

Sustainable Agro-industry Logistics Solutions using Spatial Analysis

Hartrisari Hardjomidjojo

Department of Agro-industrial Technology, Faculty of Agricultural Engineering and Technology,
IPB University (Bogor Agricultural University), Bogor 16002, Indonesia
Email: sari_rce@yahoo.com

Rindra Yusianto

Department of Industrial Engineering, Faculty of Engineering, Dian Nuswantoro University,
Semarang 53192, Indonesia
Email: rindra@staff.dinus.ac.id (*corresponding author*)

Marimin Marimin

Department of Agro-industrial Technology, Faculty of Agricultural Engineering and Technology,
IPB University (Bogor Agricultural University), Bogor 16002, Indonesia
Email: marimin@ipb.ac.id

Suprihatin Suprihatin

Department of Agro-industrial Technology, Faculty of Agricultural Engineering and Technology,
IPB University (Bogor Agricultural University), Bogor 16002, Indonesia
Email: suprihatin167@gmail.com

ABSTRACT

This study proposes a new approach to determine sustainable agro-industry logistics by minimizing supply and demand imbalances using spatial analysis. The potato food crop agro-industry at Wonosobo district, Central Java, Indonesia, was selected as the case. This study first developed a spatial-based cropland sustainability classification. Second, developed a sustainable harvest prediction by modifying the multi-thresholding using remote sensing and IoT, namely SHT15 and rain gauge sensor. Third, we developed a spatial route planning wherein we adjust the COG and spatial Dijkstra algorithm to select the optimal route. This study developed a comprehensive sustainable analysis by integrating spatial dimensions with environmental, economic, and social dimensions to support sustainable food security. Multi-criteria spatial analysis was used in an environmental measurement considering altitude, soil texture, slope, rainfall, humidity, and temperature. In the economic dimension, we compare the predicted total harvests with the current production. We consider the social dimension, namely population density, spatial-temporal congestion, and risk hazard-zones index. This study shows that spatial-based cropland sustainability classification can determine the most sustainable location for potato plants. This study shows that the sustainable harvest prediction by the modified multi-thresholding can predict the harvests more accurately, namely 89.3%. Spatial distributing route planning with adjustment of the COG obtains more rational coordinates than the classical method. In addition, spatial Dijkstra algorithm modification can show a more optimal route for agro-industrial commodities. This new approach has demonstrated that spatial analysis can be an alternative solution to minimize supply and demand imbalances in sustainable agro-industry logistics.

Keywords: *agro-industry logistics, Center of Gravity, spatial analysis, spatial Dijkstra, sustainable agro-industry*

1. INTRODUCTION

By 2030, Indonesia's population is estimated to increase by 28% to 345 million. The need for agro-industrial commodity food production is also estimated to increase by 42%. This increased need has a significant impact on sustainable food security. In addition, the SARS-CoV-2 (COVID-19) pandemic, which began to hit Indonesia at the end of 2019, led to a significant increase in food demand, which affected the stability of supply and access to food (Peng and Berry, 2019; Putri, 2020). Most agro-industry players feel the impact of COVID-19 is felt, such as difficulties in obtaining supplies of raw materials, marketing, and high price fluctuations. Responding to the challenges and impacts of the COVID-19 pandemic, the Indonesian government has a policy of increasing the productivity of staple foods, expediting agro-industrial logistics, maintaining price stability, and developing bufferstock. The target of this policy is sustainable food security, including the agro-industry sector. The challenges in realizing sustainable agro-industrial food security are multidimensional, covering environmental, economic, and social (Anderson *et al.*, 2020). However, identifying these three aspects can be made by analyzing supply and demand (Russell *et al.*, 2018). From the supply side, these challenges include the global climate change impact and competition for the use of natural resources; meanwhile, on the demand side, namely high population growth, changes in consumer tastes, and competition for raw material demand.

Complexity and uncertainty in decision making, efforts to meet demand, and environmental sustainability give birth to innovative adaptive technologies (Prause, 2019). Adaptive, innovative technology that is implemented massively in the agro-industrial sector is Artificial Intelligence (AI) which utilizes the Internet of Things (IoT) (Shanmugapriya *et al.*, 2019; Saiz-Rubio and Rovira-Mas,

2020). This technology collaboration can present intelligent agro-industry through digital innovation. This innovation makes the agro-industry an essential role in Indonesia's economic development, with an average contribution of 13.5% to Gross Domestic Product (GDP) or an increase of 1% from 2019 (Dahiri and Fitri, 2020).

A sustainable food security system consists of three subsystems: availability, affordability, and food utilization (Suryana, 2014). Sustainable logistics is related to these three subsystems and has attracted the attention of many agro-industry players (Borsellino *et al.*, 2020; Kurbatova *et al.*, 2020). Sustainable logistics related to the processing of agricultural raw materials are called agro-industry logistics (agrologistics). The main problem of agro-industry logistics is the characteristics of agricultural products with high vulnerability, complexity, and uncertainty due to the nature of perishable commodities, sensitivity to climate change, not durable, and very high price fluctuations. Quality decreases rapidly after harvest, so the potential for post-harvest losses is up to 40% (Hsiao *et al.*, 2018; Yusianto *et al.*, 2019).

Most of the previous studies discussed the logistics of sustainable food security without considering spatial analysis mathematically. We think differently. In our opinion, it is necessary to consider the spatial analysis in sustainable agro-industrial logistics. Standard mathematical calculations cannot solve complex problems, including geographic coordinates (X, Y) and spatial approaches. Therefore, this study proposes a new approach to determine sustainable agro-industry logistics solutions, i.e., material management and physical distribution solutions, by minimizing supply and demand imbalances using spatial analysis. Moreover, this study developed a spatial-based cropland sustainability classification based on demand, developed a sustainable harvest prediction by modifying the multi-thresholding method using remote sensing and IoT, namely SHT15 and rain gauge sensor. We developed a spatial distributing route planning to adjust the Center of Gravity (COG) and spatial Dijkstra algorithm.

2. LITERATURE REVIEW

2.1 Spatial-based Cropland Sustainability Analysis

The big challenge for the agro-industrial sector is how to increase agricultural production to achieve food security (Delgado *et al.*, 2019). One of the global food security issues is the imbalance of supply and demand (Saravia-Matus *et al.*, 2016). A quality and sustainable supply must keep pace with the ever-increasing demand for food (Bilali *et al.*, 2019). According to Ramankutty *et al.* (2018), cropland sustainability significantly affects the supply of agricultural commodities, including potatoes. So that cropland sustainability needs to be considered to obtain a product that can meet global potato demand. The perishable character of potatoes makes logistics systems need to consider spatial perspectives, both physical and environmental, such as climate change, the potential for increased erosion, loss of productivity due to changes in temperature, humidity, and extreme rainfall (Yusianto *et al.*, 2020b). Environmental impacts affect future food security and, at the same time, have a significant effect on social and economic aspects (Yu and Wu 2018).

This research focuses on the supply and demand balance to improve the logistics of sustainable food security considering the characteristics of agricultural products. Starting from predicting demand, cropland sustainability classification, food crop harvest prediction, and logistics distribution route planning. According to Barchia *et al.* (2017), of all these stages, the most critical step is cultivating sustainable cropland according to environmental dimensions. Environmental dimensions are consisting of physical and climatic factors (Effendi *et al.*, 2018). Physical factors include altitude, geology, soil texture, and soil slope percentage, while climatic factors are temperature, humidity, and rainfall (Yusianto *et al.*, 2020a). The positive environment dimensions consistently positively impact agro-industrial commodities' logistics (Anderson *et al.*, 2020). Agro-industrial commodities are generally susceptible to climate change and cannot grow well anywhere; therefore, it is necessary to pay attention to cropland sustainability. Cropland sustainability is a function of the needs and cultural land characteristics. Cultivating crops on sustainable land will increase productivity and reduce the risk of loss due to crop failure. Evaluation of cropland sustainability needs to be more intensive and increase productivity (Karim, 2017). Rykaczewska (2015) explains that the rainfall and temperature of an area affect the sustainability of crop land. However, physical factors and spatial analysis did not discuss.

Cropland sustainability is becoming increasingly complex, where standard statistical techniques are unable to solve this problem. Including predicting the number of harvests on sustainable cropland, innovative technology based on AI using IoT is needed (Lee *et al.*, 2013). The IoT is a global network of smart devices capable of integrating the physical and digital worlds (Vass *et al.*, 2021). Monitoring at the farm level has widely used IoT platforms. This approach is the layers' analysis containing spatial data, logistics traceability, agricultural products integrated management, and precision agriculture (Tayari *et al.*, 2015). IoT can optimize precision agriculture, manage production, and maximize crop quality (Marcu *et al.*, 2019). Remote sensing takes data and then feeds it into a machine learning algorithm (Tervonen, 2018; Araby *et al.*, 2019). Foughali *et al.* (2019) has developed the IoT-based Decision Support System (DSS). They used the IoT Node MCU platform, the DHT11 humidity sensor. Kiani and Seyyedabbasi (2018) have developed other related research. Rad *et al.* (2015) explained intelligent monitoring that the Cyber-Physical System (CPS) with precision agriculture. Araby *et al.* (2019) and Kamalakkannan *et al.* (2020) have also researched IoT applications in the agro-industry. However, most of the previous studies did not discuss spatial-based cropland sustainability.

