



Future scenario for farmland abandonment in Karawang

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Abstract. *The land plays a significant role in world life to continue its journey and fulfill living things' needs. However, there has been a noticeable increasing trend in farmland abandonment in the recent decade. Designated Karawang as a study area, remote sensing analysis reported that all the districts and subdistricts in Karawang Regency have abandoned land with varying numbers and more distributed more intensely in the region's hub. The study has discovered that the total number of farmland abandonment is 28 times of the Central Beauaru Statistics has claimed. Severnty five percent producer accuracy, minimum unit data collected, land ownership, and the ability of remote sensing to read all earth reflectan are the possible answer to the disparity. Machine learning informed that the top three essential variables are the irrigation service, the hillside, and the spatial plan that drives farmland abandonment. Thus, developing a new irrigation service to access the remote farmland and reviewing the spatial that have more flavor to agriculture is the scenario proposed by this study, while the hillside remains a constraint.*

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INTRODUCTION

The land plays a significant role in world life to continue its journey and fulfill living things' needs. It becomes unarguable, if land use is then defined as the varying activities executed by humans to exploit the landscape (Zonneveld 1993). As a basis, land use activities generally depend on the interaction among environmental, economic, and institutional systems (Barlowe 1978)—later, strengthens the existence of societal factors such as population structure and dynamics, income and affluence, technology, socioeconomic organization, culture, institutions, and political systems shape (Briassoulis 2009). As playing their vital role is triggered by an active population, land use becomes more dynamic and will constantly adjust to the needs of its users. However, the dynamic of land use has recently caused irregularities in its original behavior.

There is a noticeable increasing trend in farmland abandonment, directly affecting farmers' livelihood and food security (Paudel *et al.* 2020). Thus, the rising number of farmland abandonment worldwide, especially in the developed country, has generated various research worldwide to figure out what is happening. Unfortunately, not much research has addressed abandoned farmland in Indonesia. It is a typical, or the author has not yet found a science journal that addresses the fundamental diagnostic question such as how many and where the farmland abandonment phenomenon has occurred around this archipelago country. However,

abandoned land-related data is investigated by the Ministry of Agrarian and Spatial, but with broad terminology. The other data, the most intersected one, is published by the Central Bureau of Statistics, stated in every regency book. However, since 2019, the data is no longer published. Moreover, the published data was in tabular format and with no geographic information.

Several research studies have discussed the economic-social and environmental costs, such as the degradation of ecology services (Queiroz *et al.* 2014), significantly changed rural land use patterns (Shengfa and Xiubin 2017), striking ecological and socioeconomic (Pointereau *et al.* 2008). In 2017, there were 950 million to 1,1 billion acres of farmland abandonment (Hawken 2018) which is 2,6% of the mainland on earth -equals approximately half of Indonesia's total territory. According to the latest data published in 2015, in producing farmland abandonment, it is implied that Indonesia has contributed 3,1% of the world's abandoned farmland if according to the published Central Berau Agency. West Java, as the third-largest province in producing rice (Ministry of Agriculture 2020a) after Central Java and East Java, has 10.093 hectares of farmland abandonment.

However, even though the number of abandoned farmland in Karawang Regency is not greater than the other regencies; 290 hectares in 2015 and increased to 291 by the year 2016, 310 in 2017, this regency is the second-largest regency-producing paddy among 514 regencies/cities in Indonesia (Ministry of Agriculture 2020b). Thus, all efforts in maintaining the Karawang Regency as a significant agricultural production area, including preventing the spreading of farmland abandonment, must have the first place. The main goal of the research is to provide a future scenario to prevent the escalation of farmland abandonment, especially in Karawang. However, before securing the scenario, the study needs to produce a farmland abandonment delineation map and classify the importance degree among the driving factor that dragged from socio-economy, environment, and policy as the basic theory of land use. In this research, farmland abandonment is defined as land that was cultivated but is abandoned.

METHOD

Study Location and Period

The research conducted from June to July 2021 in Karawang Regency (Figure 1), near the capital city of Indonesia, Jakarta. Karawang is considered one of the most productive administrative areas producing paddy fields (Rafiuddin and Munibah 2016), but on the other side, it has a high land use conversion from paddy fields to other land use (Widiatmaka *et al.* 2013). Karawang has 30 sub-districts with a total area of 1.753,27 km.

