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*Corresponding author(s) email:
manessa@ui.ac.id

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The Spatial Model of Paddy Productivity Based on Environmental Vulnerability in Each Phase of Paddy Planting

Rahmatia Susanti [1,2], Supriatna [1], Rokhmatuloh [1], Masita D. M. Mannesa [1*], Aris Poniman [1], Yoniar H. Ramadhani [2]

1. *Department of Geography, Faculty of Mathematics and Natural Sciences, Indonesia University, Indonesia*
2. *Geospatial Information Agency, Indonesia*

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Abstract

The national primary always growth and increase in line with the increase in population, such as the rise of rice consumption in Indonesia. Paddy productivity influenced by the physical condition of the land and the declining of those factors can detected from the environmental vulnerability parameters. Purpose of this study was to compile a spatial model of paddy productivity based on environmental vulnerability in each planting phase using the remote sensing and GIS technology approaches. This spatial model is compiled based on the results of the application of two models, namely spatial model of paddy planting phase and paddy productivity. The spatial model of paddy planting phase obtained from the analysis of vegetation index from Sentinel-2A imagery using the random forest classification model. The variables for building the spatial model of the paddy planting phase are a combination of NDVI vegetation index, EVI, SAVI, NDWI, and time variables. The overall accuracy of the paddy planting phase model is 0.92 which divides the paddy planting phase into the initial phase of planting, vegetative phase, generative phase, and fallow phase. The paddy productivity model obtained from environmental vulnerability analysis with GIS using the linear regression method. The variables used are environmental vulnerability variables which consist of hazards from floods, droughts, landslides, and rainfall. Estimation of paddy productivity based on the influence of environmental vulnerability has the best accuracy done at the vegetative phase of 0.63 and the generative phase of 0.61 while in the initial phase of planting cannot be used because it has a weak relationship with an accuracy of 0.35.

1. Introduction

Paddy is food crops that are the staple food for most people in Indonesia, so the amount of paddy production will significantly affect food needs in Indonesia. Physical characteristics of land will have an influence on paddy productivity in a region (Widiatmaka et al., 2016). Declining land physical factors can detected from environmental vulnerabilities that can cause changes in paddy productivity. Environmental vulnerability according to Regulation of the Head of the National Disaster Management Agency Number 2 of 2012 compiled based on natural disaster hazard class or disaster-prone class factors with land use parameters. Compiled based on natural disaster hazard class or disaster-prone class factors with land use parameters. Bogor Regency is one area in Indonesia that has environmental vulnerability to natural disasters and a high paddy-producing.

Bogor Regency is known as one of the largest paddy producers in West Java Province but based on BPS data it was detected a decrease in paddy productivity by 4 tons/hectare during 2016-2017 period. The decline in paddy productivity in Bogor Regency influenced by the location of paddy fields in areas prone to natural disasters, like floods, droughts, and landslides. This study focuses on aspects of environmental vulnerability based on natural hazard-prone conditions that can affect paddy productivity in each phase of paddy planting in Bogor Regency, West Java. Remote sensing technology and geographic information systems can detect the paddy planting phase quickly, accurately and analyze environmental vulnerabilities to natural disasters.

The use of remote sensing technology is widely use in the analysis of agricultural land, especially for continuous monitoring of agricultural land. Remote sensing has great potential in monitoring paddy phenology for management and prediction of paddy production (He et al., 2018). Utilization of Sentinel-2A imagery is appropriate for mapping large-scale paddy fields because it has high spatial and temporal resolution than other remote sensing images such as Landsat 8 which has a spatial resolution of 30 meters with 16 daily temporal resolution (Dong et al., 2016). Another advantage of this satellite image is that 3 (three) bands 'red edge' are suitable for identification of vegetation (Liu et al., 2018).

