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The use of a MLP neural network for analysis and aodeling of land use changes with variations variable of physical and economic social

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Abstract. Modeling the land use changes is a method that used to understand the causes and effects of dynamic changes. The model in this research is the ANN model with Multi-layer Perceptron (MLP) network architecture and backpropagation algorithm. The Artificial Neural Network (ANN) method is a potential method for land change as well as test the predictive abilities that will be produced by the model. Land use change modeling uses a combination of ANN and GIS methods. The aim of this research are (1) predict land use and land use change in Banyumanik District in 2011, 2015 and 2019, (2) build the land use model using the ANN method and (3) predict of land use in Banyumanik District in 2027. To predict the land use change is use Markov Chain models. The purpose of modeling land changes is as well as the factors that drive these changes. Some of the drivers of land use changes are physical and socio-economic variables. Physical variables are distance to road, distance to river, distance to agricultural and vacant land, elevation, slope, and climate. Whereas the economic variables are population density, and market land prices. Physical data variables obtained from high resolution satellite image processing. For socio-economic variables data are obtained from statistical data and field surveys. In this research, the model is carried out in a framework with various variables that are different, so that the best model is obtained. Cramer's V value each variable is tested to see the relationship between these variables.

1. Introduction

The Changes in land use and land cover (LULC) can be analyzed using the model [1]. The model used is a technique or method used to determine the causes by dynamic changes caused [2]. [3] Conducted a model of land use change in Siak Regency to find out the process and patterns of changes that occur and the variables that drive these changes. [4] Modeling with changes models in demographic and physical factors in land use or closure in Costa Rica, including reciprocity of land use or self-closure of the above factors. [5] Conducted a research of decreasing availability of vacant land due to an increase in residential areas which was followed by an increase in fair market land prices in Banyumanik Regency, Semarang City.

The benefits of the land use change model are used for environmental impact studies [6]. Future land use planning and policies can be seen from the results of the final analysis of modeling changes in use. Some researchers model changes in land use using various methods. [3] Uses modeling using the Multinomial Logistic Regression (MLR) method. The results of this modeling were successfully built

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and could explain variations in land use changes at the research site making land use predictions in the next 20 years with the Markov Chain model after successfully modeling land use changes with regression analysis in Beijing, China. [7]. Another modeling method that can be used to modeling the land use change is the Artificial Neural Network (ANN) method. ANN means artificial neural network, is a computational structure developed based on biological neural network processes in the brain. The use of ANN has experienced a considerable increase in recent years due to increased computing performance [8]. [9] Simulates changes in settlements in the Tehran Metropolitan area, Iran with backpropagation Artificial Neural Networks and looks at how road factors, slopes, administrative areas, service centers and housing areas affect the changes that occur. While [10] used ANN to model settlement changes in Michigan, both on a local and regional scale. The accuracy of the resulting model is quite good at both scales. ANN in this research is used to determine the location or any area of land use that is allocated and unoccupied shrubs that have the potential to turn into plantations. GIS is used to construct spatial aspects and build driving variables that change's affect. The driver factors of land use change are physical and socio-economic variables. Physical variables are distance to the road, distance to the river, distance to agricultural and vacant land, altitude, slope, climate. While economic variables are population density, and market land prices in the form of an average indication value (NIR). Physical data variables are obtained from high resolution satellite image processing. The socio-economic variables, data obtained from statistical data and field surveys.

In this research, the model is carried out in various frameworks, so that the best model is obtained. By combining the ANN method with GIS, it is expected to provide a better answer in modeling land use change. There are three types of ANN, namely the Multilayer Perceptron, Radio Base Function, and the Kohenen Network. Multilayer Perceptron is the most widely used model for making predictions [11]. In this research, the Multilayer Perceptron model is used because this model is commonly used in prediction problems. Multilayer Perceptron is a model that maps data input sets into output sets, using nonlinear activation functions. In the Perceptron Multilayer, the dependent and independent variables can have metric or nonmetric level measurements [11]. The socio-economic variable data obtained from statistical data and field surveys. In this research, the model is carried out in a framework with a variety of different variables, so that the best model is obtained.