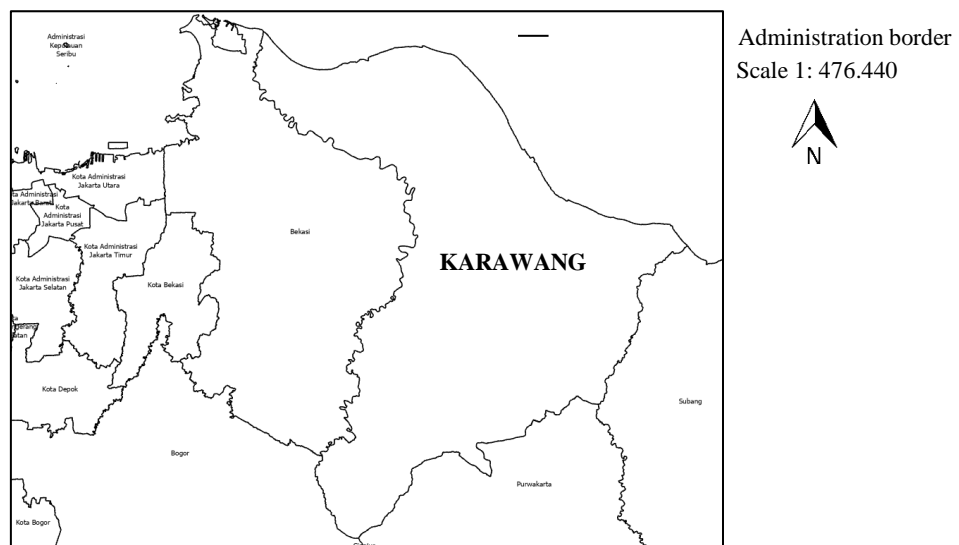


Figure 1 Research location

Tools and Materials

Windows 10 operating system and built-in applications, Microsoft Office, and ArcGIS Pro were the required software to meet the goals. All data necessary, such as satellite imagery, administration boundary, socio-economy, and policy, were collected through online sources.

Data and Analysis

Windows 10 operating system and built-in applications, Microsoft Office, and ArcGIS Pro were the required software to meet the goals. All data necessary, such as satellite imagery, administration boundary, socio-economy, and policy, were collected through online sources. Table 1 shows the relation between goal, data/source, purpose, analysis, and the output.

Table 1 Data and analysis

No	Goal	Data/Source	Purpose	Analysis	Output	
1.	To produce a farmland abandonment delineation map	Sentinel 2A year 2017-2019 scene T48 MYU dan T48 YMT (10x10 m resolution)/earthexplorer.usgs.gov	<ul style="list-style-type: none"> ▪ Raw data to become farmland abandonment map ▪ Supporting training and validation 	<ul style="list-style-type: none"> ▪ Image classification (maximum likelihood/supervised) ▪ Geoprocessing (clipped) 	Farmland abandonment map 2019 (raster 10x10m spatial resolution)	
		Google Earth/earth.google.com	To train and validate the Sentinel 2A interpretation	Visual interpretation		
		Administration border/tanahair.indonesia.go.id	To narrow the study area	Geoprocessing (clipped)		
2	To classify the importance degree among the driving factor.	Farmland abandonment map/Output 1	As the dependent variable	Forest-based classification and regression	Importance degree of driving factors	
		Socio-economy:	Farmer household/Central Beauaru Statistics (BPS)	As the explanatory variables		Tabular to spatial
			Farm workers/Central Beauaru Statistics (BPS)	As the explanatory variables		Tabular to spatial
			In-out residents/Central Beauaru Statistics (BPS)	As the explanatory variables		Tabular to spatial
		Environments:	Sun saturation/Result of hillshade analysis from earthexplorer.usgs.gov	As the explanatory variables		Hillshade analysis
			Slope/Result of slope analysis from earthexplorer.usgs.gov	As the explanatory variables		Slope analysis
		Policy:	Spatial plans/designation area/atrbpn.go.id	As the explanatory variables		
			Road services/tanahair.indonesia.go.id	As the explanatory variables		
			Irrigation/tanahair.indonesia.go.id	As the explanatory variables		
3	To develop a future scenario	Importance degree of driving factors/Output 2	Considerations	Scenario component, qualitative	Alternatives scenario	

Farmland Abandonment Spatial Distribution

The work began with the acquisition of 34 scenes of Sentinel 2A that may capture a 1.753,27 km² study area and cover the year 2017–2019 from earthexplorer.usgs.gov. Pre-processed for each imagery required, respectively geometric correction, radiometric correction, scene mosaic, and band composite before conducting image classification. To develop a complete Karawang Regency, the study employed the mosaic of two scenes; T48 MYU and T48 YMT (Figure 2). The following step was gaining the example data of five land covers: dense vegetation, agriculture, built-up, farmland abandonment, pond, and water from Google Earth. By using fourteen different locations for the training and 50 spots for visual interpretation (Figure 3) on Google Earth supported by normalized difference built-up index for its accuracy assessment, the research consequently had the farmland abandonment map of 2019 (Figure 4).