The use of GIS technology can be used for spatial modeling in monitoring the paddy planting phase and estimation of paddy productivity based on environmental vulnerability factors. Spatial modeling with GIS can produce an algorithm that can be used to estimate paddy productivity in each area of paddy fields (Muslim et al., 2015). The purpose of this study was the preparation of a spatial model estimation of paddy productivity based on the influence of environmental vulnerability in each phase of paddy planting. This spatial model is expected to be input in estimating the decline in paddy productivity due to environmental vulnerability in a region in each phase of paddy planting so that prevention or mitigation steps can be more quickly carried out.

2. Data and Methods

This research divided into several stages of work. In the first stage is the preparation stage to determine theme and choose the title of the research to be conducted, after getting the title of research then proceed with the study of literature by looking for a literature review related to this research. The next stage is to collect secondary data, as well as download Satellite Sentinel-2A imagery.

The stages of initial data processing divided into two, namely spatial data processing which processes data on environmental vulnerability variables and processing vegetation indices using Sentinel-2A imagery. The initial data processing stage is to process environmental vulnerability variable data, which is analyzing secondary data consisting of drought-prone maps, flood hazard maps, and landslide-prone maps, and conducting spatial analysis of average monthly rainfall to obtain a monthly rainfall map. The next stage is the rasterization and classification of flood-prone maps, prone to drought, landslide-prone, and average monthly rainfall, according to the provisions of each theme. Classification of the average monthly rainfall maps using the Oldeman category. Classification of flood-prone based SNI 8197: 2015, classification prone to landslides based on SNI 8291: 2016, and classification of drought-prone uses Regulation of the Head of the National Disaster Management Agency Number 2 of 2012.

The next initial data processing stage is processing remote sensing data in the form of an analysis of the vegetation index. The vegetation index used is NDVI, SAVI, EVI, and NDWI. NDVI analysis can highlight aspects of vegetation density and use Near Infrared (NIR) and Red Bands (Tucker, 1986 in Danoedoro, 2012), as follows

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

The EVI index is sensitive to changes in biomass and is resistant to canopy effects. The EVI index can reduce atmospheric influence because it uses the blue band in calculations that can correct aerosol interference in the red and blue band (Huete et al., 2002), the equation is as follows

$$EVI = G * \frac{(NIR - Red)}{(NIR + C1\ x\ Red - C2\ x\ Blue + L)}$$

This index emphasizes the background of the soil by minimizing the effect of soil brightness using soil correction factors (Huete, 1988).

$$SAVI = \frac{(NIR - Red)}{(NIR + Red + L)}\ (1 + L)$$

This index uses near-infrared (NIR) and shortwave infrared (SWIR) bands which can detect moisture content which is useful for vegetation studies (Gao, 1996).

$$NDWI = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

The results of the vegetation index analysis are used to estimate the paddy planting phase which idivided into four classifications, namely the initial planting phase (water dominance), vegetative phase, generative phase and fallow phase (LAPAN, 2015).

The field survey phase was conducted to obtain data related to the paddy planting phase and productivity at each paddy planting period. This field sample was used as a training sample and a sample validation of the spatial model of paddy planting phase and spatial model the influence of environmental vulnerability on paddy productivity. Besides, a field survey was conducted to check the physical environmental conditions in terms of areas that have flood-prone areas, are prone to drought, and prone to landslides that will affect paddy productivity.

The last stage is divided into two, namely making the spatial model of the paddy planting phase and spatial model the influence of environmental vulnerability on paddy productivity. Making a spatial phase of paddy planting model using the random forest classification model. Making a spatial model the influence of environmental vulnerability on paddy productivity using a linear regression model. The two results of the model will then be applied to Sentinel-2A remote sensing data to see the distribution of estimated paddy productivity in Jonggol, Cariu, Sukamakmur, and Tanjungsari sub-districts.

