Identification of agricultural land use change based on machine learning for regional food security analysis in the mountainous region of Kulon Progo regency

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Abstract. After New Yogyakarta International Airport (NYIA) opening, Kulon Progo continues to develop, one of which is The Bedah Menoreh route project which passes through the mountainous region. The development encourages agricultural land conversion, which impacts food security in Kulon Progo, especially in the mountainous region. This study aims to identify the conversion of agricultural land in the mountainous region of Kulon Progo Regency in 2005 – 2020 and analyze its impact on regional food security. The method used is a Normalized Difference Vegetation Index (NDVI) on Landsat Imagery using Machine Learning through Google Earth Engine (GEE) to identify land-use change and mathematical calculations in analyzing regional food security. The result of the supervised classification is a land cover map of the mountainous region of Kulon Progo Regency, which shows that every year the area of rice fields, in general, continues to decrease until 2020 the total area is 2,102.79 ha with a rate of agricultural land conversion -114.87 ha/year. It causes regional food security to be in a food-insecure condition, even though the availability of rice fields can be used for food self-sufficiency for up to 53 years. Other factors such as climate, rice seeds, soil, and water quality, in this case, are quite influential in rice production, not only productivity and agricultural land area.

1. Introduction
Kulon Progo Regency is located in the western part of the Special Region of Yogyakarta, which is quite strategically located because it is a connecting route for the economic center on the west and east sides of Java Island through the south route. Geographically, the Kulon Progo Regency ecosystem is divided into three types, namely mountainous, plains, and coastal areas. The agricultural sector dominates the economic sector in Kulon Progo Regency. However, after the opening of NYIA (New Yogyakarta International Airport), the development in the Kulon Progo Regency continues to develop. One of them is The Bedah Menoreh route project that connected NYIA with The Borobudur Temple in Magelang. The project also aims to develop tourist attractions in The Menoreh Hills area, located in a mountainous region in Kulon Progo Regency, including Kalibawang, Samigaluh, Kokap, and Girimulyo [1].
The developments have the opportunity to encourage the conversion of agricultural land. Land-use change is a land used for a specific utilization changes several times later for another utilization. The most common example is agricultural land which periods later became a settlement. One of the causes of the conversion of agricultural land into non-agricultural land is the increase in population so that the need for housing and activities continues to grow [2]. The impact of land conversion is related to food security. Food security is the fulfillment of food conditions for the community in terms of quantity, quality, safety, variety, nutrition, equity, and affordability. The food is carbohydrates in the form of rice. Classification of food security conditions in a region can be classified as follows: i) food security if the availability of rice is greater than the people's rice needs, ii) enough food if the availability of rice is the same as the rice needs of the community, and iii) food insecurity if the availability of rice is less than the people's rice needs. The availability of rice is related to the rice field area, harvested area, rice productivity, and rice production [3].

Identification of rice field objects in terms of knowing the conversion of agricultural land to non-agricultural can use remote sensing and GIS (Geographic Information System). Satellites can use for remote sensing, one of which is the Landsat Satellite. Until now, the Landsat satellite used is Landsat 8, which was launched in 2013 to complement the previous version, Landsat 7 [4]. The earth engine, which has begun to be widely used today in terms of identifying and analyzing objects on the earth's surface, is an example of the development of remote sensing technology and GIS. Google Earth Engine (GEE) is an example of an earth engine launched by Google. GEE is equipped with Machine Learning to help users to perform land cover analysis. The aims of this study are identifying machine learning-based agricultural land conversion using Landsat 7 and 8 satellite imagery with Google Earth Engine and GIS tools, knowing the condition of food security due to the conversion of agricultural land in the mountainous region of Kulon Progo Regency, and calculating the limit of food self-sufficiency based on the available paddy fields in the mountainous area of Kulon Progo Regency.

2. Materials and methods

2.1. Study site

The mountainous region of Kulon Progo Regency is located along the Menoreh Hills, which has 500-1000 meters above sea level covering the Districts of Girimulyo, Kalibawang, Kokap, and Samigaluh. Astronomically, this mountainous region is located at 07°40'27.7" – 07°51'24.1" S and 110°06'01.6" – 110°15'46" E. The location of the mountainous region of the Kulon Progo Regency is shown in Fig 1.

