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ADAPTIVE MODELS FOR DETERMINING CROPLAND SUITABILITY AND TOTAL HARVEST PREDICTION FOR POTATO USING IOT

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ABSTRACT: Potatoes are Indonesia's fourth largest food agro-industrial and leading horticultural commodities traded internationally. In 2021, the needs of the potato industry will only be met by 85.93%. This study aims to provide recommendations for adaptive models for increasing productivity based on the suitability of agricultural cropland and predicting total harvest using IoT. We modified the multi-thresholding method by installing an SHT_{15} sensor to measure temperature. We also installed rain gauge sensors and analyzed the spatial perspective. Using a drone quadcopter, we perform image processing and mapping to predict the total harvest. The research sample used a random of 12 grids in an agricultural area in Wonosobo, Indonesia. The results showed that the most suitable agricultural cropland was 11.05%, suitable was 22.9%, and cropland with several inhibiting factors was 62.01%. The most convenient location is at the coordinates 7° 15′ 12.1″ S latitude, 109° 55′ 27.5″ E longitude in Kejajar, Wonosobo District. The results also showed an average harvest of 13.79 t ha^{-1}. This model can predict an increase in yields with a production prediction of 72,765 t $year^{-1}$ and an accuracy rate of 89.35%. In addition, to balance supply and demand, this model recommends an increase in production by 30% and fulfillment from other regions by 31%.

KEYWORDS: Cropland suitability; IoT; Potato; Spatial perspective; Total harvest prediction

INTRODUCTION

Potatoes are Indonesia's fourth largest food agro-industrial commodity and leading horticultural commodities traded internationally, with good growth characteristics in the highlands of 1,100–1,300 m asl, humidity 85–90%, temperature 15.5–18.5 degrees Celsius, and rainfall 300-310 millimeters (Yusianto *et al*., 2021; Raja *et al*., 2020). The habit of farmers reduces productivity, planting potatoes on all the cropland they have. Based on the Indonesia Central Bureau of Statistics, the raw material needs for industrial potatoes in Central Java, Indonesia, ranging from 300-325 t day^{-1}. Meeting industrial needs requires a good supply strategy, and one of the strategies is the suitability of agricultural cropland. In this study, we determined the most suitable locations for potato cultivation and then calculated the estimated average and total yields. Cropland suitability evaluation needs to be done. This evaluation is a cultivation requirement, namely by measuring the suitability of agricultural cropland, assessing the suitability of alternative land uses, and comparing growth requirements, characteristics of agricultural cropland, and quality, which is evaluated by utilizing the potentially available resources (Tesfay *et al*., 2017). The suitability of agricultural cropland is to measure how the quality of agricultural land can meet land use requirements, including physical and climatic factors (Singh

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& Sandhu, 2022). Potato cultivation that meets industrial needs must be on suitable cropland—determination of the suitability of agricultural cropland to determine the potential for developing this agro-industrial commodity.

Cultivating potatoes on suitable agricultural cropland can meet the needs of industrial raw materials, reduce the risk of post-harvest losses, and increase productivity (Hardjomidjojo *et al*., 2022). The current problem is that most of the agricultural cropland in Indonesia has been converted into residential land. In addition, rapid population growth significantly affects the use of agricultural land. Therefore, decision-makers need to optimize land use so that the cultivation of agricultural commodities, including potatoes, can grow sufficiently with high productivity. In addition, decision-makers must consider various factors that influence this, namely physical and climatic factors. Rykaczewska (2017) and Yusianto *et al*. (2020) research shows that physical characteristics, namely land slope, elevation, and soil texture, and climatic factors, namely humidity, temperature, and rainfall, affect land suitability.

The Internet of Things (IoT) is a precision agricultural technology that can help meet data needs and provide information on industrial raw materials and global food security (Ramankutty *et al*., 2018). IoT can control crop quality, cropland suitability, and production (Marcu *et al*., 2019). Foughali *et al*. succeeded in developing IoT integration with DSS to increase agricultural production (Foughali *et al*., 2019). IoT can also retrieve physical and climate data using sensors and input it into machine learning algorithms (Araby *et al*., 2019). In their study, the Node-MCU and DHT_{11} temperature and humidity sensors collected temperature data. Electronic control using IoT supports real-time data collection on several conditions that precision agriculture requires, such as physical change data, spatial conditions, and climate data (Qi *et al*., 2016). Analysis of spatial requirements using GIS can provide spatial data and visual data representation of the research area. The spatial analysis also allows the presentation of information more specifically to help decision-makers make more appropriate decisions than classical analysis. GIS and IoT can handle spatial analysis with zoning and land use planning. The elaboration of spatial analysis using GIS and IoT can combine time with interactive decision-making forms, where IoT has determined the optimal planting coordinates by evaluating land suitability. In addition, IoT also relates location data quantitatively when performing spatial analysis and predicting total harvest.