3. Result and Discussion

3.1. Spatial Model of Paddy Planting Phase

The compilation of the paddy planting phase spatial model uses the random forest classification method. The random forest classification method approach can used for paddy classification by extending the data dimensions in the spectral and temporal domains that influence the characteristics of paddy that has different climate and environmental characteristics (Park et al., 2018). The training features used in this study were 3649 sample points spread over 138 locations with 33 periods (March 2017 – May 2018). Modeling uses 5 (five) variables, namely the NDVI vegetation index, EVI, SAVI, and NDWI as well as the recording phase of the planting phase. The processing results of random forest classification obtained the percentage of interest from the variables used to build the spatial model. NDWI index has the highest percentage of interest of 26%, NDVI index of 23%, SAVI index of 23%, EVI index of 22% and variable that has the smallest percentage of interest is planting time recording variable which is only 6%.

The application of random forest classification in mapping paddy fields based on the planting phase has outstanding accuracy of 0.96 using the NDVI vegetation index variable and time variable (Onojeghuo et al., 2017). The overall accuracy results in this study were 0.92. The highest accuracy is found in the water phase of 1.00, because in this phase water-dominated paddy fields have index values that are different from other planting phases, both in the NDVI index, EVI, SAVI, and NDWI. The vegetative phase has an accuracy of 0.90, the generative phase has an accuracy of 0.88, and the fallow phase has an accuracy of 0.91.

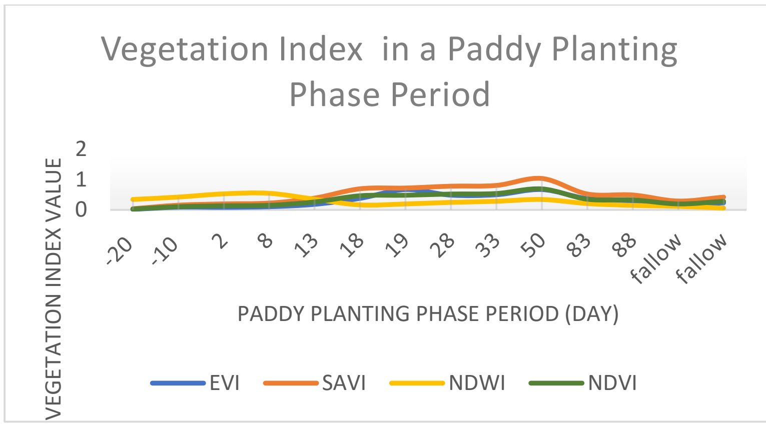

Figure 1. Vegetation index graph in a paddy planting phase period

(Data processing, 2019)

Spatial modeling of paddy planting phase using four combinations of vegetation index and time variables can be simplified by using two combinations of vegetation indexes which have different vegetation index value patterns in the planting phase period (Figure 1). The vegetation index pattern in the planting phase period can seen that the NDVI vegetation index, EVI, and SAVI have almost the same pattern, while the NDWI vegetation index is different so that the combination that can be used is the NDWI vegetation index with other vegetation indices. The results of the comparison of accuracy in the paddy planting phase model using a combination of two vegetation indices are shown in Table 1.

Table 1. Comparison of accuracy of models with a combination of vegetation index (Data processing, 2019)

Vegetation Index Combination	**Accuracy**			
	Initial Phase	Vegetative phase	Generative Phase	Fallow phase
NDWI-NDVI-EVI-SAVI	1,00	0,90	0,88	0,91
NDWI – NDVI	0,99	0,93	0,90	0,91
NDWI – EVI	0,93	0,87	0,86	0,91
NDWI - SAVI	1,00	0,92	0,90	0,94

3.2. Paddy Productivity Model based on Environmental Vulnerability

Variables of environmental vulnerability are made based on natural hazard-prone conditions that often occur in the study area. Dinas Tanaman Pangan dan Holtikultura Kabupaten Bogor in 2017 noted that the prone to natural disasters that occur on paddy fields in Bogor Regency is prone to droughts (Figure 2), floods (Figure 3), and landslides (Figure 4).