2.2 Sustainable Food Crop Harvest Prediction

The main factors affecting crop yields are input and weather. The use of data on these factors forms one approach to predicting total harvests. Zhou *et al.* (2017) have researched harvest prediction using a digital image. They made predictions using multi-temporal index methods. In their research, Liu *et al.* (2021) discuss neural network-based segmentation technology using a multi-threshold approach to increase precision in forecasts. Another technique used plant

strength as measured via IoT with remote sensing data (Panwar *et al.*, 2017). With IoT and remote sensing automation, the food crop harvest prediction will be more accurate (Saiz-Rubio and Rovira-Mas 2020). Planning, decision making, and strategic policies for sustainable agro-industry require the prediction of the total harvest. Research by Zuoza *et al.* (2015) stated that total harvest prediction accuracy increased when adding environmental variables. The accuracy of their final regression model was 3.89. Zecca and Rastorgueva (2015) also explained that the environmental, social, and economic dimensions significantly affect a harvest prediction. According to Hilker and Liz (2020), the total harvest prediction strategy with multi-threshold harvesting results in a population surplus above the established threshold. This strategy is to prevent overexploitation while obtaining higher yields than other harvesting strategies. However, their research did not discuss sustainable food crop harvest prediction.

Helm (2018) and Gonçalves (2021) have investigated predictions of sustainable food crops. They state that ecological, geophysical, social, and environmental factors, demand for availability, and data processing affect harvest prediction and represent spatial phenomena. Electronic control using sensors, Geographic Information Systems (GIS), and drones supports data collection on several critical aspects of agriculture: weather, geographic, and spatial data (Lezoche *et al.* 2020). GIS provides a visual representation of a defined area and allows specific information to make more informed decisions. GIS addresses demographics, zoning, and land use planning by combining time with an interactive form of decision-making. The availability of spatial data and digital geoinformation affects this.

Regarding sustainable harvesting, the collaboration of GIS, remote sensing, and IoT has proven to determine optimal planting coordinates by conducting continuous evaluations by quantitatively linking location data when carrying out spatial analysis and predicting total harvest (Rashed-Ali 2013). However, their research did not show any potential limitations for the application of GIS and spatial analysis. Application of spatial analysis for appropriate land management and determination of COG that considers social dimensions did not discuss. They also did not discuss the application of spatial analysis in sustainable food crop harvest prediction.

2.3 Spatial Distribution Route Selection

After predicting supply, it is necessary to discuss the optimal distribution route selection for agricultural commodities. Various methods have been explored, determining COG (Asahara and Yamamoto, 2007). The COG method has become a worldwide phenomenon. Agro-industrial logistics facilities to optimize deliveries in randomly distributed locations use this method a lot (Gutierrez and Mutuc, 2018). In the traditional COG model, the Logistics Center (LC) determination mainly uses assumptions in agro-industry logistical systems such as capacity demand and transportation (Ali and Nakade, 2015; Baez *et al.*, 2020). Determining the LC location affects fair and reasonable profits because of uncertain factors (Asrol *et al.*, 2020). However, in practice, several uncertain factors also influence the decision of LC, such as environmental,

economic, and social factors (Zhao, 2014; Das, 2020). However, they did not include a spatial analysis.

Balsa-Barreiro *et al.* (2019) has studied important global indicators in the analysis of COG shifts. This indicator can predict future economic growth trends in the next few years. Fu *et al.* (2011) have also studied the spatial mean value in the COG movement. The results of their research are recommendations for increasing consumption, which is a driving factor for economic development in Xinjiang. However, they did not specifically research spatial distribution route selection.

The sustainable agro-industry logistics system involves order processing, warehouse, and transportation (Charoenporn, 2018; Huang *et al.*, 2021). According to Uvet (2020), sustainability agro-industry logistics can also more significantly meet customer needs. In Huang and Zhu's (2014) and Shih's (2015) research, the objectives of optimizing the facility's location are to minimize transportation costs. Many facility location decisions involve distance destination functions such as genetic algorithms, metaheuristics, branch-and-bound, approximation, simulation, heuristic techniques, and decomposition. Soomro's (2015) research explains the GIS concept, the relationship between GIS and spatial equipment, and the benefits of implementing a sustainable agro-industry. In Shanwad *et al.*'s (2014) and Bach and Mauser's (2018) research, they stated that smart farming and sustainable agro-industry have shifted from the highest spatial accuracy to the most intelligent treatment. In a study conducted by Cai and Xia (2018) and Zonouzi and Kargari (2020), they examined the relationship between sustainable agriculture, logistics, big data, and spatial. However, they did not explain the supply and demand balance using spatial distribution route selection.

Spatial distribution route selection must maximize vehicle movement and utilization while minimizing vehicle emissions, traffic congestion, and optimal routing (Adetiloye and Pervez 2015). Regarding agro-industry logistics distribution, Idri *et al.* (2017) and Kilibarda (2015) stated that the shortest route algorithm could considering time. Keser *et al.* (2016) explained that the Dijkstra algorithm could optimize route calculations. However, they did not discuss spatial distribution route selection.

3. RESEARCH METHODOLOGY

3.1 Agro-industry and Location Cases

In this study, we selected potato (*Solanum tuberosum L.*) agro-industry as the case. Potatoes are an essential agro-industrial commodity globally after wheat, rice, and maize (Ali *et al.*, 2015). Currently, Indonesia is in 10th position globally, with a total production of 1.3 million tons/year and an average growth of 8.4%. Potatoes are a commodity recommended by the United Nations to support sustainable food security in many countries (Devaux *et al.*, 2014).

Wonosobo district, Central Java, Indonesia, was selected as the case location based on the average potato production in Indonesia in 2019. Central Java has the most significant output of 277,702 tons/year, where one of the largest potato-producing districts is Wonosobo, with 54,265 tons/year.

3.2 Research Framework

First, we developed a spatial-based cropland sustainability classification on demand. To classify, we performed geoprocessing and layer stacking in 16 research sample areas. We analyzed the multi-criteria evaluation in the spatial analysis of sustainable interval classes, namely six factors in the environmental dimension, three factors in the social dimension, and two economic dimensions. The

environmental dimension consists of physical and climatic factors. We use physical factors in the spatial analysis of cropland sustainability are altitude, soil texture, and slope percentage. At the same time, the climatic factors are temperature, humidity, and rainfall. We also consider the economic dimension, namely total harvest, and the social dimension, namely population density, spatial-temporal congestion, and risk hazard-zones index (Figure 1).

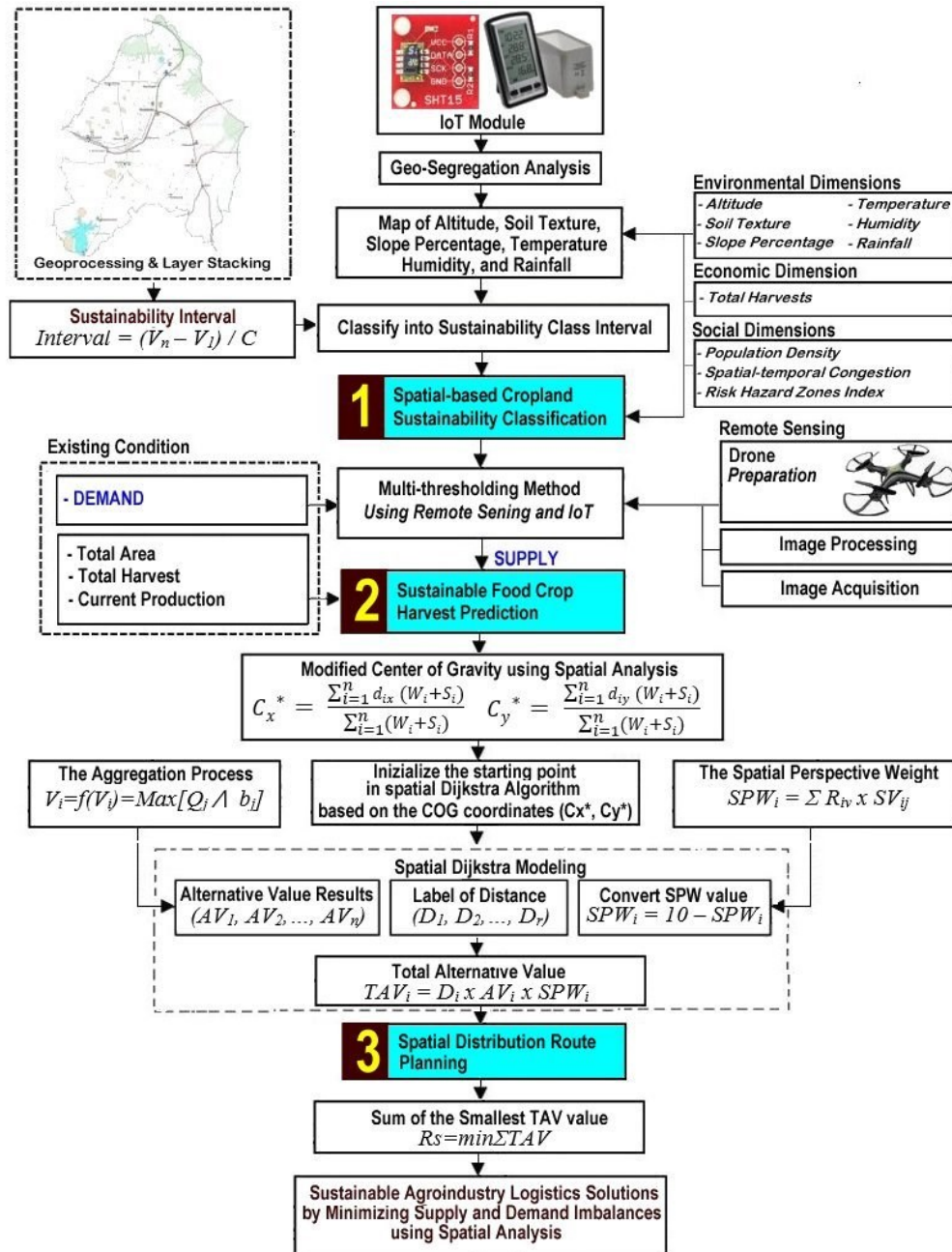


Figure 1 Research framework

We installed an IoT module, namely the SHT15 and rain gauge sensor. SHT15 is for measuring temperature and humidity, while rain gauge is for measuring rainfall. Each sensor has provided data regularly per day for 90 days. We use accuracy of ± 0.4 @5–40°C for the SHT15 sensor calibration. Geo-segregation analysis obtains altitude, soil texture, slope percentage, temperature, humidity, and rainfall maps. Thus, cropland mapping is essential to determine the

cropland sustainability level: the most sustainability, sustainability, rather sustainability, and unsustainability.