In the last ten years, determining agricultural cropland suitability has become increasingly complex. Standard statistical techniques will not be able to solve this difficult problem, including predicting the total harvest. Therefore, at this time, farmers need IoT as an innovative precision farming technology (Kiani and Seyyedabbasi, 2018).

Most of the previous studies have discussed the implementation of IoT in precision agriculture. However, they should have addressed modifications to land suitability models and harvest predictions with IoT and spatial analysis considering coordinates (X, Y) and physical factors. This study aims to provide recommendations for adaptive models to predict cropland suitability and total harvest using IoT. We modified the multi-thresholding method by installing an SHT_{15} sensor to measure temperature and humidity. We also installed rain gauge sensors and analyzed the spatial perspective. The research sample used a

random grid of 12 grids in an agricultural area in Wonosobo District, Indonesia.

MATERIALS AND METHODS

Description of the Study Area

We conducted this experiment in 15 zones of Wonosobo Regency, Indonesia, during the 2022 growing season. The area is 120 kilometers from Semarang in the southwest region of Indonesia. Geographically, this area is located at 7° 21' S, 109° 53' E, at an altitude of 250 - 2,250 meters above sea level (masl) (Figure 1).

The average elevation of the 14 zones is 674.81 masl, with the highest peak of 1,378 m and the lowest of 272 m. The soil texture is mostly andosol, podzol, and regosol. The average slope is 8–13% wavy or steep, with an average temperature above 20 degrees Celsius. The average humidity is 80–90%, and the average rainfall is above 300 millimeters month^{-1}.

Experimental Materials

The most significant need for raw material for Central Java, Indonesia industrial potatoes is for French fries, as much as 115 t day^{-1}. In addition, potato chips are 95 t day^{-1}, frozen potatoes are 52 t day^{-1}, and the remaining 63 t day^{-1} are to meet the needs for starch, concentrate, and biodegradable packaging (Balitsa, 2014). Table 1 shows the potato-based industry, varieties, and the number of industrial potatoes needed per year.



Figure 1. Map of study area

The biggest industrial demand for potatoes in Central Java, Indonesia, in 2022 is for raw material for French fries, 35% with Atlantic and median varieties. At the same time, the smallest requirement is 16% for frozen potato raw materials.

Experimental framework

We modified an adaptive model to determine cropland suitability and predict total harvest using the SHT_{15} sensor and rain gauge. Then, we conducted a spatial analysis with four variables: altitude, soil texture, temperature, and rainfall. The research sample is 12 grids using a random grid base, and we get four class intervals. The cropland unit map uses a scale of 1: 25,000 using the overlay technique. To produce elevation and soil texture maps, we analyzed the physical and climatic factors of 12 zones in Wonosobo, Indonesia. We also collect data on soil texture, temperature, and rainfall (Figure 2).

We classify the class criteria and cropland suitability level intervals. We classify them into suitability classes (S_1, S_2, S_3, and NS). Then, we carried out a spatial analysis, with the final result being a land suitability evaluation. We determined sample points based on land units and used grid intervals of 1.5 km across 12 grids. We collect data

Table 1. The number of Central Java, Indonesia industrial potatoes needed per year

Varieties	Industry	Requirement (tons year^{-1})	Percentage
Atlantic, Median	French Fries	41,400	35%
Atlantic, Maglia, Amabile	Chips	34,200	29%
Atlantic, Median	Frozen	18,720	16%
Atlantic, Median	Other	22,680	19%