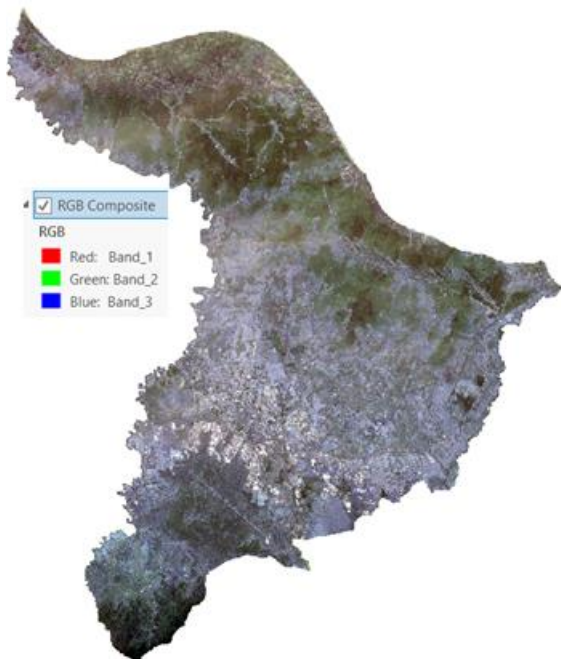


Figure 2 Sentinel 2A after pre-processing



Figure 3 Training and validation location

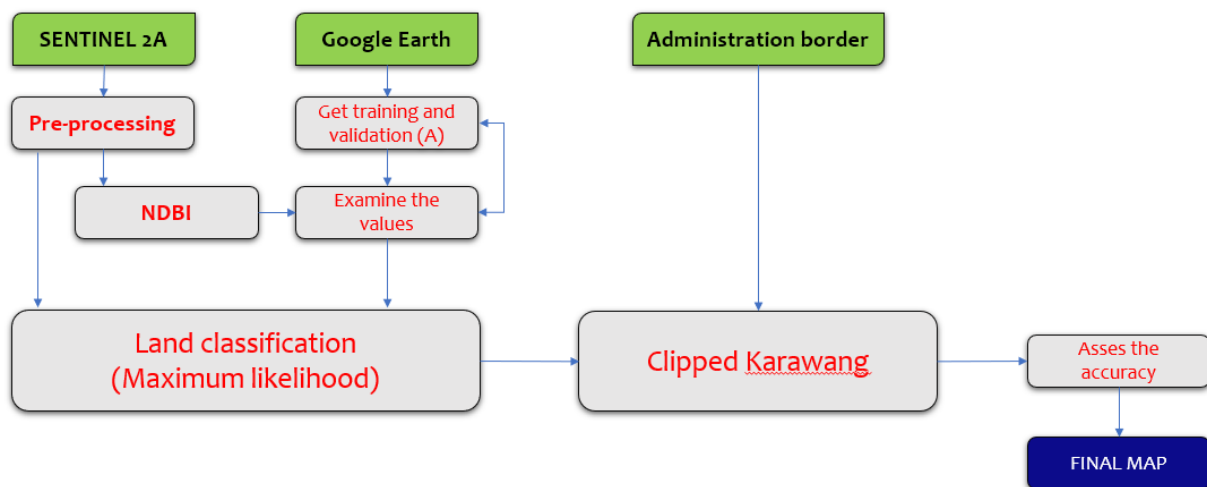


Figure 4 Farmland abandonment spatial distribution workflow

Classifying Driving Factors

Hu *et al.* (2013) stated that studies have shown that the determinants of farmland abandonment at the local scale include topographical conditions (e.g., elevation and slope) (Mottet *et al.* 2006), soil properties (e.g., soil depth and soil erosion) (Bakker *et al.* 2005), farmers’ employment choices, and accessibility (Gellrich *et al.* 2007). At the regional scale, socio-economic factors become important driving variables (Cocca *et al.* 2012). Certain researchers have used socio-ecological models to explore the drivers of farmland abandonment caused by collective behavior (Lambin and Meyfroidt 2010).