Second, we develop sustainable food crop harvest predictions based on cropland sustainability classification. We modified the multi-thresholding method using remote sensing, namely a DJI quadcopter drone for mapping activities with a maximum altitude of 100 m original. We predict food crop harvest based on potato demand data by

considering the total planted area, total harvest, and current production. The economic dimension compares the expected results with current production. This process is to ensure the sustainability of supply from farmers in meeting consumer demands. We used remote sensing and IoT for image processing based on a leaf. The method used is layer stacking with multi-thresholding. This method processes the resulting image with a size of 2.5 x 2.5 m², then separates the image into several regions based on the intensity value of grayscale pixels. We use two segments using multi-thresholding to differentiate the leaf image and the background object. We grouped the image acquisition data into 24 blocks (blocks A₁ to F₄). The data processed are the existing full harvesting conditions from the obtained coordinates, drone preparation, image processing, and image acquisition (Figure 1). So we get the coordinates of the location with the prediction of the most sustainable food crop harvest.

Finally, we develop spatial distribution route planning by modifying the COG and spatial Dijkstra algorithms to determine the LC coordinates and select the optimal route. In this study, LC is determined based on COG coordinates, where the weakness of this method is that it often finds optimal points in densely populated areas. Therefore, we measure the social dimension. We propose a spatial analysis in determining COG coordinates considering population density, spatial-temporal congestion, and risk hazard zones. To determine the optimal route, we offer a new algorithm, namely the spatial Dijkstra algorithm, to which we add a spatial analysis. This study synergizes the environmental, economic, and social dimensions with spatial analysis.

3.3 Model Development

3.3.1 Spatial-based Cropland Sustainability

In this study, cropland sustainability used spatial-based criteria (altitude, soil texture, slope percentage, temperature, humidity, and rainfall) and four classes (very good, good, rather bad, and bad).

$$interval = \frac{V_n - V_1}{c} \quad (1)$$

Where V_n = the highest total class value; V₁ = the lowest total class value; C = number of classes created.

Thus, cropland mapping is critical to determine the cropland sustainability level, which is the most sustainable (S₁), sustainable (S₂), rather sustainable (S₃), and unsustainable (NS), as expressed in Table 1.

Table 1 Cropland sustainability level interval

Class	Total value	Cropland Sustainability level
S ₁	>19.7	The most sustainable
S ₂	15.2 – 19.7	Sustainable
S ₃	10.6 – 15.1	Rather sustainable
NS	6.0 – 10.5	Unsustainable

3.3.2 Sustainable Food Crop Harvest Prediction

We developed a sustainable food crop harvest prediction based on cropland sustainability by modifying the multi-thresholding method. We use the multi-thresholding method to separate an image into several regions based on the pixel intensity value. We changed the previous image to grayscale. The modification is to combine the planting age

with segmentation based on the extract of the brownish-green component from the original image. We made modifications because the difference in the appearance of potato leaves still green with those ready to harvest is not too significant.

We modify the thresholds to two, namely 0-100 and 100-250. We use leaf images based on planting age and background objects to simplify image processing. Segmentation of the image region using multi-thresholding. Region one is the background image, and region two is the potato leaf image (Figure 2).

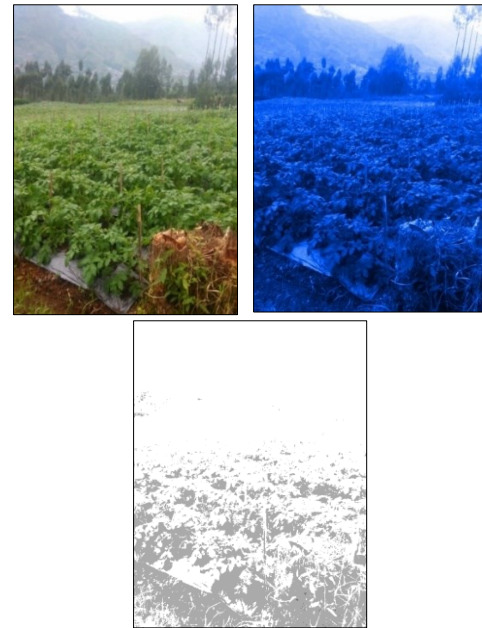


Figure 2 Image segmentation using multi-thresholding

A multi-thresholding process with a threshold value in the range of 100 and 250. The pixel intensity value between 0-100 is included in region 1. While the pixel intensity value between 100-250 is included in region 2.

```
segment_1=imquantize(green,[0 100]);
RGB = label2rgb(segment_1);
figure,imshow(RGB)
```

3.3.3 Spatial Distribution Route Selection using Modified COG and Spatial Dijkstra

After finding sustainable cropland, we predict the total yield by determining COG. Classic COG coordinates based on production capacity at each point; this method often results in densely populated COG areas, which is detrimental from a social perspective. We also add a spatial view to the COG calculations to make COG coordinates more plausible and meaningful considering the environmental and social dimensions. At this stage, the spatial perspective used is altitude, slope percentage, population density, spatial-temporal congestion, and risk hazard zones. We still use the coordinates (X, Y) of each point and capacity (Equation (2)).

$$C_x = \frac{\sum_{i=1}^n d_{ix} W_i}{\sum_{i=1}^n W_i} \quad (2)$$

$$C_y = \frac{\sum_{i=1}^n d_{iy} W_i}{\sum_{i=1}^n W_i}$$

Where C_x = latitude coordinates; C_y = longitude coordinates; d = distance; W = weight capacity; $i = 1, 2, \dots, n$; $x = 1, 2, \dots, m$; $y = 1, 2, \dots, p$.

By considering the mathematical Equation, it is obtained:

$$\begin{aligned} C_x \sum_{i=1}^n W_i &= \sum_{i=1}^n d_{ix} W_i & (3) \\ C_y \sum_{i=1}^n W_i &= \sum_{i=1}^n d_{iy} W_i \end{aligned}$$

We added a spatial perspective (S_i) to the COG equation, assuming that the effect of capacity (W) is equivalent to S . The COG equation taking into account the spatial perspective that we proposed was as in Equation (4).

$$\begin{aligned} M_x &= \frac{\sum_{i=1}^n d_{ix} S_i}{\sum_{i=1}^n S_i} & (4) \\ M_y &= \frac{\sum_{i=1}^n d_{iy} S_i}{\sum_{i=1}^n S_i} \end{aligned}$$

Where M_x = modified latitude coordinates; M_y = modified longitude coordinates; d = distance; S = spatial perspectives; $i = 1, 2, \dots, n$; $x = 1, 2, \dots, m$; $y = 1, 2, \dots, p$.

We changed it into the following Equation:

$$\begin{aligned} M_x \sum_{i=1}^n S_i &= \sum_{i=1}^n d_{ix} S_i & (5) \\ M_y \sum_{i=1}^n S_i &= \sum_{i=1}^n d_{iy} S_i \end{aligned}$$

The new COG equation is obtained as follows:

$$\begin{aligned} C_x^* &= \frac{C_x \sum W_i + M_x \sum S_i}{\sum W_i + \sum S_i} = \frac{\sum d_{ix} W_i + \sum d_i S_i}{\sum W_i + \sum S_i} & (6) \\ C_y^* &= \frac{C_y \sum W_i + M_y \sum S_i}{\sum W_i + \sum S_i} = \frac{\sum d_{iy} W_i + \sum d_i S_i}{\sum W_i + \sum S_i} \end{aligned}$$

If the assumptions are fulfilled, the new COG equation formula proposed was as in Equation (7).

$$\begin{aligned} C_x^* &= \frac{\sum_{i=1}^n d_{ix} (W_i + S_i)}{\sum_{i=1}^n (W_i + S_i)} & (7) \\ C_y^* &= \frac{\sum_{i=1}^n d_{iy} (W_i + S_i)}{\sum_{i=1}^n (W_i + S_i)} \end{aligned}$$

Where C_x^* = new latitude coordinates; C_y^* = new longitude coordinates; d = distance; S = spatial perspectives; $i = 1, 2, \dots, n$; $x = 1, 2, \dots, m$; $y = 1, 2, \dots, p$.

We use a modified Dijkstra algorithm to determine the optimal route in the physical distribution from COG to consumers considering the supply and demand balance. For agro-industrial commodities, the shortest route is not the primary choice. We added a spatial perspective to determine the optimal route, namely spatial-temporal congestion and risk hazard-zones index.

The routing problem with the shortest route is defined as follows: $G(V, E)$ shows the graph and direction of the directed arrow, where $V = \{V_1, V_2, \dots, V_n\}$ a set of vertices, $E = \{E_1, E_2, \dots, E_m\}$ a set of edges with vertex source $s \in E$ and target vertex $t \in E$. In the minimization case, the path $\rho = \{e_1, e_2, \dots, e_r\}$ among all other routes that respect ρ properties starting from s and ends at t . By using the classical Dijkstra algorithm, the path from the source vertex V_1 to target vertex V_n is:

$$P_i(V_i, V_n) = (V_1, V_2, \dots, V_n) \quad (8)$$

Where P = routes; V = vertex or nodes; $i = 1, 2, \dots, n$.