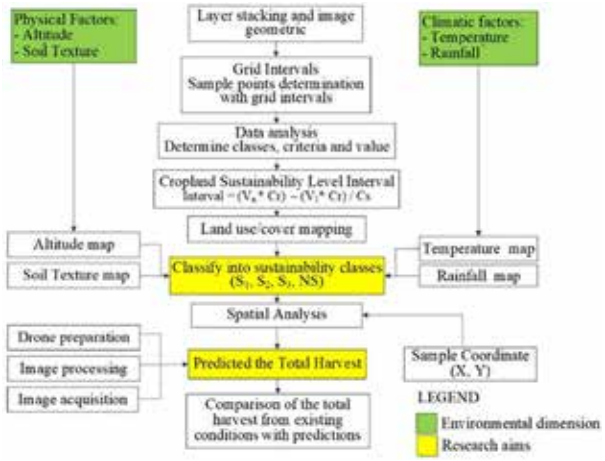


Figure 2. Experimental framework

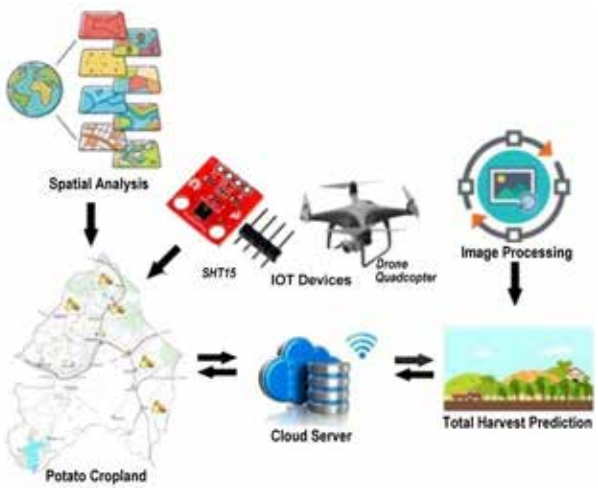


Figure 3. The system architecture

from IoT from SHT_{15} and rain gauge sensors with a calibration accuracy of ± 0.4 @ 5–40 degrees Celsius. The sensors installed in the sample area will send data 24 hours daily. After determining the most appropriate coordinates, we perform image processing and mapping to predict the total harvest using a drone quadcopter. The system architecture of this study consists of two main activities: cropland suitability and full yield prediction (Figure 2).

Class Criteria

Research by Mailangkay *et al.* (2012) has shown that altitude significantly affects the number of potato tubers and increases production capacity. Based on the average value, they do not recommend cultivation at sizes below 750 masl. Their research indicated that tuber weight and productivity were deficient for Granola and Supejhon varieties at that altitude. The highlands and mountains, where the temperature varies and often changes dramatically, significantly affect productivity due to land suitability for agricultural commodities (Porter *et al.*, 2015). Yusianto *et al.* research (2021) state that China accounts for 26.3% of world potato production. One of the keys to success is the mechanization and selection of suitable agricultural land. In the study, they explained that China mass-produced potatoes in the Guyuan region, Hebei, which has a proper soil texture and climate.

We arranged the class criteria and gave a score of 4 for excellent, 3 (good), 2 (rather bad), and 1 (bad) (Table 2). The criteria consist of physical factors: altitude, soil texture, climate, temperature, and rainfall. We compiled each score for each class criterion based on research by (Hardjomidjojo *et al.* 2022; Yusianto *et al.* 2021).

Table 2. Classes criteria for potato plants

Value	Classes	Altitude (masl)	Soil texture	Temperature	Rainfall
1	Excellent	1,300 - 2,700	Andosol	15.6–17.8	>300
2	Good	500 -1,299	Regosol	17.7–20.0	200–300
3	Rater Bad	199 - 499	Podzol	20.1–25.0	60–199
4	Bad	< 199	Latosol	>25.0	<60

Suitability Level Interval

We analyzed cropland suitability intervals for Atlantic, Median, Maglia, and Amabile varieties as industrial raw materials (Equation (1)).

$$SLI = \frac{(V_n \times Cr) - (V_1 \times Cr)}{Cs} \quad \text{.......(1)}$$

Where: SLI- suitability level interval, V_n - highest class criteria value, V_1 - lowest class criteria value, Cr- several measures, Cs- several class intervals.

We used a multi-criteria measure to determine the suitability intervals of four criteria (physical and climatic factors) and four classes interval. We arrange suitability level. Using Equation (1), we get a class interval of 4 with the lowest class criterion value of 4 (Table 3).

Spatial Analysis

Based on 12 sample points, the average height is 778.42 masl. Most soil texture is regosol, while there is no latosol texture. The average temperature is 25.25 degrees Celsius. At the same time, P_1 has the lowest average temperature, 19 degrees Celsius. At the same time, the average rainfall is 305.06 millimeters month^{-1} or an average of 1,000 millimeters year^{-1}, where the little rain is at P_7, which is 247.50 millimeters month^{-1} (Table 4).