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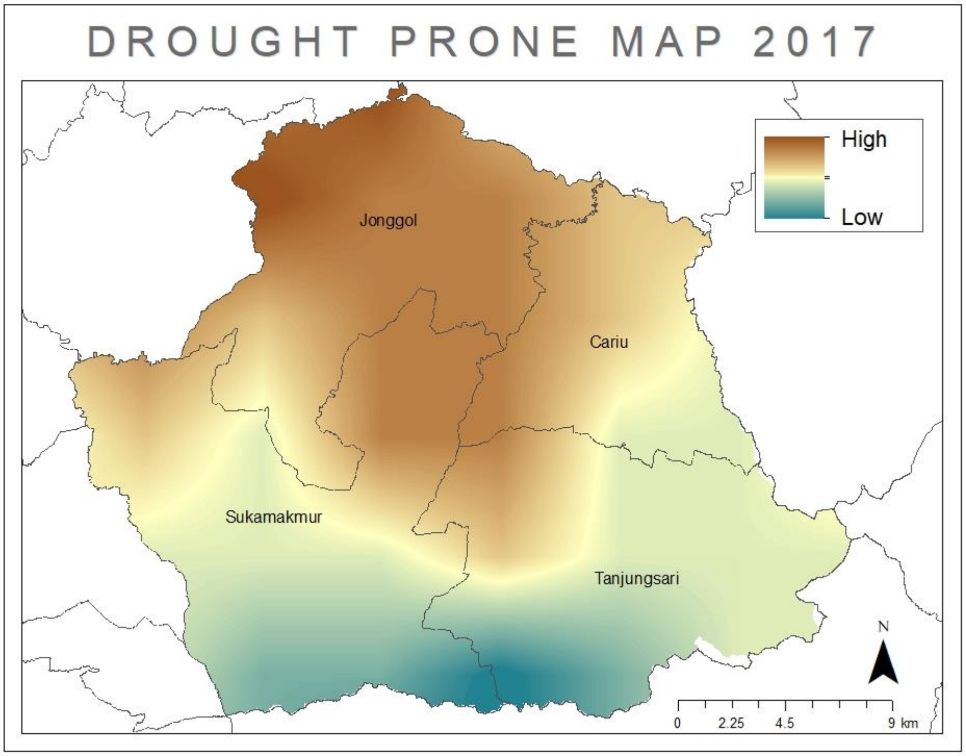

Figure 2. Drought-prone map of Jonggol, Cariu, Sukamakmur and Tanjungsari Subdistricts

(National Disaster Management Agency, 2017)

