09	24722.20
Year 2010				
Lendah	34899.29	20284.48	19609.01	26837.74
Sentolo	46608.64	27090.29	26188.18	32785.98
Pengasih	52245.52	30366.61	29355.4	33264.60
Nanggulan	67275.18	39102.289	37800.18	20057.43
Year 2015				
Lendah	57455.85	33395.01	32282.95	28590.56
Sentolo	85539.26	49717.89	48062.29	35111.12
Pengasih	51090.97	29695.55	28706.69	35693.85
Nanggulan	77036.59	44775.9	43284.87	21379.64
Year 2020				
Lendah	75377.74	43839.68	42379.81	27811.18
Sentolo	133376.45	77571.72	74988.58	34430.42
Pengasih	59034.37	34334.38	33191.05	36189.81
Nanggulan	91108.69	52988.79	51224.27	20921.09

Paddy production data is then converted into rice production using Equation 2. It considers the correction factor for paddy loss obtained from BPS Kulon Progo data, such as paddy to be used as seed, paddy for animal feed, scattered paddy, and paddy for non-industrial food. Then, food availability is calculated by considering paddy production with correction factors for rice loss. The availability of food in quintal units is obtained from this calculation in the Kulon Progo plains area.

The valuation of each district's food requirements can be calculated by multiplying the amount of rice consumed by that district's entire population. The demand for rice is initially expressed in kilograms per year, which is subsequently converted to quintals per year. The regional food security value is determined by looking for the difference between food availability and food needs. There are three classifications of food security; food security occurs when the difference in rice availability and rice demand shows a positive value (+), and sufficient food occurs when the difference shows zero (0). Food insecurity occurs when the difference shows a negative value (-) [26]. The food security condition in the Kulon Progo plains is shown in Fig. 5.

All districts in the Kulon Progo plains area experienced food security conditions in the year 2005, and this was the case throughout all of the region's districts. In 2010, the Nanggulan District was in a position of food security, while the Pengasih, Lendah, and Sentolo Districts were in a position of food insecurity. A lack of completeness in the image data may be to account for the change from food security in 2005 to food insecurity in 2010; an inaccurate interpretation of the data could have caused this. Nanggulan, Sentolo, and Lendah Districts experienced food security circumstances in 2015 and 2020; while Pengasih Districts suffered conditions of food insecurity during the same time period.