For altitude, we found that the P_1 had an altitude of 1,378 masl. As for the criteria for soil texture, we obtained the dominant surface, regosol. We mapped the altitude to an altitude map and texture map in the 12 sample areas. The lowest average temperature is 17 degrees Celsius—the rainfall, with an average of over 305 millimeters month^{-1}. We also map temperature and rain into a temperature map and rainfall map (Figure 4).

Yield prediction accuracy is essential for many issues in agriculture, national food

Table 3. Cropland suitability level interval

Suitability level	Class	Total value	Description
The Most Suitable	S_1	>=16.0	Cropland is in perfect condition.
Suitable	S_2	12.0 – 16.0	Cropland with a few inhibiting factors.
Rather Suitable	S_3	8.0 – 12.0	Cropland with several inhibiting factors.
Unsuitable	NS	4.0 – 8.0	Cropland with a deplorable condition.

Table 4. Spatial analysis for four criteria

Code	Location	Latitude	Longitude	Altitude (masl)	Soil Texture	Temperature Degrees Celsius	Rainfall (millimetres month^{-1})
P_1	Kejajar	7°14′11.8″S	109°56′29.7″E	1,378	Andosol	17	341.00
P_2	Garung	7°16′52.1″S	109°56′37.2″E	1,019	Andosol	23	326.83
P_3	Mojotengah	7°17′31.6″S	109°52′31.7″E	860	Andosol	24	317.75
P_4	Kertek	7°19′35.8″S	109°59′28.2″E	825	Regosol	22	275.00
P_5	Kalikajar	7°22′38.5″S	109°59′33.6″E	815	Regosol	20	351.92
P_6	Wonosobo	7°20′46.1″S	109°55′07.3″E	744	Regosol	26	299.81
P_7	Watumalang	7°21′33.2″S	109°52′36.5″E	910	Regosol	24	247.50
P_8	Kaliwiro	7°27′17.7″S	109°46′49.2″E	360	Podzol	27	260.75
P_9	Kalibawang	7°29′00.7″S	109°55′03.1″E	626	Regosol	26	297.60
P_{10}	Sapuran	7°26′32.4″S	109°59′14.1″E	760	Regosol	26	299.89
P_{11}	Kepil	7°33′08.2″S	110°00′45.2″E	522	Podzol	27	347.08
P_{12}	Sukoharjo	7°23′49.2″S	109°46′36.1″E	522	Podzol	27	347.08

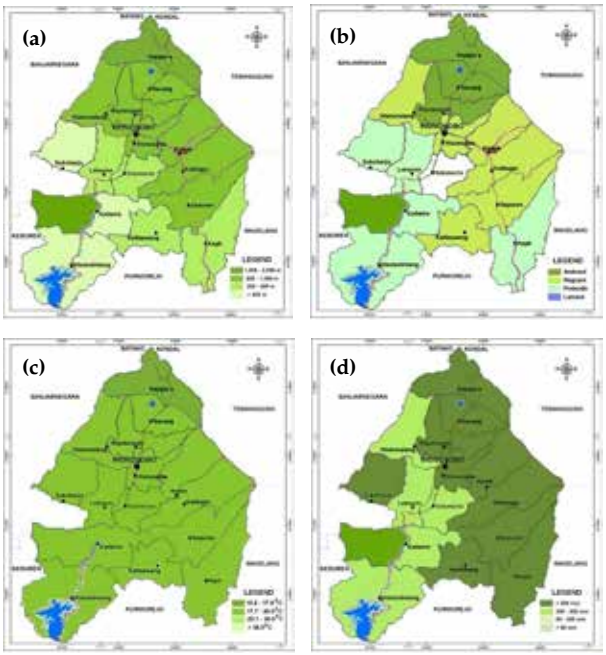


Figure 4. Altitude (a), soil texture (b), temperature (c), rainfall map (d)

policy, and international trade in agro-industrial commodities. So that various methods and approaches are used to predict crop yields, including the application of satellite imagery (Kim *et al*., 2019). With the support of IoT sensors, satellite remote sensing techniques, and image processing can transmit data over a large area continuously. This technique helps decision-makers make decisions and provides more accurate predictions of outcomes.

In this study, we obtained images of the planting area from a quadcopter drone. We mapped the cropland using a modified multi-thresholding method. We then group the image acquisition data into 24 blocks. The place we imaged per point is one hectare of cropland labeled A_{01} through F_{04}. To calculate the predicted total harvest, we use Equation (2).

$$Th = \frac{Pcp}{Ts} \quad \text{.....(2)}$$

Where: Th- Prediction of total harvest, Pcp- production capacity prediction, Ts- total sample area.