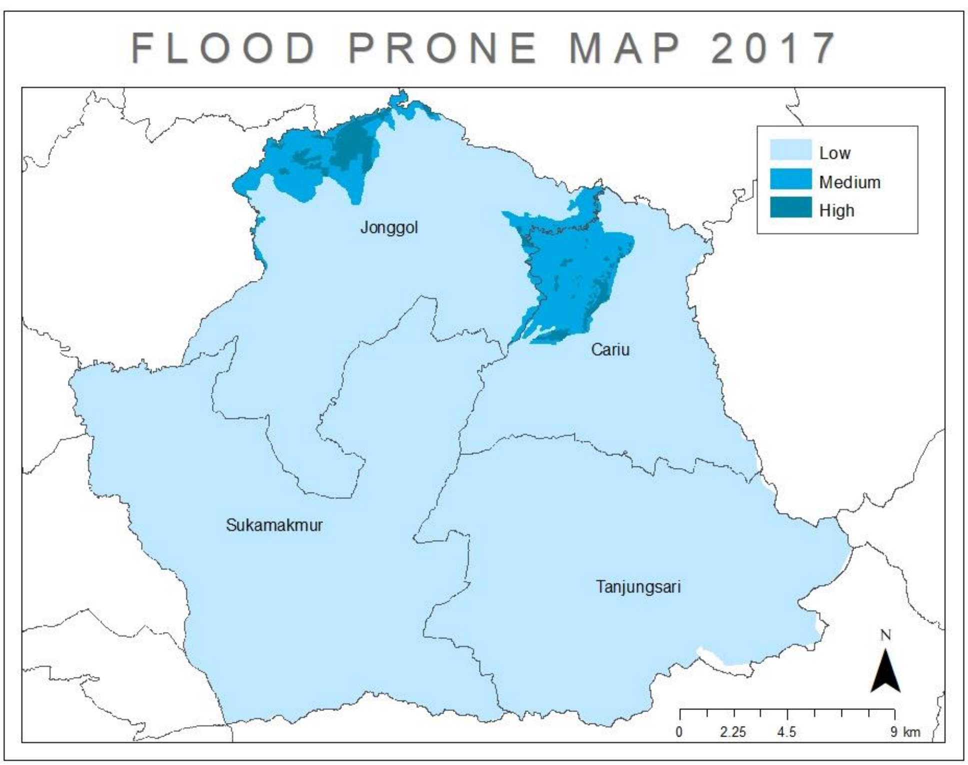

Figure 3. Flood-prone map of Jonggol, Cariu, Sukamakmur and Tanjungsari Subdistricts

(Geospatial Information Agency, 2017)

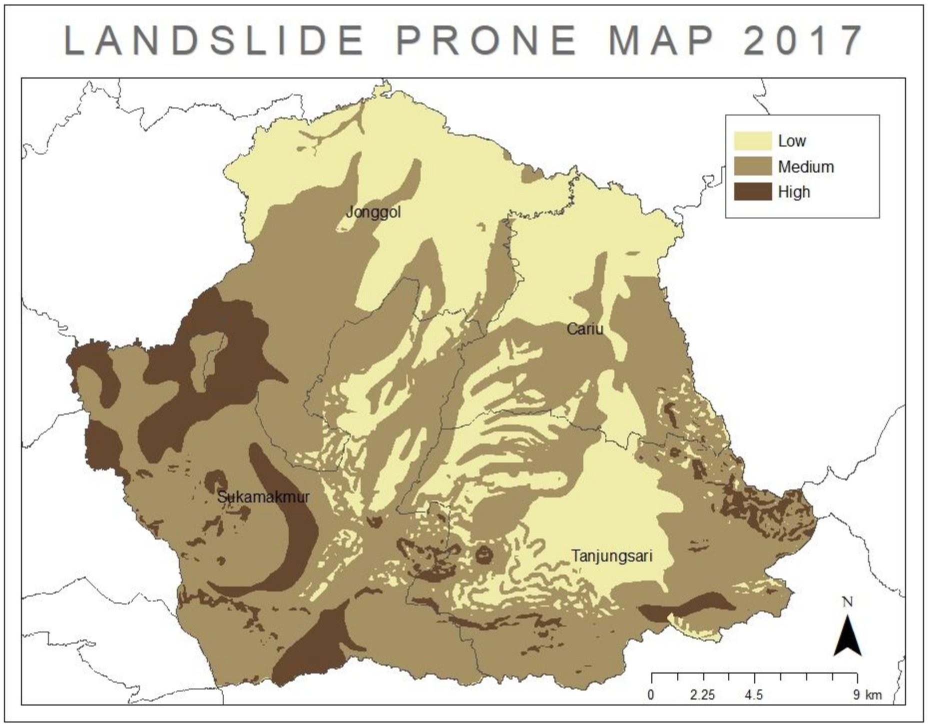

Figure 4. Landslide-prone map of Jonggol, Cariu, Sukamakmur and Tanjungsari Subdistricts

(Ministry of Energy and Mineral Resources, 2017)

Rainfall variables are also used in the preparation of the paddy productivity model because linear regression models are formed based on temporal data, while secondary data in the form of natural disaster-prone maps issued by data custodians only at maximum prone or only one map in one year. Spatial analysis of rainfall is used to determine the distribution of rainfall distribution in each month so that it can determine the effect of rainfall with the planting phase time and paddy productivity. The growth of paddy plants is very dependent on water sources, one of which comes from rainfall that is used to meet the needs of plants for water and good water management is needed for irrigating paddy farms (Thakur et al., 2013). Rainfall analysis based on Oldeman classification shows that Jonggol, Tanjungsari, Cariu, and Sukamakmur sub-districts only have dry months and humid months (Figure 5). Dry months are from May to October, at that time the condition of paddy fields in the condition of the final generative phase is at the time of cooking until the condition of the fallow phase or not during the paddy planting period. Humid months are in the period from November to April, at that time is the initial phase of planting in November and March. In the humid months it can be produced two times the paddy planting period.