2. Material and methode

2.1. Studi area

The area of this research is in Banyumanik District, Semarang City, Central Java, Republic of Indonesia. The area is located on the outskirts of the city and is at an average altitude of 300 meters above sea level. Banyumanik District located in the most southern region of the Central Government of Semarang City with hilly topography and settlement areas. The boundaries of the District Banyumanik Region are as follows : North is Candisari and Gajah Mungkur District, East is Tembalang District, South is Semarang District, in the West is Gunungpati District. Map Administration of the Banyumanik District show in Figure 1a.

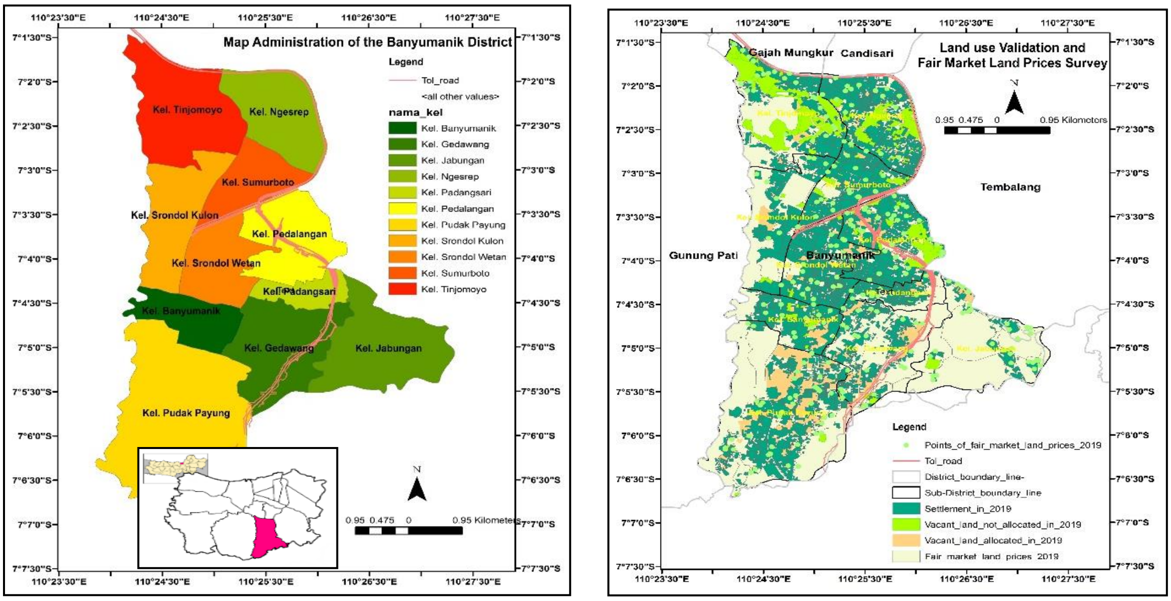
2.2. Research data

The data in this research includes data spatial and non-spatial, there are:

- Rectified satellite imagery data from recording Quickbird in 2010, Ikonos in 2015 and Spot 6 in 2019.
- Map Administration of the Banyumanik District, Semarang City from Development Planning Agency.
- Fair Market Land Prices in period 2011, 2015 and 2019 obtained from the field survey, fair market land price survey data in the field using a sample point distribution work map as in Figure 1 (b).

- Land use map in 2011 used secondary data from the results of field interpretation and validation by the authors themselves in previous studies.
- Scale 1: 25,000 RBI map from BIG to get road and river data
- In this study the driving force variable we limit to physical variables are elevation, slope, climate, land movement, type of soil from Development Planning Agency. Population density and infrastructure obtained from statistical data. Land use, distance to road, distance to river, distance to agricultural land, vacant land and toll gate obtained the digitizing on satellite imagery.