Figure 1. Administrative map of the Kulon Progo mountainous area.
The area of this mountainous is 25,095 ha, with a different population density in each district. In 2020, population density in Kalibawang was the highest at 556 people/km², Kokap’s is 478 people/km², Girimulyo’s is 439 people/km², and Samigaluh has the lowest population density at 393 people/km². According to the Schmidt-Ferguson classification, the mountainous area of Kulon Progo Regency has Q’s value of 25%, so it is included in the B climate type (wet area). This area is dominated by slopes < 40° and the widest is Kokap District (3,634.63 ha). The primary function of this area is a protected area. The cultivation area is dominated by gardens and rice fields, either irrigated or rainfed. The dominant soil type is latosol soil which is brown, red, to yellow. This soil type has a crumb to lumpy structure and clay texture [5].

2.2. Material collection
This study uses data for 2005, 2010, 2015, 2020, including satellite imagery of Landsat 7 (for 2005 and 2010) and Landsat 8 (for 2015 and 2020) accessed via GEE, Kulon Progo district administration maps, agricultural land productivity, data on population and rice consumption per capita.

2.3. Satellite image processing in GEE
This stage is divided into several steps, namely as follows [6].
- Making the boundaries of the study area using geometric features in the form of polylines and then calling the image using `ee.ImageCollection` script and select the best image that has the least cloud cover using `ee.ImageCollection.sort('CLOUD_COVER').first()` script within the defined region and time range using `filterBounds` and `filterDate` scripts.
- Patching the best image pixels that have holes through the masking method using `image.select('BQA')` and `qa.bitwiseAnd().eq()` scripts. Then do the gap filling using `focal_mean()` and `blend()` scripts.
- Defining the composite image that will facilitate interpretation, namely true color and false color, which includes healthy vegetation, agriculture, atmospheric penetration by entering the bands used. Then it is displayed using `Map.addLayer()` script.
- Calculating the Normalized Difference Vegetation Index (NDVI) based on the red and near-infrared band reflected by the vegetation with a value closer to -1 indicates that the vegetation is getting rarer, and closer to +1 indicates that the vegetation is denser. The NDVI equation is shown in the following equation 1:

\[
NDVI = \frac{(\text{Near Infrared} - \text{Red})}{(\text{Near Infrared} + \text{Red})}
\]

- Creating the training point for the cover of paddy fields, water bodies, built-up land, vegetation, and open land. There are two training points made; sampling and testing points. These training points will be algorithm-defined in the machine learning process. The way to make it is by activating the function Add a marker to the Geometry tools. The marker can be a point or a polygon. After that, add the desired classification class in the configue geometry import tab here, then add other information on the added property with property ‘LC’ and value. Furthermore, the results will appear on the geometry imports tab. The scriptwriting is done by combining and defining the training points created using the `merge()` script and entering the bands that will be used with the `select()` function, and specifying the name of the feature collection that has been created in the properties section.
- Land cover classification in images uses the supervised classification method. This classification involves CART (Classification and Regression Trees Algorithm) machine learning using `ee.Classifier.smileCart()` script then inserts the bands that have been defined previously with `select()` script.
- Testing the suitability of image classification using the Kappa Accuracy method. This test uses the confusion matrix by defining testing points that have been created using `sampleRegions()` script and then displaying the confusion matrix form with `print(confusionMatrix())` script. Then the match of the sample point with the test point is made using the `errorMatrix()` script, and the results can be calculated kappa accuracy using the `print(kappa())` script.
- Calculating the land cover class area for each district by importing the administrative boundary shapefile of each district then cut according to the shapefile using .clip() script, and then the area of each class cover is calculated using ee.Image.pixelArea() script.
- Converting NDVI calculation raster data to vector form using ee.Reducer.countEvery(). Then it is exported in the form of a shapefile and imported each land cover in the form of a shapefile using Export.table.toDrive() script to find out the range of NDVI values for each land cover

2.4. Field testing/validation
Testing the suitability of image classification in addition to being carried out on GEE, field validation is also carried out for 2020 land cover data. Land cover data for 2005, 2010, and 2015 were validated through Google Earth Pro. Then the annual land cover data is made a confusion matrix to calculate the kappa accuracy value with the provisions of land suitability approaching the field condition of more than 80% [7].