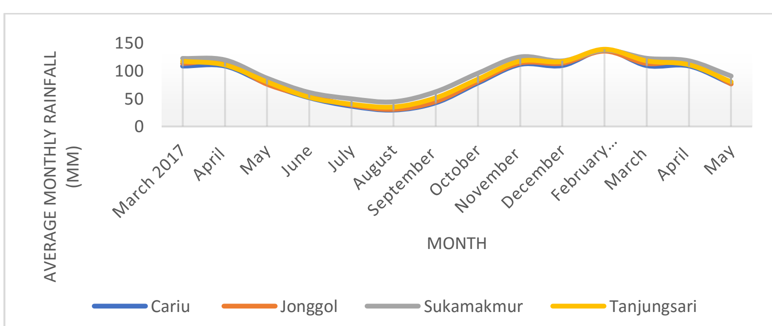

Figure 5. Average monthly rainfall patterns in Jonggol, Cariu, Sukamakmur and Tanjungsari Subdistricts

(Data processing, 2019)

The method used in making a model of paddy productivity is a linear regression model with the OLS method or the least-squares method. The OLS method will produce an estimator that is unbiased, linear and has a minimum variance (best linear unbiased estimators - BLUE) (Frost, 2018). The results of the linear regression model in the form of an algorithm that can be used to estimate paddy productivity based on the conditions of the paddy planting phase. The results of the spatial model in the form of an effective algorithm, one of which is paddy rice planting index (PRPI), which is used to map rice paddies nationally in China (Song et al., 2018). The algorithm produced in this study is as follows.

a. Paddy productivity in the initial phase of planting = 66.40 – (1.033 * rainfall) – (0.204 * prone to landslides) – (0.430 * prone to drought) – (0.486 * prone to floods)

b. Paddy productivity in the vegetative phase = 69.46 – (1.59 * rainfall) – (0.35 * prone to landslides) – (1.33 * prone to drought) – (0.50 * prone to floods)

c. Paddy productivity in the generative phase = 68.51 + (0.73 * rainfall) – (0.69 * prone to landslides) – (2.15 * prone to drought) – (0.62 * prone to floods)

The influence of environmental vulnerability and rainfall in the vegetative phase has an inverse relationship, which decreases the level of flood-prone, prone to landslides, prone to drought and rainfall will result in higher paddy productivity. The increase in minimum temperature, rainfall, and relative humidity has a positive impact on paddy productivity even though it is not significant (Grover & Upadhya, 2014). In the vegetative and generative phase, drought-prone variables have a large influence on the estimation of paddy productivity, so that if there is an increase in prone drought it will cause a decrease in paddy productivity. Rainfall variables also have a large influence on productivity predictions, but in the vegetative phase there is no need for high rainfall or in the dry to moist months. The comparison of the relationship of environtmental vulnerability to paddy productivity in each paddy planting phase can be seen in Table 2.

Table 2. Comparison of the relationship of environmental vulnerability to paddy productivity in each paddy planting phase (Data processing, 2019)

No	Planting Phase	Variable	Relationship to Paddy Productivity	Adjusted r^2
1	Initial Planting Phase	Rainfall	Negative	0.35
		Prone to flooding	Negative	
		Drought-prone	Negative	
		Prone to landslides	Negative	
2	Vegetative phase	Rainfall	Negative	0.63
		Prone to flooding	Negative	
		Drought-prone	Negative	
		Prone to landslides	Negative	
3	Generative Phase	Rainfall	Negative	0.61
		Prone to flooding	Positive	
		Drought-prone	Negative	
		Prone to landslides	Negative	

The adjusted r2 results in the vegetative phase and the generative phase has a strong enough relationship to predict paddy productivity using the paddy planting phase classification model (McLean et al., 1980), while the initial phase of planting has a weak or cannot be used to predict paddy productivity.