Physical and socio-economic variables as driver factors of land use change such as elevation, land slope, climate and land movement, and population density and market land prices can be seen in **Table 1.**



(a) (b)

Figure 1. (a) Map administration of the Banyumanik District and (b) Overlay of settlement and a distribution of 300 sample points for field check land used for field surveys.

2.3. Modeling changes in land use

The definition of a spatial based model was put forward by [12], where the model is an abstraction from the real world system that has a significant detail problem with the problem being studied, and also has transparency, so that the mechanisms and key factors that influence change can be identified. Modeling changes in land use is one form of modeling that has attracted the attention of several researchers in the world. They study the existence of a causal relationship between the management of a land and changes in land use that occur. Modeling land use change has several uses, among others, to explore a variety of activities in which a change in land use is driven by socio-economic factors [13], predicting the economic and environmental impacts of these changes and evaluate the impact of government policies in determining land use and land management [14].

2.4. Modeling change in land use by Artificial Neural Network (ANN) method

Modeling land use changes is one form of modeling that has attracted the attention of several researchers in the world. They study the existence of a causal relationship between the management of a land and changes in land use that occur. Modeling of land use change has several uses, among others, to explore various activities where the occurrence of a change in land use is driven by socio-economic factors [13],

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Artificial Neural Network (ANN) is a method, technique or approach that has the ability to measure and model a complex behavior and pattern. ANN has been used in various disciplines such as economics, health, landscape classification, pattern recognition, prediction of climatic conditions, and remote sensing [15]. Multi-layer Perceptron (MLP) is one of the most widely used ANN network architectural forms. MLP generally consists of three types of layers with a network topology as shown in **Figure 2**, namely the input layer, hidden layer and output layer that can be used to identify a non-linear relationship in real life [16].

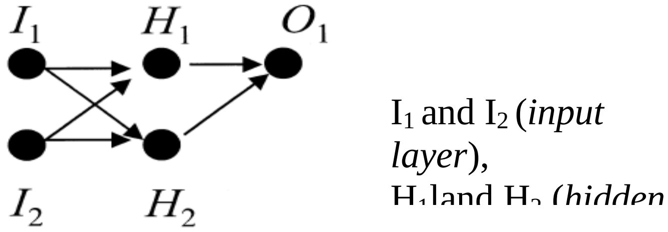

Figure 2. Illustration of Multi-layer Perceptron [10].

2.5. Data Processing

- Digitizing on satellite imagery starting with preparations that include Quickbird in 2010, Ikonos in 2015 and Spot 7 in 2019 high-resolution image procurement activities, image cutting, geometry correction, visual classification and field checking. Furthermore the image is geometry corrected by ground control point with GPS measurement has the same coordinates. After geometry correction, visual classification is based on interpretation according to size, pattern, hue, texture and color in the image. The results of the interpretation produced a 2011 land use map, 2015 and 2019 with 5 land use classes namely Settlement, Vacant Land Allocated, Vacant Land Not Allocated, Vegetation and Shrub.
- Field validation for land use, fair market land prices surveys conducted simultaneously. The data collection was conducted using some sample. The land that provides the bid and transactions price is a 24 land last month for non-agricultural and 48 land last month for farmland. The results of land use interpretation are validated in the field with a sampling method with a plan of 300 samples with a distribution as shown in Figure 1b.
- Classification of land use for vacant land results from interpretation of satellite imagery. The vacant land resulting from this interpretation is brought to the field to be validated as allocated unoccupied land and unallocated land. The difference is that vacan land allocat is characterized in the form of dry land, open land and land that has been done by land clearing that has been utilized by humans, while those not allocated in the field are characterized in the form of vacant land not yet in land clearing.
- Projection and Modeling of Land Use Stage with ANN model with Multi-layer Perceptron (MLP) network architecture and packpropagation algorithm using LCM (Land Change Modeler) application. The land use map that is used is only two year points, the 2011 and 2019 land use maps.
- Then the stage of change analysis (Change Analysis), modeling changes in land use (Transition Potentials). Each class of land use change will be modeled with the aim of predicting locations that have the potential to change into other land uses.
- Correlation test between the variables of Cramer's V value to see the relationship between these variables with the 5 classes of land use.
- The land use projection stage, a land use projection map made with the Land Change Modeler. The method is Markov Chain with the projected year is 2027.