Formulating the driving factors can generally be surfed through the analytical hierarchy process approach. However, this study tried to discover the answer through forest-based classification and regression, which is part of spatial statistics and machine learning. Forest-based classification and regression create models and generate predictions using an adaptation of Leo Breiman’s random forest algorithm Abdelghany *et al.* 2021. In its principle, the forest-based classification and regression train a model based on experienced values known as a training dataset. Further, it may predict a landscape in the future by peering at the generated model -the model shows which components are strongly governed in contributing to the farmland abandonment appearance (Figure 5).

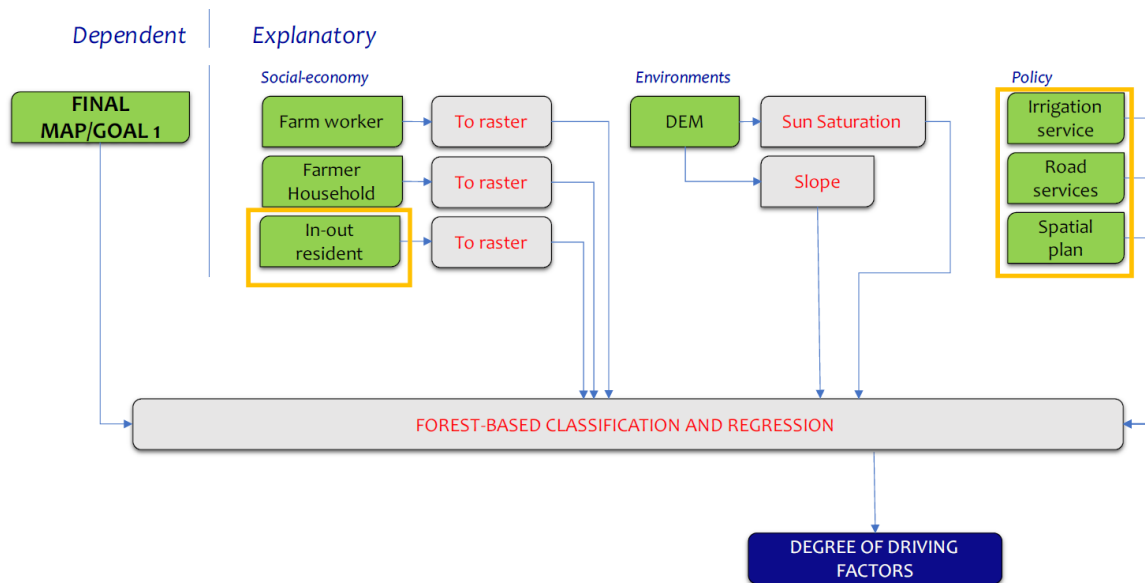


Figure 5 Driving factor workflows

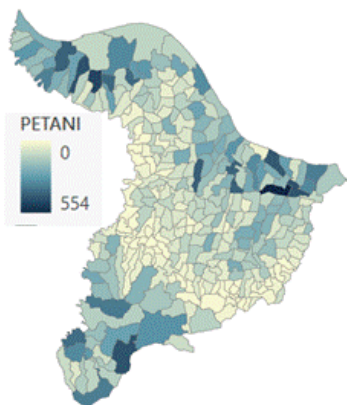


Figure 6 Farmer household

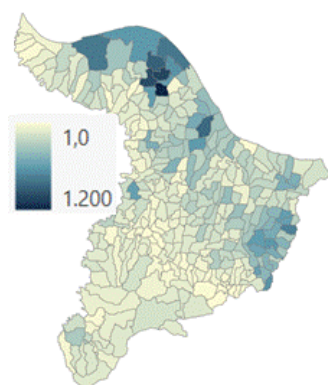


Figure 7 Farm workers

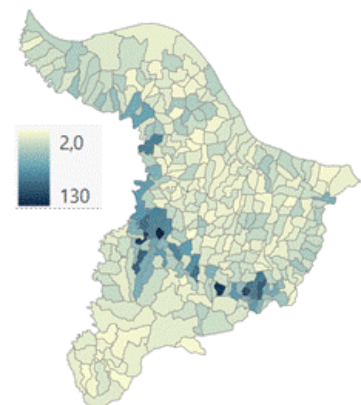


Figure 8 In-out residents

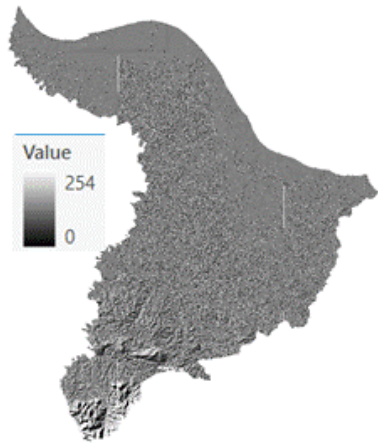


Figure 9 Sun saturation

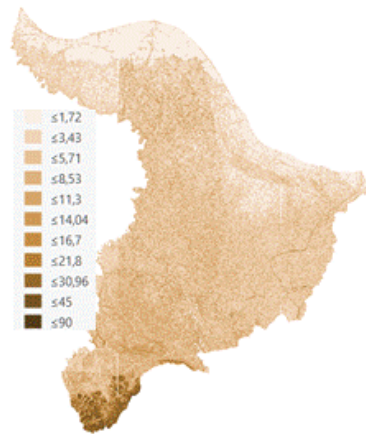


Figure 10 Slope

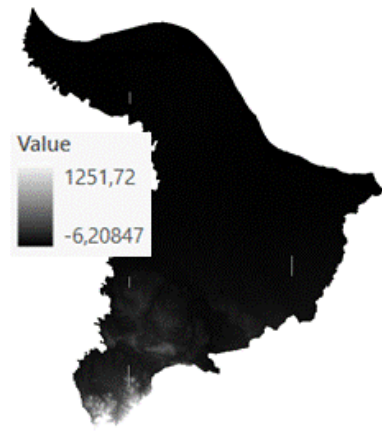


Figure 11 Digital elevation model



Figure 12 Road



Figure 13 Irrigation

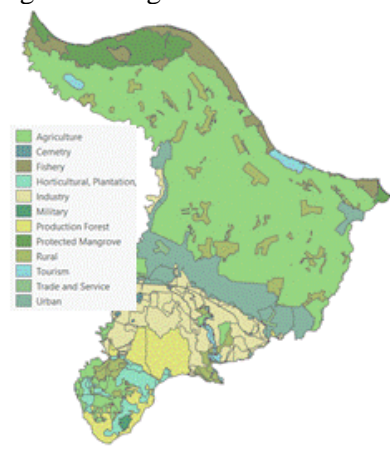


Figure 14 Spatial plans

The second work began with dragging the potential factors that may drive the emerge of farmland abandonment. Those data were socio-economy; the farmer household number (Figure 6), the farm workers (Figure 7), in-out residents (Figure 8), the environment; sun saturation (Figure 9), slope (Figure 10) that was derived from digital elevation model (Figure 11), and road service (Figure 12), irrigation service (Figure 13), the policies; spatial plans/designation area (Figure 14). The socio-economy data were tabular; thus, it needed to be transformed into spatial data.

Developing Future Scenario

There are two primary models of scenario planning: normative scenario planning and exploratory scenario planning. Both are viable approaches for a planning effort, but each helps address different challenges that organizations commonly face. The primary purpose of normative scenario planning is to reach a specific target. In contrast, the primary purpose of exploratory scenario planning is to navigate uncertainty (Futrell 2019). Intentionally, a direction-setting has been applied, starting from determining the desired outcome (preventing farmland abandonment from spreading in the future) and listing all stakeholders. In the approach development, the driving factors are the key to the tactic, and it already has stakeholders behind to propose. In this step, the research already had all the required data before developing a future scenario. The scenario component table is ready to be developed in qualitative method analysis by considering the top three driving factors of farmland abandonment that were analyzed in the previous objective (Figure 15).