Mapping the spatial distribution of agricultural land can increase accuracy when predicting crop yields. We compared the total harvest prediction results with existing conditions to ensure the accuracy of the total harvest prediction (Equation (3)).

$$Ar = \frac{Thp}{Existing\ condition} \times 100 \quad \text{.....(3)}$$

Where: Ar- Accuracy rate, Thp- Total harvest prediction.

RESULTS AND DISCUSSION

Spatial analysis for each criterion

We provide recommendations for adaptive models to determine agricultural land suitability, especially agricultural commodities and predict the total harvest using IoT. We also analyze the spatial perspective and modify the multi-thresholding method by installing an SHT_{15} sensor to measure temperature and a rain gauge sensor. We use four criteria (Table 5) and assign a weight value using Equation (1) for each standard. Based on the cropland suitability level interval, we get a spatial analysis for each criterion.

Based on spatial analysis, 3 locations correspond to a total score of 13. Nine areas are rather suitable, with a total score of 9-11, and 1 very suitable location, with a total score of 16.

The cropland suitability area

Using spatial analysis and geoprocessing using a geo-segregation analysis, we get the result that of the 12 research sample locations, we compiled the distribution of the suitability cropland area (Figure 5). The suitability level of 8.01% belongs to the very suitable category scattered in the north of the research area and centered at coordinates 7° 14′ 11.8″ S latitude, 109° 56′ 29.7″ E longitude. Then 24.96% belongs to the suitable type, which is spread over the top and middle of the research area. Meanwhile, 67.03% belonged to the rather suitable category. It has scattered

Table 5. Spatial analysis for each criterion

Code	Altitude		Texture		Temperature		Rainfall		Total Value	Result
	m ASL	V[1]	Texture	V[1]	^{0}C	V[1]	mm / month	V[1]		
P_1	1,378	4	Andosol	4	19	3	341.00	4	16	Very Suitable
P_2	1,019	3	Andosol	4	23	2	326.83	4	13	Suitable
P_3	860	3	Andosol	4	24	2	317.75	4	13	Suitable
P_4	825	3	Regosol	3	22	2	275.00	3	11	Rather Suitable
P_5	815	3	Regosol	3	20	3	351.92	4	13	Suitable
P_6	744	3	Regosol	3	26	2	299.81	3	11	Rather Suitable
P_7	910	3	Regosol	3	24	2	247.50	3	11	Rather Suitable
P_8	360	2	Podzol	2	27	2	260.75	3	9	Rather Suitable
P_9	626	3	Regosol	3	26	2	297.60	3	11	Rather Suitable
P_{10}	760	3	Regosol	3	26	2	299.89	3	11	Rather Suitable
P_{11}	522	3	Podzol	2	27	2	347.08	4	11	Rather Suitable
P_{12}	522	3	Podzol	2	27	2	347.08	4	11	Rather Suitable

Where: V[1]- Value.

in the center of the map and partly to the south of the study area.

Based on the spatial distribution, we validate the spatial region. Regions with suitable criteria have the most significant production, 447,060 t year^{-1} (Table 6). Next, we estimate the amount of harvest by using data from drone quadcopters, IoT, and sensors. Then, we abuse land suitability results and spatial distribution maps to calculate the expected yield. In Indonesia, 80–85% of total potato production is vegetable potatoes with the Granola L. variety, while potatoes for industrial raw materials are only around 15–20%.

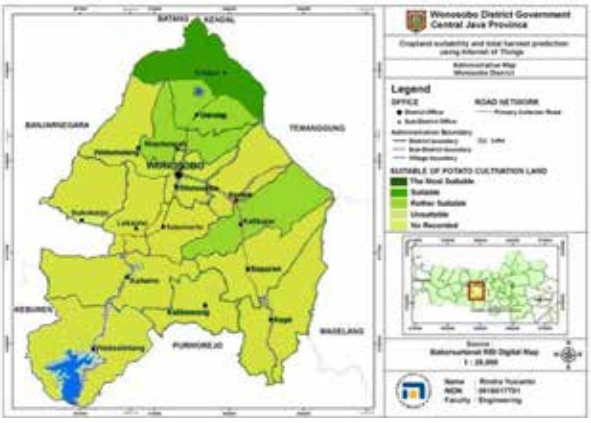


Figure 5. Spatial distribution cropland suitability area

The most suitable location is Kejajar (P_1) at coordinates 7° 14′ 11.8″ S latitude, 109° 56′ 29.7″ E longitude, so to meet industry needs, we suggest that decision-makers prioritize this location. However, we were still able to optimize several areas with