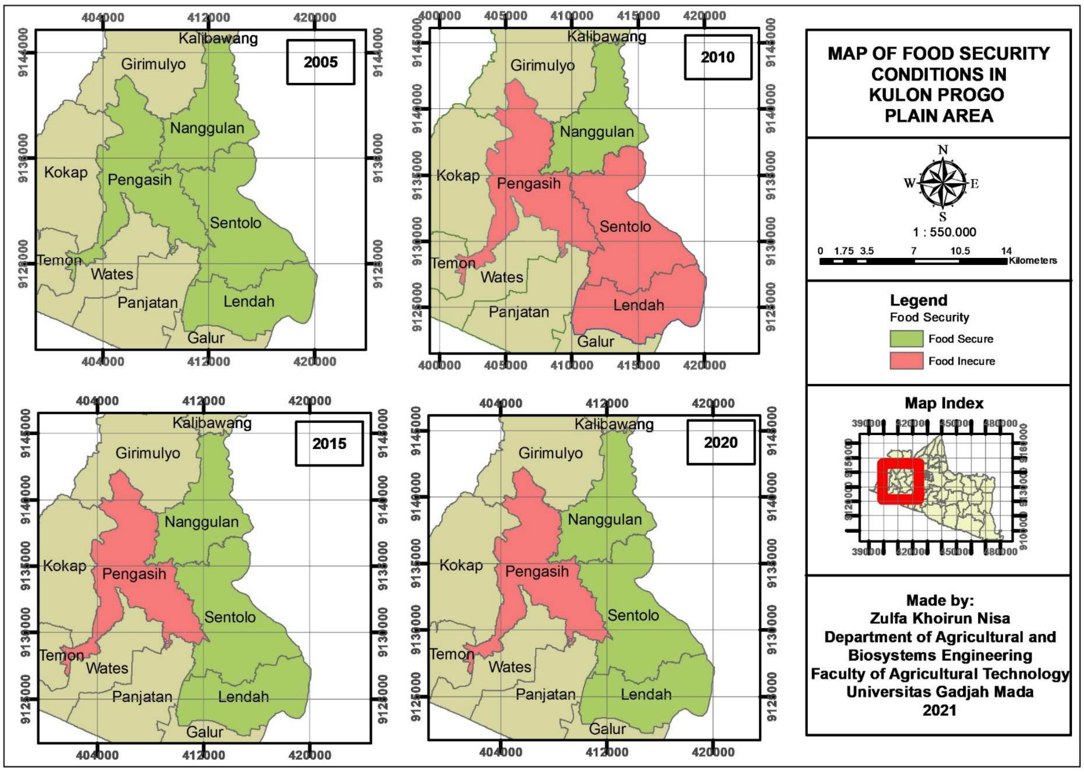


Fig. 5 Food security map

The newly built rice field can cause this food insecurity condition. It causes the new paddy fields not to be optimally used for rice growth so that the productivity of the new paddy land is not maximized. The new paddy fields also need good irrigation support to meet their water needs. Meanwhile, according to the Department of Agriculture and Food Kulon Progo some of the new printed paddy fields in the Pengasih District do not have adequate irrigation. According to [32], stabilizing the new paddy fields ecosystem takes approximately ten years. So that although the area of paddy fields increases with the presence of new paddy fields, the quality of the new paddy fields tends to decrease. In addition, it can also be caused by external factors such as climate change and disturbances from pests.

D. Land Transfer Function Impact on Food Security

Multiple linear statistical tests were conducted to determine the land conversion impact on food security. Regression analysis is a data analysis technique in statistics used to examine the relationship between several variables [33]. The f-test was conducted to determine the effect of the independent variables simultaneously on the dependent variable. The F test results obtained a significance of more than 0.05; this indicates that the conversion of paddy fields and population growth together have no significant effect on rice production. Then T-test was conducted to test each variable partially. The T-test results are more than 0.05; it indicates no considerable impact between each independent variable, the conversion of paddy fields, and population growth to the dependent variable, particularly rice production.

E. Self-Sufficiency Limit Prediction

The rice self-sufficiency limit is defined as a limit for an area that is still fulfilled the rice needs of the population in its area [27]. A number of assumptions are made in order to make an accurate prediction of this self-sufficiency limit. Because the plains area of Kulon Progo does not export and does not get imports from other regions, it is assumed that the population is stable; it does not fluctuate, and the rate of land conversion is expected to always decline. Neither of these factors contribute to population growth.

TABLE III
PREDICTION OF PADDY FIELD CONDITIONS

District	Paddy Field 2020 (ha)	Paddy Field Needed (ha)	Information
Lendah	990.709	291.305	Surplus
Sentolo	1713.821	352.577	Surplus
Pengasih	810.387	395.912	Surplus
Nanggulan	1120.999	205.142	Surplus

Based on Table 3, Lendah, Sentolo, Pengasih, and Nanggulan Districts have more paddy fields than the required paddy fields. Furthermore, the calculation of the self-sufficiency limit is carried out. The self-sufficiency limit can be known by looking at the intersection between the graph of the rate of land conversion and the graph of population growth rate. This cut-off point describes a condition of the inability of an area to meet the rice needs in that area. Prediction of self-sufficiency limit is made by referring to Equation 5 and Equation 6. Wherefrom this calculation for the conversion of agricultural land functions is $f(x) = 4635.96(e^{-0.04485x})$, where the value 4635.96 is the existing land area, and the value -0.04485 indicates the rate of reduction of agricultural land. Then, the population growth rate equation to the need for agricultural land is $f(x) = 1244.9(e^{0.004243x})$. Where 1244.9 is the value of land needed, 0.004243 is the population growth rate. The limit of food self-sufficiency can be seen in Fig. 6.