2.5. Calculating food security for each district
This step is carried out using Microsoft Excel 365. Previously, a mathematical calculation of productivity data for 2020 was carried out because there was no data in the field. This calculation uses a mathematical approach to the relationship between population (X) and rice land productivity (Y) through SPSS. The selected model is a model that has a moderate to strong correlation value. The resulting equation is to find the value of rice production in 2020. Equation 2 – equation 5 used for calculating food security [8]
- Rice production equation
  \[ \text{Rice production (ton)} = \text{rice productivity (ton/ha)} \times \text{land area (ha)} \] (2)
- Availability of rice equation
  \[ \text{Availability of rice} = P \times (1 - (S + F + W)) \times C \] (3)
  where:
  \( P \) = rice production (tons/year)
  \( W \) = scattered (tons)
  \( S \) = seeds (tons)
  \( C \) = conversion of rice to rice (tons)
  \( F \) = animal feed (tons)
- Calculation of food consumption
  \[ \text{Rice consumption per capita (kg/year)} = \frac{\text{Rice consumption (Rp/year)}}{\text{Price of rice (Rp/kg)}} \] (4)
- Calculation of food needs
  \[ \text{Need for rice (ton)} = \text{rice consumption per capita (ton/year)} \times \text{population (person)} \] (5)

2.6. Self-sufficiency limit
Food self-sufficiency is the ability of land in an area to produce rice to meet the rice needs of the local community, even to the point that it can be declared a rice surplus. Food self-sufficiency limit is the limit for a region to be self-sufficient in food. This limit is determined from the meeting (break-even point) of the two equations of the rate of change, namely the equation of the rate of change in land-use and the rate of population growth on land requirements. The limit of food self-sufficiency is determined in equation 6 as follows [9].
\[ P = \frac{L \times Pr \times Pl \times R}{K} \] (6)
where:
\( P \) = total population (people)
\( L \) = area of paddy fields (ha)
\( Pr \) = paddy field 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/person/year)
Equation 6 is used to know paddy field needs that can meet the rice needs. If the paddy field needs that must be met are known, then a graph of agricultural land conversion rate is made by equation 7.

\[ f(x) = a_1 e^{b x} \]  

(7)

where:
- \( f(x) \) = the need for paddy fields at the rate of conversion of agricultural land (ha)
- \( a_1 \) = existing rice field area (ha)
- \( x \) = time is taken (years)

Then if it is known the value of the rate of population growth against the need for agricultural land, it will obtain an equation due to population growth rate in an exponential function such as equation 8.

\[ f(x) = a_2 e^{b x} \]  

(8)

where:
- \( f(x) \) = existing rice field area (ha)
- \( a_2 \) = land requirement (ha)
- \( x \) = time is taken (years)

From equation 7 and equation 8, one cut point \((x, y)\) will be formed that can be read as the limit of rice self-sufficiency. Suppose there is a continuous conversion of land use and the population growth rate towards the need for agricultural land that continues to increase. In that case, there will be a condition of food security that will run out.

3. Results and discussion

3.1. Normalized Difference Vegetation Index (NDVI) Visualization

The results of NDVI calculations carried out through GEE show that the darker the green color displayed, the denser the vegetation in that location. Figure 2 below shows the visualization of the NDVI calculation results.

![Figure 2. Visualization of NDVI calculation results.](image)

Based on figure 2, it can be seen that from year to year, the vegetation density at the study site is relatively stable, dominated by medium and high green. This can happen because the region is a highland area of the Menoreh Hills.

3.2. Land Cover Classification

The supervised classification process in GEE is carried out using Classification and Regression Trees Algorithm (CART) machine learning. CART is a type of machine learning for classification analysis by breaking down input attributes into several parts so that target attributes can be predicted more accurately, where both attributes can be described in the decision tree structure [10]. Land covers are classified as water bodies, paddy fields, vegetation, built-up land, and open land. Figure 3 shows the visualization of the land cover classification results.
Based on figure 3, it can be seen that from year to year, the class of paddy fields shown is light green that the length decreases so that it can affect the value of rice production.

3.3 Classification Suitability Test

The results of the land cover classification that have been made need to be tested to determine suitability in the field using the kappa accuracy method. This method uses a confusion matrix based on the value of the user's accuracy, producer's accuracy, and overall accuracy. These three values are obtained by comparing the number of pixels of the correct test point to the conditions in the field [11]. The number of test points is 6 for each class which is chosen randomly. Table 1 shows the results of calculating kappa accuracy using GEE, field validation (for 2020), and Google Earth Pro (for 2005, 2010, and 2015).

| Year | Google Earth Engine (%) | Manual Validation (%) |
|------|-------------------------|-----------------------|
| 2005 | 89.34                   | 83.33                 |
| 2010 | 82.08                   | 83.33                 |
| 2015 | 95.60                   | 87.50                 |
| 2020 | 94.07                   | 91.67                 |

Based on table 1, it can be seen that the overall kappa accuracy value obtained is more than 80%, so it can be said that the land cover classification made is close to the situation in the field.