The shortest route using the classical Dijkstra algorithm is sometimes not sustainable for agro-industrial commodities. So, besides distance (D_i), we added alternative values (AV_i) and spatial perspective weight (SPW_i). Route selection uses the shortest distance and Total Alternative Value (TAV_i) (Figure 3).

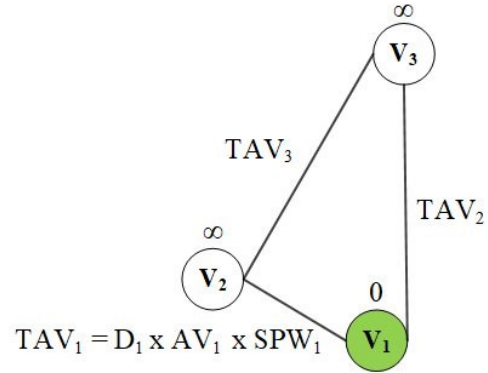


Figure 3 Single graph network using spatial Dijkstra

Based on Figure 3, the alternative route is $P_1(V_1, V_3) = (V_1, V_2, V_3)$ or $P_2(V_1, V_3) = (V_1, V_3)$. The steps for the spatial Dijkstra algorithm are as follows:

- Step 1:** Label each node with a number, while the path with a distance of $D = \{D_1, D_2, \dots, D_r\}$ from one node to the next node (i, j) .
- Step 2:** Determine spatial perspective variables. The spatial variable in this method determines the spatial perspective $S = \{S_1, S_2, \dots, S_v\}$.
- Step 3:** Calculate the ratio of each spatial variable. Determine the ratio of each spatial variable $R = \{R_1, R_2, \dots, R_v\}$ where the total ratio is equal to 100%. Give score to each spatial variable in each path (node to the nearest node) $SV = \{SV_1, SV_2, \dots, SV_j\}$.
- Step 4:** Calculate the spatial perspective weight (SPW_i) of each path.

$$SPW_i = \sum R_{iv} \times SV_{ij} \quad (9)$$

Where SPW = spatial perspectives weight; R = ratio of each spatial variable; SV = spatial variable; $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$; $v = 1, 2, \dots, p$.

- Step 5:** Convert the SPW value of each path to remain consistent with the classical Dijkstra algorithm; we convert the SPW value. The objective of the conversion was to get the optimal value from the spatial perspective.

$$SPW_i = 10 - SPW_i \quad (10)$$

Where SPW = spatial perspectives weight; $i = 1, 2, \dots, n$.

- Step 6:** Calculation of total alternative value.

$$TAV_i = D_i \times AV_i \times SPW_i \quad (11)$$

Where TAV = total alternative value; D = distance;
 $i = 1, 2, \dots, n$.

We get the result that this new method is not always the shortest route. However, getting the TAV accumulated was the smallest, and then this was determined as the most optimal alternative route (R_s) with the sum of the smallest TAV values, where $TAV = \{TAV_1, TAV_2, \dots, TAV_i\}$.

$$R_s = \min \sum TAV \tag{12}$$

Where R_s = the most optimal route; TAV = total alternative value.

3.4 Data Collection

We have collected data from 16 samples in 14 sub-districts in Wonosobo District, Indonesia. We selected sample locations based on mapping using a 1.5 km grid interval in all areas (**Figure 4**) so that the number of grids obtained is 16 grids.

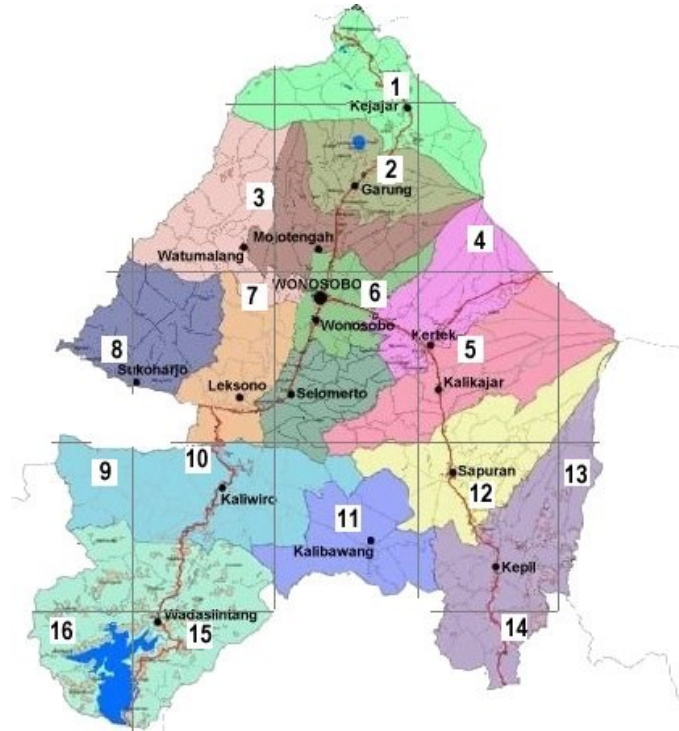


Figure 4 Sample points based on intervals

We processed spatial data using geoportal data sets in Central Java, Indonesia, field research, and data collection. We collected 16 samples to determine the sample

coordinates using GIS, namely the map overlay with grid techniques (**Table 2**).

Table 2 The sample nodes coordinates

Sub-Districts	Total Area (sq. km)	Population Density (sq.km)	Sample Point	Id	Latitude (X)	Longitude (Y)
Kejaran	57.52	757.70	Tieng	P ₁	7°14'11.8"S	109°56'29.7"E
Garung	51.22	974.58	Jengkol	P ₂	7°16'52.1"S	109°56'37.2"E
Mojotengah	45.07	1378.41	Deroduwur	P ₃	7°17'31.6"S	109°52'31.7"E
Kertek	95.70	843.87	Tlogomulyo	P ₄	7°19'35.8"S	109°59'28.2"E
Kalikajar	83.29	704.25	Tegalombo	P ₅	7°22'38.5"S	109°59'33.6"E
Wonosobo	33.00	2,754.73	Wonokerso	P ₆	7°20'46.1"S	109°55'07.3"E
Watumalang	68.22	726.56	Limbangan	P ₇	7°21'33.2"S	109°52'36.5"E
Sukoharjo	54.28	620.60	Rogojati	P ₈	7°23'49.2"S	109°46'36.1"E
Kaliwiro	100.08	448.46	Lamuk	P ₉	7°27'17.7"S	109°46'49.2"E
Leksono	44.07	945.02	Sawangan	P ₁₀	7°26'43.8"S	109°49'49.9"E
Kalibawang	47.81	475.34	Kalialang	P ₁₁	7°29'00.7"S	109°55'03.1"E
Sapuran	77.73	738.25	Ngadisalam	P ₁₂	7°26'32.4"S	109°59'14.1"E
Kepil	92.86	617.48	Ropoh	P ₁₃	7°27'40.6"S	110°02'44.9"E

Sub-Districts	Total Area (sq. km)	Population Density (sq.km)	Sample Point	Id	Latitude (X)	Longitude (Y)
Wadaslintang	127.16	412.56	Bener	P ₁₄	7°33'08.2"S	110°00'45.2"E
			Tirip	P ₁₅	7°32'59.1"S	109°49'59.8"E
			Lancar	P ₁₆	7°32'24.7"S	109°45'34.1"E

We determine the classes to be very good with a value of 4, good (3), rather bad (2), and bad (1). The values for each class on physical factors in the environmental dimension are altitude 1,300-2,658 m asl (4), 500-1,299 m asl (3), 200-499 m asl (2), and <200 m asl (1). Altitude uses the Van Zuidam method developed by Verstappen and van Zuidam (Cahyadi *et al.*, 2016). FAO classifies soil texture for agriculture in 2015 and world soil reports (Akiyama *et al.*, 2020). The values for soil texture andosol are (4), regosol (3), latosol (2), and podzol (1). The standard slope percentage uses the provisions in Bermans's research (2006), namely 0-2% (4), 3-7% (3), 8-13% (2), and > 13% (1). Regarding the sustainable logistic agro-industry, climatic factors include temperature, humidity, and rainfall. The most suitable temperature for growing potatoes is 17.4 – 20.0°C. Based on the Rykaczewska (2017) study, in this research, the temperature was classified as 15.6-17.8°C (4), 17.7-20.0°C (3), 20.1-30.0°C (2), and >30.0°C (1). Potato plants will grow best with humidity between 80-90% (Backhausen *et al.*, 2005; Sugiharyanto, 2017). Humidity classes and their criteria value are >89% (4), 80-89% (3), 70-79% (2), <70% (1). Rainfall affects potato growth and the consistency of production. Rainfall that is too high can leach out the nutrients needed for potato growth (Zeyayen *et al.*, 2017;

Hou *et al.*, 2020). Average rainfall classes and their criteria are >300 mm/month (4), 200-300 mm/month (3), 60-299 mm/month (2), <60 mm/month (1).

We measure the economic dimension by comparing the predicted results with current conditions and more reasonable prices at the farm level. Based on SNI 03-1733-2004, the classification of population density is <150 people/ha (4), 151-200 people/ha (3), 201-400 people/ha (2), >400 people/ha (1). The traffic system affects social life, where traffic congestion affects temporal traffic congestion (Saragi, 2015). Temporal congestion is classified by the value smooth (4), rather smooth (3), a little jam (2), and traffic jam (1). Based on Central Java Geoportal data, the classification of risk hazard zones is the safe zone (4), slightly landslide (3), flood (2), and flood and landslide (1).