3.3. Spatial Model of Paddy Productivity based on Environmental Vulnerability in Each Paddy Planting Phase

The Spatial Model of Paddy Productivity based on Environmental Vulnerability in Each Paddy Planting Phase is a combination of paddy planting phase classification models and linear regression models of paddy productivity so that it can be used to estimate paddy productivity spatially. The application of the two models was carried out on Sentinel 2A images with Recording Date 31 in 2017. The results of the paddy planting phase prediction produced according to the planting calendar issued by UPT Jonggol and UPT Cariu. Planting phase based on cropping calendar shows that paddy plants at the end of December 2017 are in the vegetative phase condition for Jonggol, Sukamakmur, Cariu and Tanjungsari sub-districts. The results of the spatial modeling of the paddy planting phase on December 31, 2017, were dominated by the vegetative phase in all sub-districts (Figure 6).

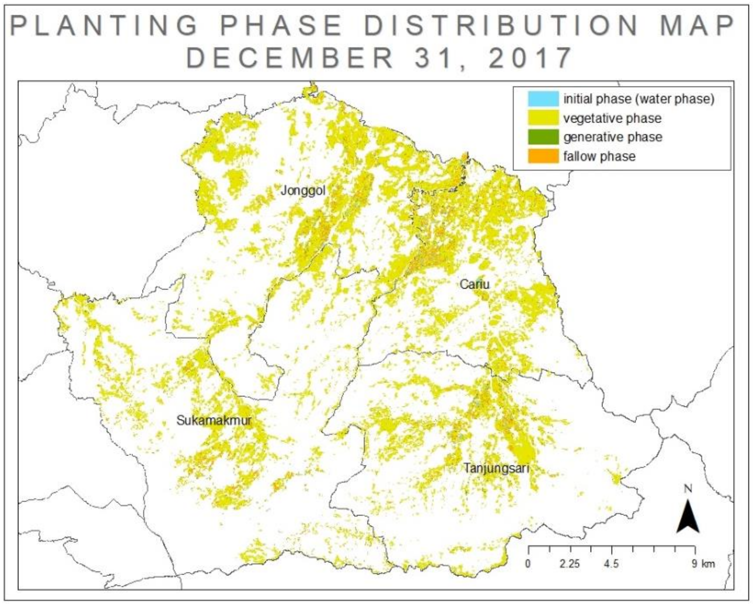

Figure 6. Planting phase distribution map December 31, 2017

(Data processing, 2019)

The prediction results of the distribution of the paddy planting phase based on the random forest classification model need to be validated again to determine the product accuracy of the paddy planting phase distribution map on December 31, 2017. Validation is done by testing the accuracy using the Confusion Matrix method. The data used in the accuracy test is the planting phase data from the prediction of the random forest classification model which is used as primary data which then compared with the planting phase data resulting from field data processing. The results of the test using the Confession Matrix method are of the overall accuracy of 87.5% in Sentinel-2A processing images on December 31, 2017. The distribution map of the paddy planting phase on December 31, 2017 is acceptable because the overall accuracy is greater than 85%, which according to the United States Geological Survey (USGS) that the level of accuracy of classification or minimum interpretation using remote sensing data is 85%.

The results of the distribution of the paddy planting phase then calculated for estimating the paddy productivity algorithm. The highest estimated productivity of paddy or greater productivity of 6.17 tons/ha found in Mekarwangi Village, Cariu District. The results of predictions of paddy productivity from both spatial models illustrate that paddy productivity in a region is very influential on the geographical and climate conditions of a region. The geographical conditions of research with varied topography provide different environmental vulnerabilities. This environmental vulnerability illustrates environmental degradation that will affect paddy productivity.