3.4 Land Conversion Rate

Table 2 shows the results of the area of each land cover in hectares.

| Year | Water Bodies | Vegetation | Paddy Field | Build-up Land | Open Land |
|------|--------------|------------|-------------|---------------|-----------|
| 2005 | 128.96       | 20,704.28  | 2,469.19    | 810.70        | 145.14    |
| 2010 | 188.85       | 20,722.94  | 2,816.66    | 286.12        | 243.70    |
| 2015 | 192.68       | 19,956.21  | 2,677.15    | 407.62        | 1,024.60  |
| 2020 | 143.33       | 21,472.17  | 2,102.80    | 389.21        | 144.75    |

Rice field class each period changes quite significantly. However, the class of water bodies in 2020 is decreased, which previously increased for three periods. Likewise, the class of built-up land and open land changes quite extreme every period. These changes were because the field is actually like that, or there is a pixel leak in the image. Pixel leaks can occur due to user errors in interpreting objects or Landsat errors because the Scan Line Corrector (SLC) Landsat 7 was damaged in 2003, thereby reducing the accuracy of the data [12]. After that, the area of paddy fields shown in table 2 is
calculated the rate of change in the paddy field area every five years. The results of these calculations are shown in table 3.

### Table 3. Paddy fields conversion.

| Year       | Conversion of Paddy Fields | Land Area (ha) | Average Rate (ha/yr) | Percentage (%) |
|------------|----------------------------|----------------|----------------------|----------------|
| 2005 – 2010|                            | 347.46         | 69.49                | 70.92          |
| 2010 – 2015|                            | -139.50        | -27.90               | -16.77         |
| 2015 – 2020|                            | -574.35        | -114.87              | -10.88         |

Table 3 shows that from 2005 to 2010, there was an increasing area in the paddy fields. It is indicated by a positive sign in the average rate of change. From 2010 to 2020, the paddy fields area was decreased. It is characterized by a negative symbol in the average rate of change. One of the causes of the decrease in the 2015 – 2020 period was the construction of YIA in 2017, and the Bedah Menoreh route project began in 2020.

#### 3.5. Food Condition

Rice production is obtained using equation 2. The paddy fields area used to calculate rice production is the paddy fields area classified in GEE. Data on paddy field's productivity can be seen in figure 4.

Then the value of rice production is reduced by the conversion value that is mutually agreed upon by the statistic center (BPS) and the Department of Agriculture and Food as shown in equation 3 to produce the value of rice availability. The value of rice needs is first calculated by per capita rice consumption using equation 4, and then rice needs are calculated using equation 5. The results of food availability and rice needs calculations in the mountainous region of Kulon Progo Regency are shown in table 4.

### Table 4. Calculation of food availability and food needs result.

| District | Paddy Production (ton) | Total Population | Rice Availability (ton) | Rice Needs (ton) |
|----------|------------------------|------------------|-------------------------|-----------------|
| **Year 2005**                                      |                 |                  |                        |                |
| Kokap    | 2,697.83               | 41,417           | 1,527.93               | 3,094.44        |
| Girimulyo| 3,242.84               | 29,071           | 1,836.60               | 2,172.02        |
| Kalibawang| 4,640.40             | 33,478           | 2,628.11               | 2,501.28        |
| Samigaluh| 2,436.23               | 30,757           | 1,379.77               | 2,297.99        |
| **Year 2010**                                      |                 |                  |                        |                |
| Kokap    | 4,844.76               | 31,124           | 2,722.14               | 2,291.82        |
| Girimulyo| 4,993.39               | 21,893           | 2,805.66               | 1,612.09        |
| Kalibawang| 3,812.27             | 26,802           | 2,142.02               | 1,973.56        |
| Samigaluh| 3,180.34               | 24,681           | 1,786.95               | 1,817.39        |
Based on table 4, it shows the difference in the value of rice needs and rice availability. This difference can determine the condition of food in the districts, whether it is in a condition of food security, sufficient food, or food insecurity. The following figure is a map of food conditions based on the data from table 4.

**Figure 5.** Food condition maps of Kulon Progo mountainous region.

Based on figure 5, it can be seen that from 2005 to 2020, some districts are being categorized as food insecure, which means that the paddy fields area in the districts in producing rice have not been able to meet the rice needs.