This study used a spatial distribution based on the GIS stacking layer covering altitude, soil texture, slope percentage, temperature, humidity, and rainfall (**Table 3**). Based on the spatial analysis, we obtained an average height of 674.8 m asl. Soil texture is predominantly podzol and regosol. We did not get the latosol texture, while andosol was present in P₁, P₂, and P₃ samples. The average slope is 8-13% (slightly steep).

Table 3 The spatial analysis results for 16 sample points

Sample Code	Altitude m asl	Soil Texture	Slope Criteria	Temperature °C	Humidity (%)	Rainfall mm/month
P ₁	1,378	Andosol	Bumpy	19	90-95	341.00
P ₂	1,019	Andosol	Sloping	23	80-90	326.83
P ₃	860	Andosol	Bumpy	24	80-90	317.75
P ₄	825	Regosol	Hilly	22	80-90	313.33
P ₅	815	Regosol	Sloping	23	80-90	351.92
P ₆	744	Regosol	Flat	26	75-80	306.67
P ₇	910	Regosol	Bumpy	24	80-90	247.50
P ₈	400	Podzol	Bumpy	26	80-90	325.91
P ₉	360	Podzol	Flat	27	75-80	260.75
P ₁₀	512	Podzol	Bumpy	26	75-80	240.05
P ₁₁	626	Regosol	Bumpy	26	80-90	350.42
P ₁₂	760	Regosol	Flat	26	80-90	336.17
P ₁₃	522	Podzol	Flat	27	80-90	347.08
P ₁₄	522	Podzol	Bumpy	27	80-90	347.08
P ₁₅	272	Podzol	Sloping	29	75-80	234.25
P ₁₆	272	Podzol	Sloping	29	75-80	234.25

4. RESULT AND DISCUSSIONS

4.1 Potato Cropland Sustainability Classification

Almost all research areas are sustainable for potato crops, especially in the eastern and northern parts. Only the P₁ and P₂ are most sustainable based on the altitude (>1,300 m asl) (Table 4). Meanwhile, based on soil texture (andosol), the appropriate area for potato plants is in the northern part of the research area. Based on the slope factor (8-13%), the middle part is more sustainable, while the north of the site is less sustainable because it is > 14% (hilly). The average temperature is above 20°C. The average humidity is 77.86%, the average daily rainfall for all samples is above 300 mm/month.

Table 4 Cropland sustainability classification

Sub-district	Sample code	Sample Point	Result	
			Total value	Land sustainability level
Kejajar	P ₁	Tieng	20	Very Sustainable
Garung	P ₂	Jengkol	20	Very Sustainable
Mojotengah	P ₃	Deroduwur	17	Sustainable
Kertek	P ₄	Tlogomulyo	16	Sustainable
Kalikajar	P ₅	Tegalombo	17	Sustainable
Wonosobo	P ₆	Wonokerso	19	Sustainable
Watumalang	P ₇	Limbangan	16	Sustainable
Sukoharjo	P ₈	Rogojati	15	Rather Sustainable
Kaliwiro	P ₉	Lamuk	15	Rather Sustainable
Leksono	P ₁₀	Sawangan	15	Rather Sustainable
Kalibawang	P ₁₁	Kalialang	17	Sustainable
Sapuran	P ₁₂	Ngadisalam	19	Sustainable
Kepil	P ₁₃	Ropoh	17	Sustainable
	P ₁₄	Bener	15	Rather Sustainable
Wadasintang	P ₁₅	Tirip	14	Rather Sustainable
	P ₁₆	Lancar	14	Rather Sustainable

4.2 Spatial Analysis of the Total Harvest Prediction

Based on the spatial analysis, the cropland sustainability values were 62.01% scattered in the east and southern parts of the research area (Figure 5). The most sustainable site is 11.05% in the northern part of the study area with conformity without limiting factors. 22.9% of unsustainability land is scattered in the southwest part of this study area. Meanwhile, 4.03% was not recorded, namely in the Selomerto sub-district. Based on the validation, this region has the most significant production, namely 447,060 tons/year. Next, based on data from remote sensing, and IoT namely SHT15 temperature and humidity and rain gauge sensor, we predict the number of potato harvests. We used the results of cropland sustainability (Figure 5) to calculate

the predicted total harvest, namely in samples P₁ and P₂ (the most sustainable area).

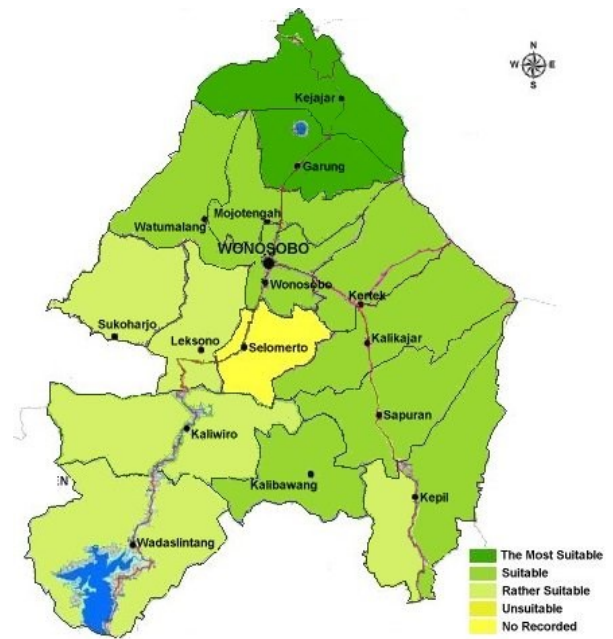


Figure 5 Spatial analysis of potato cropland sustainability

The separation of regions using the multi-thresholding method. Where region 1 is the background image, and region 2 was the potato leaf image. The average sample weight was 8.62 kg or had productivity of 1.38 kg/m² (13.79 tons/ha) (Table 5).

Table 5 The result of weighing harvest data

Block	Weight (Kg)	Block	Weight (Kg)
A1	8.50	D1	9.89
A2	9.67	D2	9.96
A3	8.20	D3	8.10
A4	8.98	D4	9.87
B1	7.70	E1	9.50
B2	7.30	E2	10.10
B3	8.20	E3	9.78
B4	10.50	E4	8.10
C1	8.90	F1	7.20
C2	7.98	F2	7.25
C3	7.20	F3	7.00
C4	7.05	F4	9.96

Based on the current production condition, which is 15.44 tons/ha, this method can predict the total harvest with an accuracy rate of 89.3%.

According to Parker *et al.* (2019), sustainable potato cultivation lands have an altitude of 1,300 - 1,700 m asl to optimize crop yields. Soil texture significantly affects the sustainability of potato cultivation; according to Akiyama *et al.* (2020) and Gondwe *et al.* (2017), andosol soil has the nutrients needed for potato growth. Sharp sloping land is at risk of nutrient loss required by potato growth so that sustainable cropland is in the middle of this study area with

an average slope of 8-13%. Accordance with Escobar and Galindo (2015) states that slope has an essential effect on agriculture cultivation. The best temperature for potato growth is below 17.8°C, and from 16 sample points, P₁ dan P₂ is located in Kejajar and Garung sub-district, so this area is suitable. Rykaczewska's (2015) opinion states that optimal potato growth is at a temperature of 17 - 20°C. Almost all of the 16 sample regions have an average rainfall of 200-300 mm/month. According to Nyawade *et al.* (2020), the rain needed for optimal potato growth is 300 mm/month or 1000 mm/year.

4.3 Distribution Route Selection using Spatial Analysis

4.3.1 Determine the Logistic Center using modified COG

In this study, spatial distribution route selection to balance supply and demand so that the COG coordinates must be in a location that accommodates all stakeholders. To determine the most optimal COG, the coordinates of farmers (Kuripan, Garung sub-district), LC (Wringinanom Market,

Kertek sub-district), trading centers (Muntilan and Cepogo wholesalers), and customer (Johar) are determined. In this study, logistics by trucking starts when the LC picks up potato commodities from farmers until the LC sends them to the customer. Based on **Equation (10)**, we converted the scores for the spatial variables (**Table 6**).

Table 6 Spatial variable score result

ID	Nodes	Score Average (SPW _i)	Conversion (SPW _i = 10 - SPW _i)
V ₁	Kuripan, Garung	7.25	2.75
V ₂	Wringinanom, Kertek	4.75	5.25
V ₃	Muntilan	4.75	5.25
V ₄	Cepogo	3.25	6.75
V ₅	Johar	5.50	4.50

We determine the coordinates, capacities, and spatial conversion values of the variables at each node (**Table 7**).

Table 7 Coordinate, capacity, and spatial conversion values

ID	Nodes	Latitude (X)	Longitude (Y)	Capacity (Tons) (W)	Conversion (SPW _i = S _j)
V ₁	Kuripan, Garung	-7.35	109.86	120.50	2.75
V ₂	Wringinanom, Kertek	-7.37	109.93	70.50	5.25
V ₃	Muntilan	-7.58	110.28	50.00	5.25
V ₄	Cepogo	-7.51	110.52	60.20	6.75
V ₅	Johar	-6.97	110.42	50.35	4.50

Based on **Equation (7)**, the optimal coordinates (X, Y) can be determined using the modified COG method that we proposed.