Table 6. The existing production

Location	Latitude	Longitude	Existing Production (t)	Granola L 85%	Industry 15%
Kejajar	7°14′11.8″S	109°56′29.7″E	447,060	380,001	67.059
Garung	7°16′52.1″S	109°56′37.2″E	74,240	63,104	11,136
Kalikajar	7°22′38.5″S	109°59′33.6″E	19,683	16,731	2,952
Mojotengah	7°17′31.6″S	109°52′31.7″E	905	769	136
		Total	541,888	460,605	81,283

the criteria of several inhibiting factors, namely Garung (P_2), Kalikajar (P_5), and Mojotengah (P_3).

Image acquisition

We develop predictions of total harvest based on cropland suitability. Then, we modify the multi-thresholding and separate the pixel intensity values into several regions. We obtained data and the image from a quadcopter drone with a flying area at 12 coordinate points that we have determined using the deploy smartphone application. In this modification, we register the site to determine the flight altitude, overlap, shooting direction, and shooting location according to points in 12 grids. After setting, the quadcopter drone will send an image map. We acquired the image just before harvest, 90 days after planting (Figure 6).

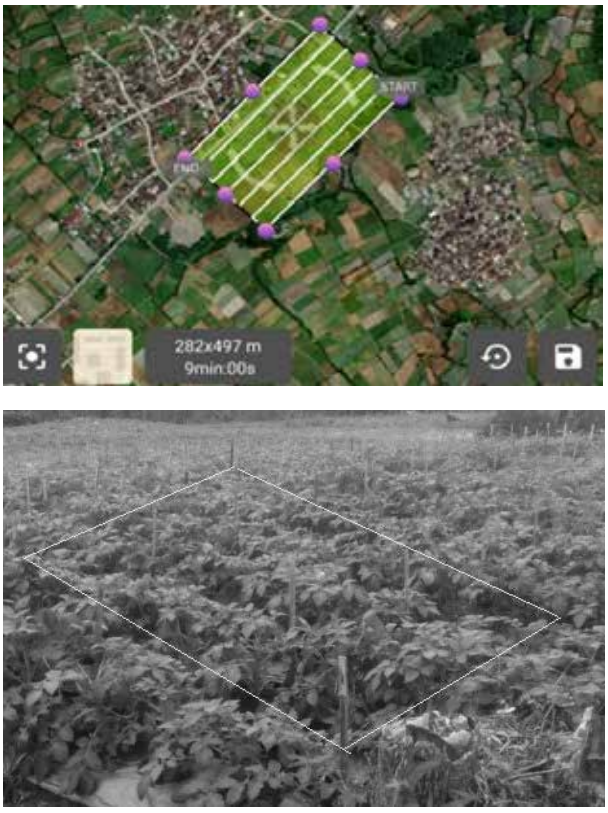


Figure 6. Image acquisition

Image segmentation

We converted the last image we modified to grayscale. We map the land into 12 grids based on grid-based. We then modify the planting age data on each grid with a segmentation technique. We extract the brownish-green components in the leaf image and then modify the original image.

Furthermore, we converted to multi-thresholding because, in the case of agriculture, especially potatoes, we could not distinguish in detail and significantly the color and appearance of the leaves. Leaves that are still green and leaves that are ready to harvest are almost the same. Therefore, we modified the threshold values for this multi-threshold method to be 0–100 and 100–250. In this research, we use a leaf image. Our images are modified based on the age of the plants, the color of the leaves, and the background objects in each grid to make image processing easier (Figure 7). Then we segmented the region using modified multi-thresholding; we defined area one as the background image and area two as the leaf image.

So that the color of the young leaves and those ready for harvest are slightly different, we modified the threshold value in the multi-thresholding process. The proportional value that we give is between 100 and 250. As for the pixel intensity in region one, we give a value between 0–100. Whereas in region two, we give a score between 100–250.

segment_1 = imquantize (green, [0 100]);

RGB = label2rgb (segment_1);

number, imshow (RGB)

We calculate the segmentation result using the percentage of segmentation pixels.