Appropriate use of paddy plantations and not in areas prone to natural disasters will provide higher paddy productivity. Jonggol and Cariu sub-districts which have relatively flat topography and have a lot of river flow, making the potential of irrigation in these two sub-districts easier. Whereas in Tanjungsari and Sukamakmur Subdistricts faced with limiting factors such as the relatively high topography conditions, the slope is relatively steep so that it has relatively high landslide vulnerability and poor agricultural irrigation factors which are highly dependent on rainfall which causes lower paddy productivity. Beside geographical conditions, climate conditions also widely affect paddy productivity, especially in paddy fields, whose primary source of irrigation comes from rainfall. This can be seen from the results of the paddy productivity model (Figure 7) that produced that the variables prone to drought and rainfall are the variables that have the highest influence on the estimation of paddy productivity and have a direct impact on paddy crops.

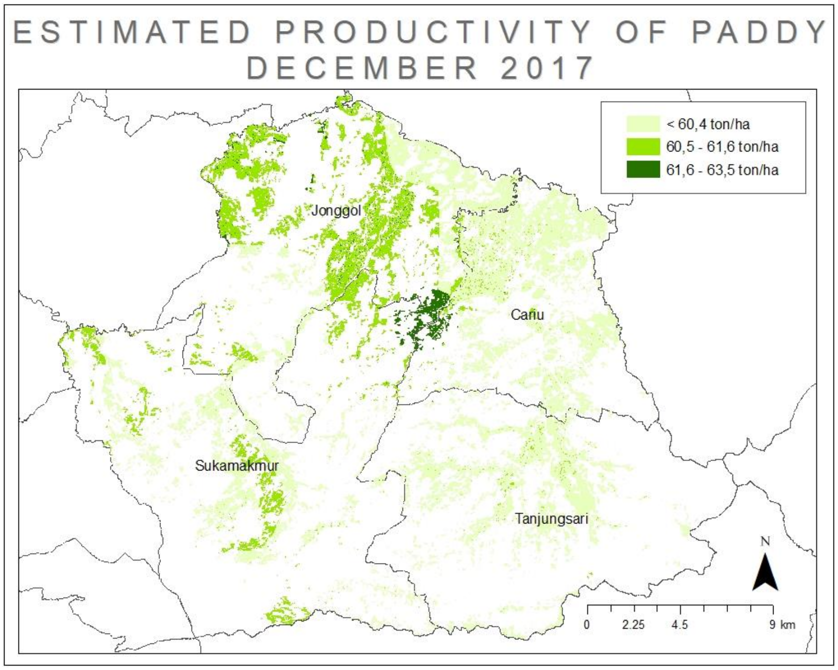

Figure 7. Map of estimated productivity of paddy in December 2017

(Data processing, 2019)

4. Conclusion

The spatial model of the paddy planting phase with a beneficial random forest classification method is used to see the distribution of the paddy planting phase in an area. The factors used to estimate the planting phase, namely the combination of vegetation indexes consisting of NDVI, EVI, SAVI, and NDWI are mutually temporal with overall accuracy of the model of 92 %. The spatial model of the influence of environmental vulnerability on paddy productivity which consists of variables prone to flooding, prone to drought, prone to landslides and rainfall in each phase of paddy planting can use as a tool to estimate paddy productivity. The difference in the influence of environmental vulnerability in productivity estimation occurs in each phase of paddy planting. Estimation of paddy productivity by spatial modeling influence of environmental vulnerability can be detected in the vegetative and generative phases because it produces a relatively stable accuracy of 0.63 in the vegetative phase and 0.61 in the generative phase. Whereas the initial phase of planting cannot use in estimating paddy productivity because it has a weak accuracy of 0.35. The highest environmental vulnerability variables that affect paddy productivity are prone to drought and rainfall.

5. Acknowledgements

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