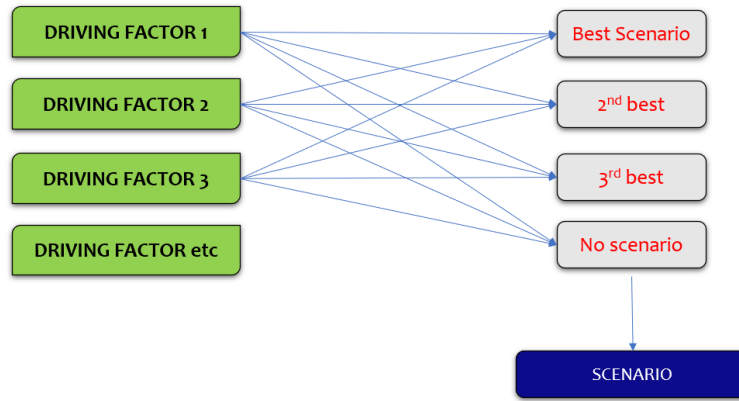
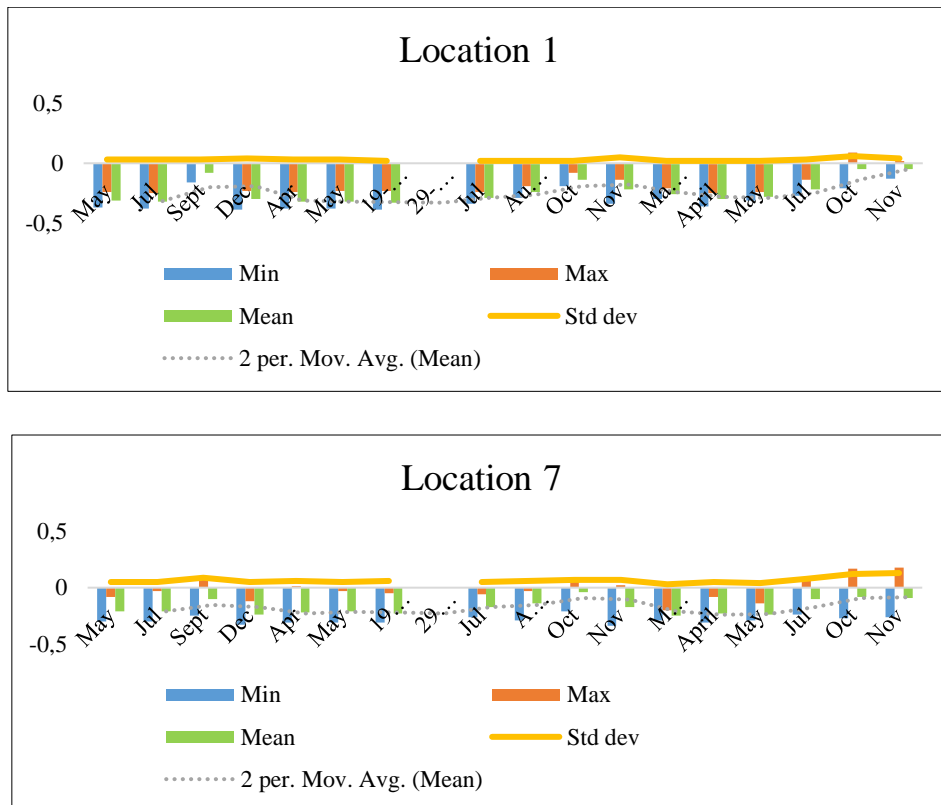


Figure 15 Scenario workflows

RESULT AND DISCUSSION

Farmland Abandonment Spatial Distribution

The normalized difference built-up index for farmland abandonment has a pattern, as shown in Figure 16, was below zero—except for some locations. These might happen if the land had just been backfilled and dominated by the light grass, read by the machine as farmland abandonment. Second, there was an anomaly in surface reflectance. This pattern was further utilized for assuring that the training data were passing the quality to overcome the subsequent analysis.