Table 8 Latitude (X) coordinates result

	d _{ix}	W _i	S _i	$\sum_{i=1}^n d_{ix} (W_i + S_i)$	$\sum_{i=1}^n (W_i + S_i)$	C _{xi}
C _{X1}	-7.35	120.50	2.75	-905.42	123.25	-7.35
C _{X2}	-7.37	70.50	5.25	-558.30	75.75	-7.37
C _{X3}	-7.58	50.00	5.25	-418.83	55.25	-7.58
C _{X4}	-7.51	60.20	6.75	-503.06	66.95	-7.51
C _{X5}	-6.97	50.35	4.5	-382.40	54.85	-6.97

Using **Equation (7)**, we get C_x* as follows:

$$C_x^* = \frac{-2768.02}{376.05}$$

$$C_x^* = -7.36$$

Table 9 Longitude (Y) coordinates result

	d _{iy}	W _i	S _i	$\sum_{i=1}^n d_{iy} (W_i + S_i)$	$\sum_{i=1}^n (W_i + S_i)$	C _{yi}
C _{Y1}	109.86	120.50	2.75	13540.37	123.25	109.86
C _{Y2}	109.939	70.50	5.25	8327.36	75.75	109.93
C _{Y3}	110.28	50.00	5.25	6093.11	55.25	110.28
C _{Y4}	110.52	60.20	6.75	7399.07	66.95	110.52
C _{Y5}	110.42	50.35	4.5	6056.80	54.85	110.42

Using **Equation (7)**, we also get C_y^* .

$$C_y^* = \frac{41416.71}{376.05}$$

$$C_y^* = 110.13$$

Based on **Table 6**, the optimal coordinate (C_x^* , C_y^*) is -7.36, 110.13 or 7°21'38.8"S, 110°08'10.2"E, using Google Maps, the location most optimal COC point is obtained with capacity and spatial analysis being in Kemloko, Tembarak (**Figure 6**).

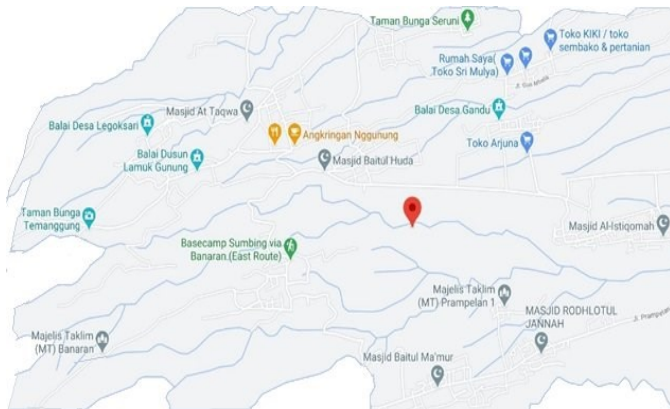


Figure 6 The optimal coordinates 7°21'38.8"S, 110°08'10.2"E

Based on **Figure 6**, the COG points are optimal, with flat access and more accessible. This study shows that spatial analysis in a modified multi-thresholding method can more accurately predict the number of harvests. Adjustment of the COG method obtains more rational coordinates (C_x^* , C_y^*) for agro-industrial commodities. The demand and spatial considerations on our proposed COG are in line with the opinion of Zhao (2014), which states that the COG method is an approach that requires a point of demand and a fact of logistical resources. According to Borges et al. (2018), need, and resources are essential. COG is considered the optimal set point of the logistics node, determining the position of the logistics network by finding the COG. The spatial data results considerations improve the conventional COG method. Kincses & Tóth (2014) explained in their research entitled the application of the gravity model in investigating spatial structure. Strijker (2008) and Balsa-Barreiro et al. (2019) has conducted research on spatial gravity.

This study modified the COG method with spatial analysis and added a supply and demand perspective to the Dijkstra method. Our proposed research strengthens Fu et al. (2011), which states that route analysis using spatial data in the COG method can increase delivery efficiency, a driving factor for economic development in Xinjiang. Dubey et al.'s (2014) research stated that transportation route selection depends on many factors, including spatial data.

4.3.2 Optimal Route Selection using Spatial Dijkstra

In this research, we used five nodes to give the code $V = \{V1, V2, \dots, V5\}$. We measure the distance between one node and another node. The COG coordinates are at V1, namely 7°21'38.8"S, 110°08'10.2"E. We used the classical Dijkstra algorithm to calculate the shortest potato distribution route. By using the classical Dijkstra's algorithm obtains the shortest route. Second, the shortest potato distribution route is determined using a modified Dijkstra

algorithm. Google APIs server with coordinates (X, Y) will make it easier to determine the shortest route. Third, the radian approach is applied to display all nodes in the database.

The route using the classical Dijkstra algorithm was the shortest route with a distance of 133 km. Through the route V1-V2-V5, $P(V1, V5) = (V1, V2, V5)$. Whereas the most optimal way using the new approach that we proposed, namely the spatial Dijkstra, was $P(V1, V5) = (V1, V2, V3, V5)$ with a TAV weight of 1,547 (**Figure 7**).

The new method, spatial Dijkstra, can be verified to get the optimal route by considering multi-alternative with conflicting multi-criteria, suitable for solving the distribution of agro-industrial products. This research has shown that the spatial Dijkstra can provide a more reasonable solution than the classical Dijkstra.

By using spatial analysis, the result obtained was different from the classical Dijkstra algorithm. The spatial Dijkstra algorithm considers distance, cost, risk and utility criteria, and spatial variables, namely population density, spatial-temporal congestion, and risk hazard zones. Based on the research results on the problem case using the new method spatial Dijkstra, the optimal sustainable route for the agro-industry sector is determined based on the shortest distance and needs to consider various criteria. Jeong et al. (2019) and Aksha et al. (2020) explained that spatial conditions also need to be considered.

4.4 Research Limitations and Managerial Implications

The sustainable agro-industry logistics solution we propose uses spatial analysis. We consider a spatial perspective using spatial databases and GIS to facilitate user interaction with actual conditions. We modify the multi-thresholding method using remote sensing and IoT to determine the prediction of total harvest based on demand. We also adjust the COG method and spatial Dijkstra algorithm. The spatial analysis considers the economic, social, and environmental dimensions. The complexity in the logistics and supply chain, combined with the speedy and unpredictable growth in demand and supply, is challenging (Heikkila, 2002). In this study, however, logistical efficiency is included in the model yet can be investigated for future research.

The principle of logistics is to optimize cost, time, and quality. The timely and safe delivery of agro-industrial commodities is essential. The sustainability agro-industry logistics that we have developed considers a spatial perspective by considering the environmental, economic, and social dimensions. We invented the ISDSS framework and modified the multi-thresholding method using IoT to determine COG coordinates. Decision-makers can use this method to determine a more optimal and meaningful COG for agro-industrial commodities. We expect the most optimal COG-based sustainable logistics route to meet the demand.

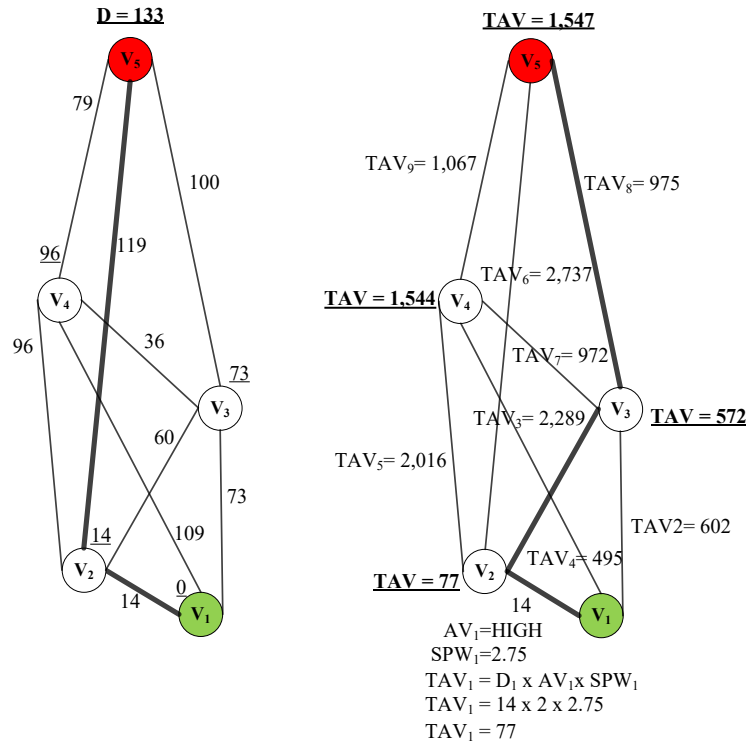


Figure 7 Comparison route using classical and spatial Dijkstra

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This research has succeeded in developing a model for a spatial-based cropland sustainability classification based on demand. Based on the spatial analysis, the cropland sustainability values were 62.01% scattered in the east and southern parts of the research area. The most sustainable site is 11.05% in the northern part of the study area with conformity without limiting factors. 22.9% of unsustainability land is scattered in the southwest part of this study area. While 4.03%, we did not record it.

This research has also succeeded in developing a sustainable harvest prediction model by modifying the multi-thresholding method. This study succeeded in predicting the harvest more accurately based on remote sensing data and IoT, namely SHT15 and rain gauge sensors. Adjustment of COG method obtains more rational coordinates (X, Y) for agro-industrial commodities. The results of this study indicate that the spatial analysis using the modified COG method and the proposed spatial Dijkstra method obtains the most optimal LC location, namely at coordinates -7.36, 110.13, or 7°21'38.8"S, 110°08'10.2"E. This study showed that the demand prediction accuracy was 89.3 when compared with the actual total harvest.

This research has successfully developed a spatial distributing route planning wherein we adjust the COG and spatial Dijkstra algorithm to determine the LC coordinates and select the optimal route. The results of this study also indicate that the more rational COG coordinates are

7°21'38.8"S, 110°08'10.2"E with the most optimal route through P (V1, V2, V3, V5) with a TAV value of 1,547.

This new approach has shown that spatial analysis can be the alternative in material management and physical distribution solutions by minimizing supply and demand imbalances in sustainable agro-industry logistics.