### 3.6. Land Transfer Function Impact on Food Security

The method used is the multiple linear regression method. The linear regression method is a statistical study that is formed from the relationship of one variable with one or more other variables. Multiple linear regression predicts the value of the dependent variable \((Y)\) if the values of the independent variables \((X)\) are known. The influence of the independent and dependent variables can be known through the results of the determination test \((R^2)\) [13]. In this study, the independent variables
(X) are the conversion of agricultural land (X1) and population growth (X2), while the dependent variable (Y) is the amount of rice production. The following table shows the results of the f test on the independent variable on the dependent variable in table 5. Table 5 shows that the significant value generated is more than 5%, which means that population growth and conversion of agricultural land have no significant effect on the amount of rice production. Then each independent variable was partially tested with the dependent variable. The results of the t-test carried out can be seen in table 6. Table 6 shows that the significant value in X1 and X2 is > 5%, which means that the conversion of agricultural land and population growth partially has no significant effect on rice production.

| Table 5. F test results. |
|--------------------------|
| **ANOVA**a |
| Model | Sum of Squares | df | Mean Square | F | Sig. |
| Regression | 4761648.270 | 2 | 2380824.135 | 1.531 | .321b |
| 1 Residual | 6220309.753 | 4 | 1555077.438 | |
| Total | 10981958.02 | 6 | |
| a. Dependent Variable: Rice_production |
| b. Predictors: (Constant), Population_growth, Land_function_transfer |

| Table 6. T-test results. |
|--------------------------|
| **Coefficients**a |
| Model | Unstandardized Coefficients | Standardized Coefficients | t | Sig. |
| (Constant) | B | Std. Error | Beta | 6.065 | 0.004 |
| 1 Land_function_transfer (X1) | -68.094 | 41.882 | -0.648 | -1.626 | 0.179 |
| Population_growth (X2) | -0.191 | 0.167 | 0.456 | -1.145 | 0.316 |
| a. Dependent Variable: Rice_production |

3.7. Self-Sufficiency Limit Prediction

Prediction of food self-sufficiency limit is carried out to find out the point at which the mountainous region of Kulon Progo Regency can become self-sufficient in rice. The assumption is that there is no export or import of rice, constant population growth rate, and constant agricultural land conversion. It needs to determine the paddy fields to achieve food self-sufficiency. It was calculated using equation 6. Table 7 shows the condition of the available and the required paddy fields.

| Table 7. The condition of the available and required paddy fields. |
|--------------------------|
| **District** | **Paddy Field 2020 (ha)** | **Paddy Field Needed (ha)** | **Condition** |
| Kokap | 320.64 | 356.58 | Deficit |
| Girimulyo | 535.55 | 217.32 | Surplus |
| Kalibawang | 771.82 | 251.05 | Surplus |
| Samigaluh | 474.78 | 251.77 | Surplus |
| **Total** | **2,102.79** | **1,076.72** | **Surplus** |

Based on table 7, it can be seen that the total area of the available paddy fields has met the paddy field needs for rice production in the mountainous region of the Kulon Progo Regency. After knowing the needs, a graph of the conversion of agricultural land rate and a chart of the population growth rate against the paddy field needs are made. The two graphs will intersect at one point where the condition of the existing paddy fields can meet the food needs.
The graph of the conversion of agricultural land rate can be modeled using equation 7, which results in \( f(x) = 2102.79(e^{-0.007493x}) \), where the value of 2102.79 shows the available paddy field area and the value of -0.007493 indicates the rate of decline in paddy fields. The graph of the population growth rate against the paddy field needs is modeled using equation 8, which results in \( f(x) = 1076.72(e^{0.004964x}) \), where the value of 1076.72 shows the area of paddy fields needed and the value of 0.004964 shows the rate of population growth. The two equations are graphed for the food self-sufficiency limit to determine the cut-off point. The intersection point obtained \((x;y)\) is (53.73;1353.13), which means that after the next 53 years (around 2073) on an area of 1,353.13 ha based on the assumptions that have been used, the mountainous region will be able to self-sufficient in rice. The graph of the self-sufficiency limit prediction can be seen in figure 6.

4. Conclusions
The conversion of agricultural land in the mountainous region of Kulon Progo Regency in the 2005-2010 period was 69.49 ha/yr, in the 2010-2015 and 2015-2020 periods were -27.90 ha/yr and -114.87 ha/yr with a negative sign indicating the rate of agricultural land reduction. During the research year, food conditions in Samigaluh District were categorized as food insecure, Kokap District was categorized as food insecure in 2005 and 2020, Girimulyo District was categorized as food insecure in 2005, and Kalibawang District being categorized as food security during the research year. Overall, based on the availability of paddy fields, the mountainous region will be food self-sufficient in 2073, with an area of agricultural land of 1,353.13 ha. The assumptions used for that prediction are no export or import of rice, constant population growth rate, and constant agricultural land conversion rate so the limit prediction can be applied.

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