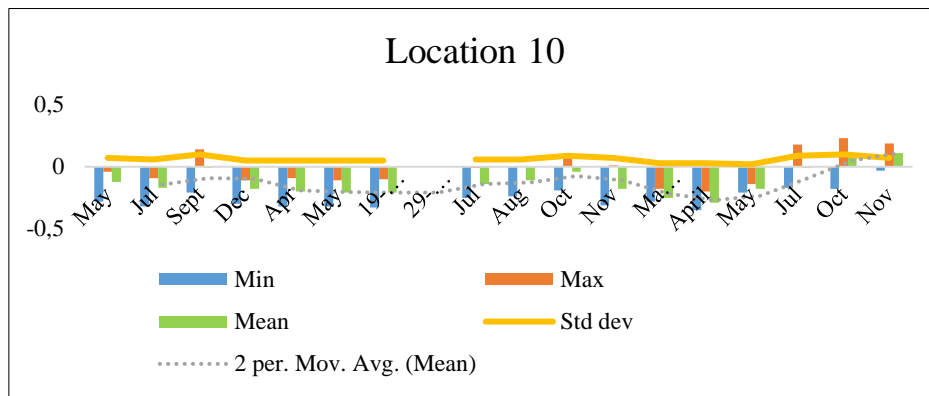


Figure 16 Normalized difference built-up index examples

Remote sensing analysis reported that all the districts and subdistricts in Karawang have an abandoned land total of 8.481,8 hectares, with varying numbers of each district highlighted in Figure 17. Parungmulya Village in District Ciampel has the highest farmland abandonment number of 276,8 hectares, while Waluya Village in District Kutawaluya has the lowest one of 0,1 hectares. However, the study may not conclude that Parungmulya was the worst and Waluya was the greatest, as statistically, Parungmulya indeed has a more spacious area (7.880 hectares) than Waluya (3.753 hectares). Therefore, the study stated in Chapter 1 that it could be biased when investigating conducted by using administration boundary only.

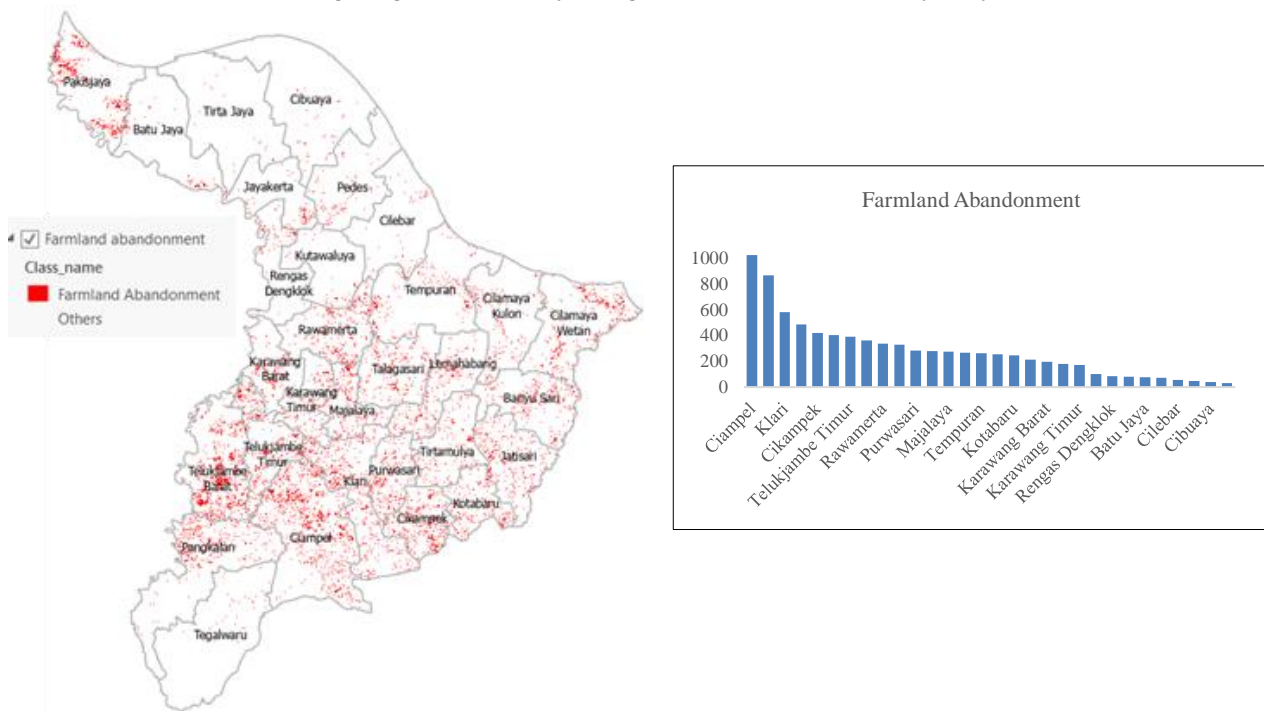


Figure 17 Farmland abandonment map and graph

Compared to the data published by Central Beauaru Statistics (BPS), there was a significantly different value among them. In 2017 and 2018, BPS claimed the abandoned farmland in Karawang Regency was 310 hectares for both years, meaning there were no increments or decrease meant. But, there was an increasing farmland abandonment from 2016, 291 hectares to 310 hectares in 2017. Further investigation was assessed and discovered the probable answer. The producer accuracy for the farmland abandonment was 75%, user accuracy was 60%, with the overall Kappa 50%. Although this value of accuracy was considered very good for remote sensing, the potential to obtain different results was still available. Similar to the image processing mechanism, 100% accuracy was quite sticky.