5.2 Recommendations

At present, sustainability analysis is significant attention to agro-industry. One way to ensure agro-industrial sustainability activities is that the decision-maker suggested applying our model in predicting suppliers' capacity and consumer needs to balance inventory and demand. The spatial perspective logistics solution that we have developed make it possible to do this. Decision-makers should apply this new approach to determine sustainable agro-industry logistics solutions by minimizing inventory and demand imbalances. Decision-makers can also use the multi-threshold modification using remote sensing and IoT to predict total harvest on request. Decision-makers should also apply the COG method and the spatial algorithm of the Dijkstra that we propose in determining logistical route planning that considers environmental, economic, and social dimensions.

It is possible to develop this model within the framework of an ongoing Spatial Intelligence Decision Support System (ISDSS) and be implemented into a mobile application using the Android operating system for future research.

REFERENCES

Adetiloye T, Pervez G. 2015. A macro and micro-level evaluation of stakeholders' collaboration for sustainable city logistics

- operations. *Operations and Supply Chain Management: An International Journal* 8(2):p.90–100.
- Akiyama H, Yamamoto A, Uchida Y, Hoshino YT, Tago K, Wang Y, Hayatsu M. 2020. Effect of low C/N crop residue input on N₂O, NO, and CH₄ fluxes from andosol and fluvisol fields. *Science of the Total Environment* 713(1):p.1–10.
- Aksha SK, Resler LM, Juran L, Jr LWC. 2020. A geospatial analysis of multi-hazard risk in Dharan, Nepal. *Geomatics, Natural Hazards and Risk* 11(1):p.88–111.
- Ali SM, Nakade K. 2015. A Mathematical optimization approach to supply chain disruptions management considering disruptions to suppliers and distribution centers. *Operations and Supply Chain Management: An International Journal* 8(2):p.57–66.
- Ali SW, Nawaz A, Irshad S, Khan AA. 2015. Potato waste management in Pakistan's perspective. *Journal of Hygienic Engineering and Design* 1(12):p.100–107.
- Anderson T, Liu Z, Cruz J, Wang J. 2020. Social and environmental sustainability: An empirical analysis of supply chain profitability and the recession. *Operations and Supply Chain Management* 13(2):p.176–193.
- Araby AA, Abd Elhameed MM, Magdy NM, Said LA, Abdelaal N, Abd Allah YT, Darweesh MS, Fahim MA, Mostafa H. 2019. Smart IoT monitoring system for agriculture with predictive analysis. In *2019 8th International Conference on Modern Circuits and Systems Technologies, MOCASST*. pp. 3–6.
- Asahara S, Yamamoto S. 2007. A Method for the determination of the Center of Gravity during manual wheelchair propulsion in different axle positions. *Journal Physic Ther Science* 18(1):p.57–63.
- Asrol M, Marimin, Machfud, Yani M, Taira E. 2020. Supply chain fair profit allocation based on risk and value-added for sugarcane agro-industry. *Operations and Supply Chain Management* 13(2):p.150–165.
- Bach H, Mauser W. 2018. Sustainable agriculture and smart farming. *Earth Observation Open Science and Innovation* 15(1):p.261–269.
- Backhausen JE, Klein M, Klocke M, Jung S, Scheibe R. 2005. Salt tolerance of potato (*Solanum tuberosum* L. var. Desire) plants depends on light intensity and air humidity. *Plant Science* 169(1):p.229–237.
- Badan Pusat Statistik Indonesia. 2020. *Jumlah penduduk hasil proyeksi menurut provinsi dan jenis kelamin*. p. 1-3.
- Baez YP, Sequeira M, Hilletoft P. 2020. Local and organic food distribution systems: Towards a future agenda. *Operations and Supply Chain Management* 13(4):p.336–348.
- Balsa-Barreiro J, Li Y, Morales A, Pentland A "Sandy." 2019. Globalization and the shifting centers of gravity of world's human dynamics: Implications for sustainability. *Journal of Cleaner Production* 239(1):p.1–17.
- Barchia MF, Sukisno, Widiyono H, Utama SP. 2017. Land suitable areas refer to red potato planted on medium-altitude in Rejang Lebong Bengkulu Province Indonesia. *International Journal on Advanced Science, Engineering and Information Technology* 7(3):p.885–891.
- Bermana I. 2006. Klasifikasi geomorfologi untuk pemetaan geologi yang telah dibakukan. *Bulletin of Scientific Contribution* 4(2):p.161–173.
- Bilali H El, Callenius C, Strassner C, Probst L. 2019. Food and nutrition security and sustainability transitions in food systems. *Food and Energy Security* 8(2):p.1–20.
- Borges REP, Dias MAG, Dória Neto AD, Meier A. 2018. Fuzzy pay-off method for real options: The center of gravity approach with application in oilfield abandonment. *Fuzzy Sets and Systems* 353:p.111–123.
- Borsellino V, Schimmenti E, El Bilali H. 2020. Agri-food markets towards sustainable patterns. *Sustainability (Switzerland)* 12(6):p.1–35.
- Cahyadi H, Jabbari I, Tri E, Ismawan. 2016. Geomorphology characteristic of Ciangsana and Surrounding areas, Cikembar sub-district, Sukabumi regency, West Java. In *Seminar Nasional Kebumian ke-9*. pp. 34–41.
- Cai Y, Xia C. 2018. Interpretive Structural analysis of interrelationships among the elements of Characteristic Agriculture Development in Chinese rural poverty alleviation. *Sustainability (Switzerland)* 10(3).
- Charoenporn P. 2018. Smart logistic system by IoT technology. In *The 6th International Conference on Information and Education Technology*. pp. 149–153.
- Dahiri, Fitri H. 2020. Sektor pertanian : Berperan besar, realisasi investasi belum optimal. *Buletin APBN* 5(14):p.7–11.
- Das K. 2020. Planning environmental and economic sustainability in closed-loop supply chains. *Operations and Supply Chain Management* 13(1):p.64–81.
- Delgado JA, Short NM, Roberts DP, Vandenberg B. 2019. Big data analysis for sustainable agriculture on a geospatial cloud framework. *Frontiers in Sustainable Food Systems* 3(7):p.1–13.
- Devaux A, Kromann P, Ortiz O. 2014. Potatoes for sustainable global food security. *Potato Research* 57(3–4):p.185–199.
- Dubey SK, Mishra D, Arkatkar SS, Singh AP, Sarkar AK. 2014. Route choice modeling using fuzzy logic and adaptive neuro-fuzzy. *Modern traffic and transportation research* 2(4):p.11–19.
- Effendi R, Salsabila H, Malik A. 2018. Scientific understanding of the sustainable environment. *Modul* 18(2):p.75–82.
- Escobar C, Galindo J. 2015. Fuzzy control in agriculture: Simulation software. In *Industrial Simulation Conference*. pp. 45–49.
- Foughali K, Fathallah K, Frihida A. 2019. A Cloud-IoT-based decision support system for potato. *Procedia Computer Science* 160(1):p.616–623.
- Fu J, Gao Z, Huang L, Zhang L. 2011. The movement route of consumption gravity center of Xinjiang from 1965 to 2009 based on GIS. *Procedia Earth and Planetary Science* 2(1):p.321–326.
- Gonçalves AB. 2021. Spatial analysis and geographic information systems as tools for sustainability research. *Sustainability (Switzerland)* 13(2):p.1–3.
- Gondwe RL, Kinoshita R, Sano M, Suminoe T, Aiuchi D, Koaze H, Palta J, Tani M. 2017. Lack of yield response in potato (*Solanum tuberosum* L.) to phosphate fertilizer under contrasting soil types varying in phosphate absorption coefficient and available phosphate. *Soil Science and Plant Nutrition* 63(2):p.171–177.
- Gutierrez MTE, Mutuc JES. 2018. A model for humanitarian supply chain: An operation research approach. *Procedia Engineering* 212(11):p.659–666.
- Heikkila J. 2002. From supply to demand chain management: Efficiency and customer satisfaction. *Journal of Operations Management* 20(6):p.747–767.
- Helm M. 2018. Sustainable logistics as a source of competitive advantage in remote locations. *Journal of Sustainable Development of Transport and Logistics* 3(3):p.6–26.
- Hilker FM, Liz E. 2020. Threshold harvesting as a conservation or exploitation strategy in population management. *Theoretical Ecology* 13(4):p.519–536.
- Hou X, Li R, He W, Ma K. 2020. Effects of planting density on potato growth, yield, and water use efficiency during years with variable rainfall on the Loess Plateau, China. *Agricultural Water Management* 230(11):p.1–9.
- Hsiao Y, Chen M, Lu K, Chin C. 2018. Last-mile distribution planning for fruit-and-vegetable cold chains. *The International Journal of Logistics Management* 29(3):p.862–886.
- Huang H, Zhu Y. 2014. Research article the location of logistics center by AHP-GP based on a convenient idea. *Journal of Chemical and Pharmaceutical Research* 6(7):p.1098–1102.
- Huang, Q., Ohmori, S., & Yoshimoto, K. (2021). Incorporating