Total harvest comparison

Before comparing yields, we grouped the sample image acquisition into 24 sample

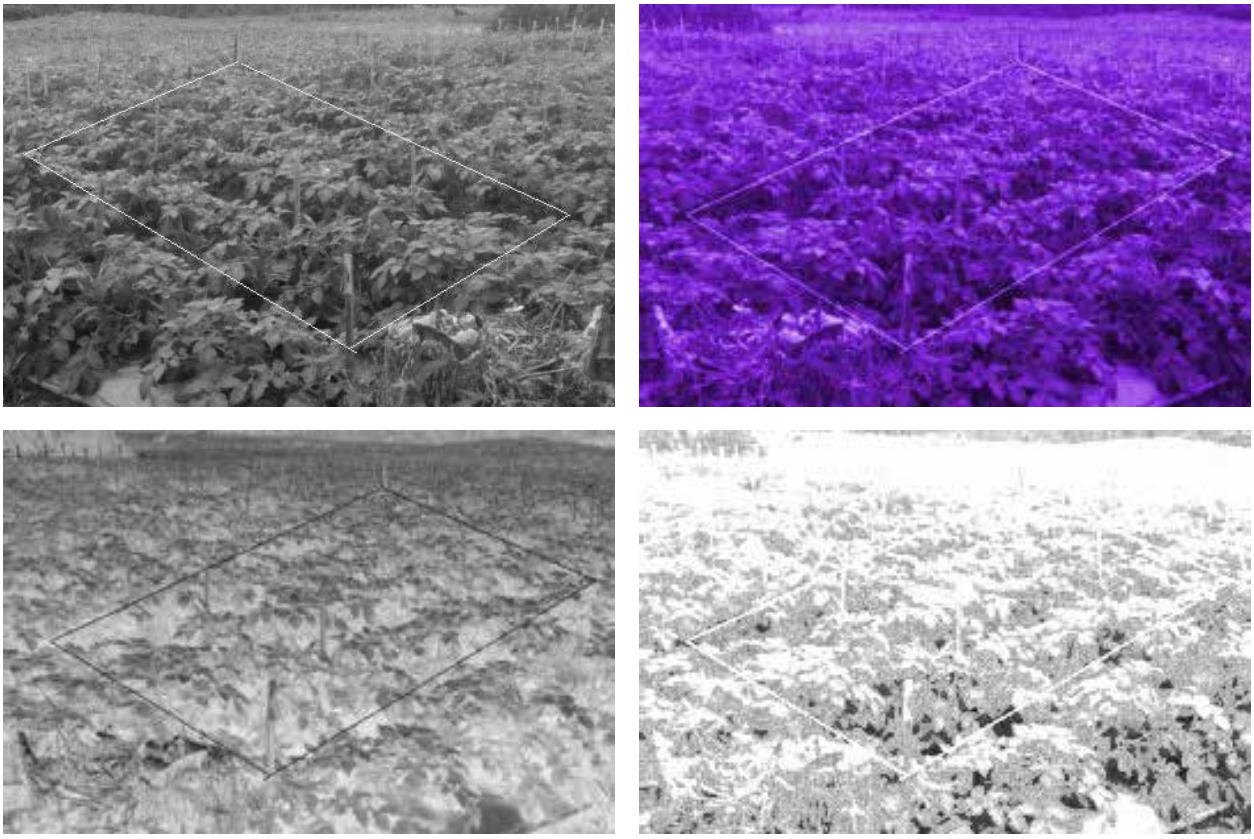


Figure 7. Modified and image segmentation

blocks (Table 7). We provide an index from A_{01} to F_{04}. Then we process the pixel data for each region into a percentage of pixels. After that, we weighed the samples for each harvest.

The results showed that the average sample weight was 862.12 kg (0.862 t), with an average yield of 13.79 t ha^{-1}. Then we compared the condition of the crop yields in the 24 blocks with the predicted harvest using spatial analysis (Table 8).

The Scenario of an alternative strategy

Based on the analysis of the spatial distribution of predicted yields, we found four suitable areas, namely Kejajar (P_1), Garung (P_2), Mojotengah (P_3), and Kalikajar (P_5). We calculate the existing production and predicted total harvest in the four areas (Table 9).