Second, Sentinel 2A has ten times ten-meter spatial resolution. Therefore, the pixels in a computer that might be classified as abandoned land were, at minimum, 100 meter square. At the same time, it is unidentified the minimum unit data collected by BPS. If the dimension benchmark is larger, the study has more capability to indicate abandoned land. Third, BPS was intended to specify agriculture, and hence abandoned farmland owned by the government and/or private (not a farmer) was not included in the list. In contrast, remote sensing accommodated all characteristics on the ground. Therefore, all abandoned farmland was reflected by reading the range of spectral colors. Since the location of the abandoned land is attached to the company, it was not listed in BPS document.

Fourth, BPS localized their data only for agriculture areas, while user-defined remote sensing generalized the data and the limitation. It means the analysis browsed all spectra provided in the study area and justified the pixel into user-defined categories (in this study: abandoned, agriculture, built-up, dense vegetation, pond, and water). The last, BPS limited its survey to two years. Thus, any farmland abandonment that was reported after two years will not be counted. A combination of all factors above has caused the discrepancy in farmland abandonment numbers. Nonetheless, in general, the study and BPS have shown the same symptoms that abandoned farmland has existed and is concentrated in the region's center. Further, it would be more exciting if the further study aims to challenge the BPS data year by year.

Classifying Driving Factors

Abandoned farmland is the result of the farmers' final decision by considering the interaction between the activities they do and the land they have from the perspective of cost and benefit. Benefits are not always about wealth but also the results earned in the form of personal consumption. Costs do not always mean how much they have spent and the energy spent on the farmland. Farmers' households and their successors, farm workers, and in-out residents were part of the social economy. Sun saturation and slope were grouped into the environment. At the same time, the designation area plan, irrigation service, and road service were grouped into policies.

The decision tree technique was utilized as machine learning to determine the relationship between all variables. To get more accurate results, several decision trees were made and named random forests (Breiman 2001), which is part of artificial intelligent science. The concept of random forest is a basis of deep learning, which is used to forecast a condition and/or to create an innovation. Deep learning is the important key to innovation. This technique produces an accurate classifier and understanding of the predictive structure of the problem (Petri 2010).

Top Variable Importance

Variable	Importance
Irrigation	2,42
Hillshade	2,19
Spatial Plan	2,11
Farmer household	2,04
Farmer worker	2,02
Slope	1,93
Road	1,87
In-out resident	1,65

Training Data: Classification Diagnostics

Category	F1-Score	MCC	Sensitivity	Accuracy
Farmland Abandonment	0,92	0,88	1,00	0,94
Others	0,95	0,88	0,91	0,94

Validation Data: Classification Diagnostics

Category	F1-Score	MCC	Sensitivity	Accuracy
Farmland Abandonment	0,77	0,67	1,00	0,80
Others	0,83	0,67	0,71	0,80

Note: predictions for the data used to train the model compared to the observer categories for those features

Figure 18 Forest-based classification and regression result

The results of machine learning for farmland abandonment with dependent and exploratory variables as presented in Figure 18. The accuracy of the analysis was showing almost 100%, which is considered as a good result. In its implementation, farmland abandonment was identified by using respective pixels, which consist of three main elements, i.e., forming social economy, environment, and policy. The top three driving factors are the irrigation service, hillshade, and spatial plan. This result may be utilized as a guideline of the Karawang Regency in the future, especially for regional development. In addition, this model can also be used for other regions outside the study area by completing the required data.

Future Scenario

The last stage of the study was to develop a scenario. As a decision-making process starts from describing what is happening, the study then dragged the degree of the driving factors; the irrigation service, the hillside, and the spatial plan. The farther the agricultural land from the irrigation service, the more potential it becomes farmland abandonment. The more unsupported a land with a policy to remain as agricultural land, the more potential it becomes. Hillshade is a given and maybe interpreted as a constraint. Developing a new irrigation service to access the remote farmland and reviewing the spatial that have more flavor to the agriculture are proposed by this study.

CONCLUSION

Although concentrated in the region's hub, farmland abandonment appears in all Karawang Regency districts, with varying numbers in each district. The irrigation service, the hillside, and the spatial plan are the top three factors that drive farmland abandonment. Thus, developing a new irrigation service to access the remote farmland and reviewing the spatial that have more flavor to agriculture is the scenario proposed by this study, while the hillside remains a constraint.

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