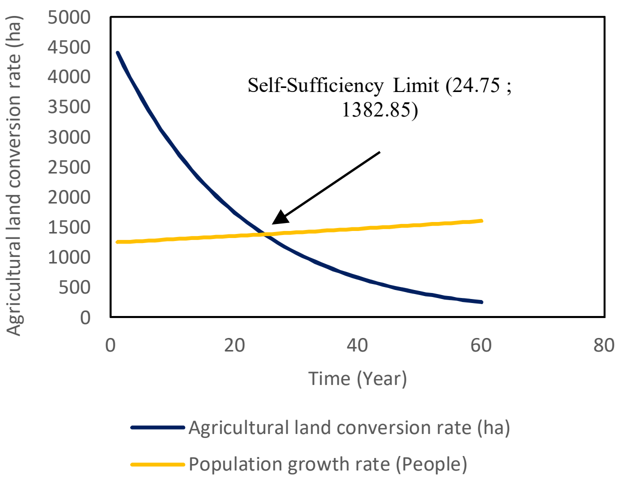


Fig. 6 Food self-sufficiency limit

This cut-off point indicates that in 1382.85 ha and 24.75 years in the future, the Kulon Progo plain area can only meet the need for food for its residents or cannot export. This will occur if there is not an increase in paddy fields either through intensification, which refers to efforts to increase agricultural yields by optimizing agricultural land to obtain optimal results, or extensification, which refers to expanding land by opening up new land that can be planted with crops. Both of these methods are referred to as land optimization.

IV. Conclusion

The establishment of the Yogyakarta International Airport (YIA) and the Bedah Menoreh road in Kulon Progo has resulted in the rapid conversion of agricultural land. This has affected food production and security, particularly in the Kulon Progo plains area. The essential materials required are administrative maps of Kulon Progo, Landsat 7 and 8 images, and statistics on land productivity, population, and consumption per capita. Machine learning was utilized to classify land-use changes and look at the state of food security. Google Earth Engine (GEE) is the main tool used for this.

The results showed that the conversion rate of agricultural land in the Kulon Progo plains from 2005 to 2010 decreased by 97.6 ha/year; in the period 2010 to 2015, it increased by 108.8 ha/year; in the period 2015 to 2020, it was 126.02 ha /year. It resulted in the food security status in 2010 in Pengasih, Lendah, and Sentolo Districts being categorized as food insecure; in 2015 and 2020, food security conditions in Pengasih District were found to be in the unsure food category. The productivity of the land produced is not optimal. With the availability of agricultural land in 2020 (1382.85 ha), food self-sufficiency will be limited for the next 24.75 years if there is no effort to increase paddy fields.

Nomenclature

p	paddy production	quintal/yr
S	seeds	
F	animal feed	
W	scattered	
C	conversion of paddy to rice	
P	total population	people
L	area of paddy fields	ha
Pr	paddy fields productivity	kg/ha
Pl	rotation of rice crops in a year	planting/ rice/year
R	yield of rice or shrinkage of grain into rice	1/100
K	average consumption of rice per person in a year	kg/prsn/yr
Fx	the need for paddy fields at the rate of conversion of agricultural land	ha
a1	existing paddy fields area	ha
fx	existing paddy fields area	ha
a2	land requirement	ha
x	time is taken	years
D	district	
p	paddy production	quintal
R	rice production	quintal
A	rice availability	quintal
N	food needs	quintal

Acknowledgment

We are entirely grateful to the Research Directorate of Universitas Gadjah Mada, who provide the funding system for this study through the grant of final project recognition. We also thank the Department of Agriculture and Food and Central Bureau of Statistics of Kulon Progo Regency, who provide data and information related to this research.

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