- transportation mode decisions into production-shipping planning: Considering shipping consolidation. *Operations and Supply Chain Management*, 14(1), 62–72.
- Idri A, Oukarfi M, Boulmakoul A, Zeitouni K, Masri A. 2017. A new time-dependent shortest path algorithm for the multimodal transportation network. *Procedia Computer Science* 109C(1):p.692–697.
- Jeong M, Lee E, Lee M, Jung J. 2019. Multi-criteria route planning with risk contour map for smart navigation. *Ocean Engineering* 172(10):p.72–85.
- Kamalakkannan S, Kulatunga AK, Bandara LADAD. 2020. The conceptual framework of IoT based decision support system for life cycle management. *Procedia Manufacturing* 43(2018):p.423–430.
- Karim AZ. 2017. Impact of a growing population in agricultural resource management : Exploring the global situation with a micro-level example. *Asian Social Science* 9(15):p.14–22.
- Keser SB, Yazici A, Gunal S. 2016. A multi-criteria heuristic algorithm for personalized route planning. *Anadolu University Journal of Science and Technology Applied Sciences and Engineering* 17(2):p.299–313.
- Kiani F, Seyyedabbasi A. 2018. Wireless sensor network and Internet of Things in precision agriculture. *International Journal of Advanced Computer Science and Applications* 9(6):p.99–103.
- Kilibarda M. 2015. Forecasting demand in the logistics market : A case study of the logistics center. In *2nd Logistics International Conference*. pp. 241–246.
- Kincses Á, Tóth G. 2014. The application of the gravity model in the investigation of spatial structure. *Acta Polytechnica Hungarica* 11(2):p.5–19.
- Kurbatova SM, Aisner LY, Vlasov VA. 2020. Agrologistics: The concept, significance, types. *IOP Conference Series: Materials Science and Engineering* 918(1).
- Lee M, Hwang J, Yoe H. 2013. Agricultural production system based on IoT. In *16th IEEE International Conference on Computational Science and Engineering, CSE*. pp. 833–837.
- Lezoche M, Panetto H, Kacprzyk J, Hernandez JE, Alemany Diaz MME. 2020. Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. *Computers in Industry* 117(3):p.1–37.
- Liu J, Geng Y, Zhao J, Zhang K, Li W. 2021. Image semantic segmentation use multiple-threshold probabilistic R-CNN with feature fusion. *Symmetry* 13(2):p.1–12.
- Nyawade SO, Gachene CKK, Karanja NN, Gitari HI, Schultegeldermann E, Parker ML. 2020. Geoderma regional controlling soil erosion in smallholder potato farming systems using legume intercrops. *Geoderma Regional* 17(2019):p.1–11.
- Panwar S, Singh KN, Kumar A, Gurung B, Sarkar SK, Sivaramane N, Rathore A. 2017. Pre-harvest forecasting of crop yield using non-linear regression modeling: A concept. *Indian Journal of Agricultural Sciences* 87(5):p.117–121.
- Parker ML, Low JW, Andrade M, Schulte-geldermann E, Andrade-piedra J. 2019. Climate change and seed systems of roots, tubers, and bananas : The cases of potato in Kenya and sweet potato in Mozambique. In *Climate Change and Seed Systems*. pp. 99–111.
- Peng W, Berry EM. 2019. The concept of food security. *Encyclopedia of Food Security and Sustainability* 2(1):p.1–7.
- Prause M. 2019. Challenges of Industry 4.0 technology adoption for SMEs: The case of Japan. *Sustainability (Switzerland)* 11(20).
- Putri RN. 2020. Indonesia dalam menghadapi pandemi Covid-19. *Jurnal Ilmiah Universitas Batanghari Jambi* 20(2):p.705–709.
- Rad C-R, Hancu O, Takacs I-A, Olteanu G. 2015. Smart Monitoring of potato crop: A cyber-physical system architecture model in the field of precision agriculture. *Agriculture and Agricultural Science Procedia* 6(1):p.73–79.
- Ramankutty N, Mehrabi Z, Waha K, Jarvis L, Kremen C, Herrero M, Rieseberg LH. 2018. Trends in global agricultural land use: Implications for environmental health and food security. *Annual Review of Plant Biology* 69(4):p.789–815.
- Rashed-Ali H. 2013. Spatial analysis for neighborhood sustainability assessment. In *42nd ASES National Solar Conference 2013*. pp. 107–114.
- Russell DM, Swanson D, Blinge M. 2018. Sustainable logistics and supply chain management: A holistic view through the lens of the wicked problem. *World Review of Intermodal Transportation Research* 7(1):p.36–56.
- Rykaczewska K. 2017. Impact of heat and drought stresses on size and quality of the potato yield. *Plant Soil Environment* 63(1):p.40–46.
- Rykaczewska K. 2015. The Effect of high temperature occurring in subsequent stages of plant development on potato yield and tuber physiological defects. *American Journal of Potato Research* 92(1):p.339–349.
- Saiz-Rubio V, Rovira-Más F. 2020. From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy* 10(207):p.1–21.
- Saragi TE. 2015. The effect of sustainable transportation management systems on the environment in urban areas. *Jurnal Fakultas Teknik* 1(3):p.49–63.
- Saravia-Matus S, Paloma SGY, Mary S. 2016. Economics of food security: Selected issues. *Bio-based and Applied Economics* 1(1):p.65–80.
- Shanmugapriya P, Rathika S, Ramesh T, Janaki P. 2019. Applications of remote sensing in agriculture - A review. *International Journal of Current Microbiology and Applied Sciences* 8(01):p.2270–2283.
- Shanwad UK, Patil VC, Dasog GS, Mansur CP, Shashidhar KC. 2014. Global Positioning System (GPS) in precision agriculture. In *GPS in Agriculture Global*. pp. 1–6.
- Shih H. 2015. Facility location decisions based on driving distances on spherical surfaces. *American Journal of Operations Research* 5(9):p.450–492.
- Soomro TR. 2015. GIS enabling smart agriculture. In *Smart agriculture: An approach towards better agriculture management*. pp. 1–6.
- Strijker D. 2008. Centers of Gravity on the move: Agriculture. *European Spatial Research and Policy* 15(2):p.55–56.
- Sugiharyanto S. 2017. Prospek pengembangan budidaya tanaman kentang di Indonesia. *Geomedia: Majalah Ilmiah dan Informasi Kegeografian* 6(2):p.43–52.
- Suryana A. 2014. Toward sustainable Indonesian food security 2025 : Challenges and its responses. *Agro Ekonomi* 32(2):p.123–135.
- Tayari E, Jamshid AR, Goodarzi HR. 2015. Role of GPS and GIS in precision agriculture. *Journal of Scientific Research and Development* 2(3):p.157–162.
- Tervonen J. 2018. Experiment of the quality control of vegetable storage based on the Internet-of-Things. *Procedia Computer Science* 130:p.440–447.
- Uvet H. 2020. Importance of logistics service quality in customer satisfaction: An empirical study. *Operations and Supply Chain Management* 13(1):p.1–10.
- Vass T, Shee H, Miah SJ. 2021. IoT in supply chain management: Opportunities and challenges for businesses in early industry 4.0 context. *Operations and Supply Chain Management* 14(2):p.148–161.
- Yu J, Wu J. 2018. The sustainability of agricultural development in China: The agriculture-environment nexus. *Sustainability (Switzerland)* 10(6):p.1–17.
- Yusianto R, Marimin M, Suprihatin S, Hardjomidjojo H. 2019. Intelligent spatial logistics DSS for tracking and tracing in horticultural food security. In *International Seminar on Application for Technology of Information and*

- Communication: Industry 4.0: Retrospect, Prospect, and Challenges, iSemantic*. pp. 73–77.
- Yusianto R, Marimin, Suprihatin, Hardjomidjojo H. 2020a. Iot Based Smart Agro-Industrial Technology With Spatial Analysis. *Jurnal Teknologi Industri Pertanian* 30(30):p.319–328.
- Yusianto R, Marimin, Suprihatin, Hardjomidjojo H. 2020b. Spatial analysis for cropland suitability evaluation : A case study of potatoes cultivation in Wonosobo, Indonesia. *International Seminar on Application for Technology of Information and Communication (iSemantic)* 1(1):p.313–319.
- Zecca F, Rastorgueva N. 2015. Supply chain management and sustainability in agri-food system: Italian evidence. *Journal of Nutritional Ecology and Food Research* 2(1):p.20–28.
- Zeyayen S, Fattahi E, Ranjbar A, Vazifedoust M. 2017. Classification of rainfall warnings based on the TOPSIS method. *Climate* 5(33):p.1–12.
- Zhao X. 2014. Based on the gravity method of logistics distribution center location strategy research. In *International Conference on Logistics, Engineering, Management, and Computer Science*. pp. 584–587.
- Zhou X, Zheng HB, Xu XQ, He JY, Ge XK, Yao X, Cheng T, Zhu Y, Cao WX, Tian YC. 2017. Predicting grain yield in rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery. *ISPRS Journal of Photogrammetry and Remote Sensing* 130(8):p.246–255.
- Zonouzi MN, Kargari M. 2020. Modeling uncertainties based on data mining approach in emergency. *Computer & Industrial Engineering* 1(4):p.1–27.
- Zuoza A, Zuoza AK, Gargasas A. 2015. A harvest prediction model based on public data for large regions. *Management Theory and Studies for Rural Business and Infrastructure Development* 37(1):p.135–140.

Hartrisari Hardjomidjojo holds a PhD degree in Industrial Systems Engineering. Currently, she is working as an Associate Professor in the Department of Agro-Industrial Technology, Faculty of Agricultural Engineering and Technology, IPB University (Bogor Agricultural University), Bogor, Indonesia. Her current research interests include Spatial, Expert Systems, and Decision Support Systems.

Rindra Yusianto holds a PhD degree in Agro-Industrial Engineering. He works as an Associate Professor in the Department of Industrial Engineering, Faculty of Engineering, Dian Nuswantoro University, Semarang, Indonesia. His current research interests include Green Logistics, Spatial Information Systems, and Intelligent Spatial Decision Support Systems.

Marimin is a Professor of Industrial System Engineering at IPB University (Bogor Agricultural University), Bogor, Indonesia. His current research interests include Intelligent Systems, Decision Analysis and Decision Support Systems, Supply Chain Management, Green, and Sustainable Industrial Development.

Suprihatin is a Professor of Environmental Engineering and Management at IPB University (Bogor Agricultural University), Bogor, Indonesia. His current research interests are green process engineering, environmental management system, cleaner production, water and wastewater treatment technology, and hazardous wastes management.