Table 7. The result of weighing harvest data

Sample Block	Weight (kg)	Sample Block	Weight (kg)	Sample Block	Weight (kg)
A_{01}	850	C_{01}	890	E_{01}	950
A_{02}	967	C_{02}	798	E_{02}	1,010
A_{03}	820	C_{03}	720	E_{03}	978
A_{04}	898	C_{04}	705	E_{04}	810
B_{01}	770	D_{01}	989	F_{01}	720
B_{02}	730	D_{02}	996	F_{02}	725
B_{03}	820	D_{03}	810	F_{03}	700
B_{04}	1,050	D_{04}	987	F_{04}	996

Table 8. Harvest comparison

Total Harvest Comparison	Unit	Existing Condition	Prediction
Harvest Production	t	44,615	0.862
Area	ha	2,895	0.063
Productivity	t ha-1	15.41	13.79

Table 9. Prediction of potato production of industrial raw materials

Code	Location	Latitude	Longitude	Existing production (t)	Prediction (t)
P_1	Kejajar	7°14′11.8″S	109°56′29.7″E	67,059	59,917
P_2	Garung	7°16′52.1″S	109°56′37.2″E	11,136	9,950
P_3	Mojotengah	7°17′31.6″S	109°52′31.7″E	136	121
P_5	Kalikajar	7°22′38.5″S	109°59′33.6″E	2,952	2,638
	Total			81,438	72,765

Table 10. The scenario of an alternative strategy

Scenario	Description	Percentage (%)	Production (t)	Total (t)
	Production shortage	100		44,235
1	Increase production	30	21,829	
2	Fulfill from another region	31	22,406	
Total			44,235	44,235

The predicted total industrial potato production from four sub-districts with suitable cropland sustainability is 72,765 t year^{-1}. Based on the demand for raw materials for industrial potatoes in Central Java of 117,000 t, there is a production shortage of 44,235 t (37.81%).

The first alternative strategy is to increase production by 61% to 117,151 tons in five potato-producing sub-districts in Kejajar, Garung, Mojotengah, and Kalikajar. The second scenario meets the production shortage of 44,235 t from other regions (Banjarnegara and Brebes District, Indonesia) to balance supply and demand. Based on Kementan (2015), the maximum ability to increase the production of agro-industrial commodities for normal conditions is 30%, so the recommendation of this model is to increase production by 30% in 5 potato-producing districts by 21,829 t (first scenario) and fulfill from other regions by 31%, namely 22,406 t (second scenario).

The total demand (Q_d) is 42,170 t month^{-1} or 506,040 t year^{-1}. The prioritized supplier is P^1 (Kejajar), with a supply capacity (Q_s) of 399,448 t year^{-1}, so it is necessary to meet supply shortages. The concept of a logistics transparency approach is to know the amount of demand at one point and the supply capacity at another. A more analytical balance is obtained by increasing the supply from P_2 (Garung) 66,333 t, P_3 (Mojotengah) 809 t, and P_5 (Kalikajar) 17,587 t. This research has succeeded in showing the level of accuracy at the application level. The spatial-based logistics transparency approach can predict food availability, affordability, and utilization compared to the actual condition with a balanced level of 485,098 tons or 95.86%.

4. CONCLUSION

The results showed that the most suitable agricultural land was 11.05%; according to 22.9%, land with several inhibiting factors was 62.01%. The most convenient location is in Kejajar, Wonosobo District, Indonesia. The results also showed an average harvest of 13.79 t ha^{-1}. This model can predict the amount of crop with a production prediction of 72,765 t year^{-1} and an accuracy rate of 89.35%. This study's results align with Kumar & Bhardwaj, who stated that predicting the total harvest using a modified model produces better accuracy (Bhardwaj & Kumar, 2022). The results of this study also strengthen the opinions of Jayasinghe & Withanage, which state that GIS

can provide better spatial data and visual data representation to improve prediction accuracy (Jayasinghe & Withanage, 2020).

This study succeeded in predicting a total production of 72,765 t year^{-1}. There needed to be more industrial potato production of 44,235 t (37.81%). So, the recommendation from this model is an increase in output by 30% in 5 potato-producing districts in Wonosobo, Central Java, by 21,829 t (first scenario) and fulfillment from other regions by 31%, namely 22,406 t (second scenario), to balance supply and demand. This study also managed to show the level of accuracy at the application level. A spatial-based logistics transparency approach can predict food availability, affordability, and utilization compared to actual conditions with a balanced level of 485,098 t or 95.86%. It shows that an adaptive model can predict cropland suitability and total harvest.

CONFLICT OF INTEREST

The authors confirm that this manuscript has no conflict of interest.

ETHICAL STATEMENT

This article does not contain any studies with human participants or animals performed by any of the authors.

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