- Perform processing with three strategies, first physical variables as a driver factor of change, the second with socio-economic variables, and the third with physical variables and socio-economic, then the results are analyzed for area.

3. Results and discussion

4.1. The physical and economic-social variables
a. The physical and social variables
Some driving variables are changes in land use including closeness to the road, closeness to the river, closeness to settlements, population density and elevation. the closeness to roads, rivers and settlements is used as a factor of change in terms of the culture of the community, meaning that the closer the land is used to roads, rivers and settlements, the faster the land use changes will occur. Population density are included in socio-economic factors that drive change, where these factors illustrate concretely the amount of demand for residential land. Data on physical and economic-social variables in the figure are calculated distances. The driving factor can be seen in **Figure 3**.

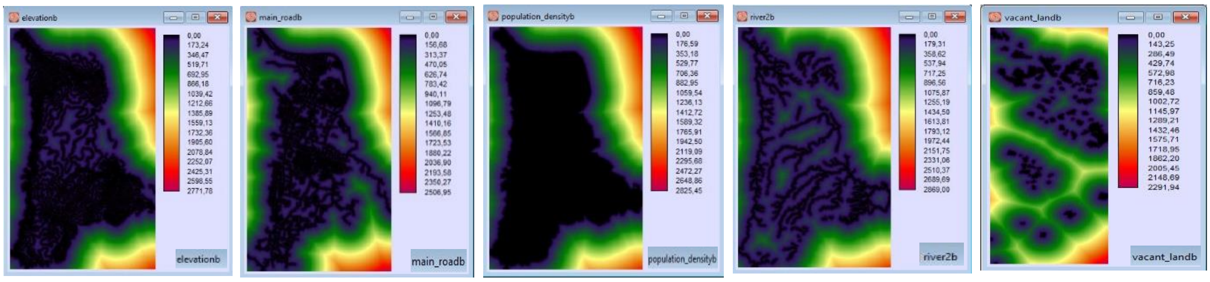

Figure 3. Data on physical and social variables.

b. The economic variables
Fair market land price data from the field survey is used as a driving force variable in predicting changes in land use. The result of the Field survey results and data processing of fair market land price in 2011, 2015 and 2019 show in **Tabel 1.**

Tabel 1. NIR fair market land price in 2011, 2015 and 2019.

Name of Village	NIR 2011	NIR 2015	NIR 2019
Banyumanik	1.580.500	3.378.500	7.692.000
Gedawang	2.201.500	2.730.000	3.775.000
Jabungan	660.000	1.622.500	1.496.000
Ngesrep	1.962.500	3.250.000	5.012.000
Padangsari	2.530.500	3.842.500	5.720.000
Pedalangan	3.384.500	4.342.500	6.227.450
Pudak Payung	3.636.500	4.568.500	2.976.000
Srondol Kulon	3.306.500	4.307.509	5.876.000
Srondol Wetan	3.379.500	4.402.000	3.978.000
Sumurboto	4.893.000	7.377.500	7.991.000
Tinjomoyo	1.995.500	3.355.000	4.063.000

From **Table 1** and **Figure 4** it can be seen that all Sub-District in Banyumanik District experienced increases in land prices, both minimum and maximum. Each village experienced the highest increase in land prices starting from Sumurboto, Tinjomoyo, Srondol Kulon and Banyumanik. The increase in almost every period is very high because it is a central region and business. In the past few years, land use changes and land prices in the 4 sub-district areas have shown an interesting phenomenon. The use of land previously in the form of open space, agriculture, and vacant land, turned into settlements and trade in services which were considered to have more commercial value strategic and competitive.While the villages experiencing the lowest price increase are Jabungan, which is a rural area and far from the city center. This is because land is an economic good whose availability continues to decrease every year.

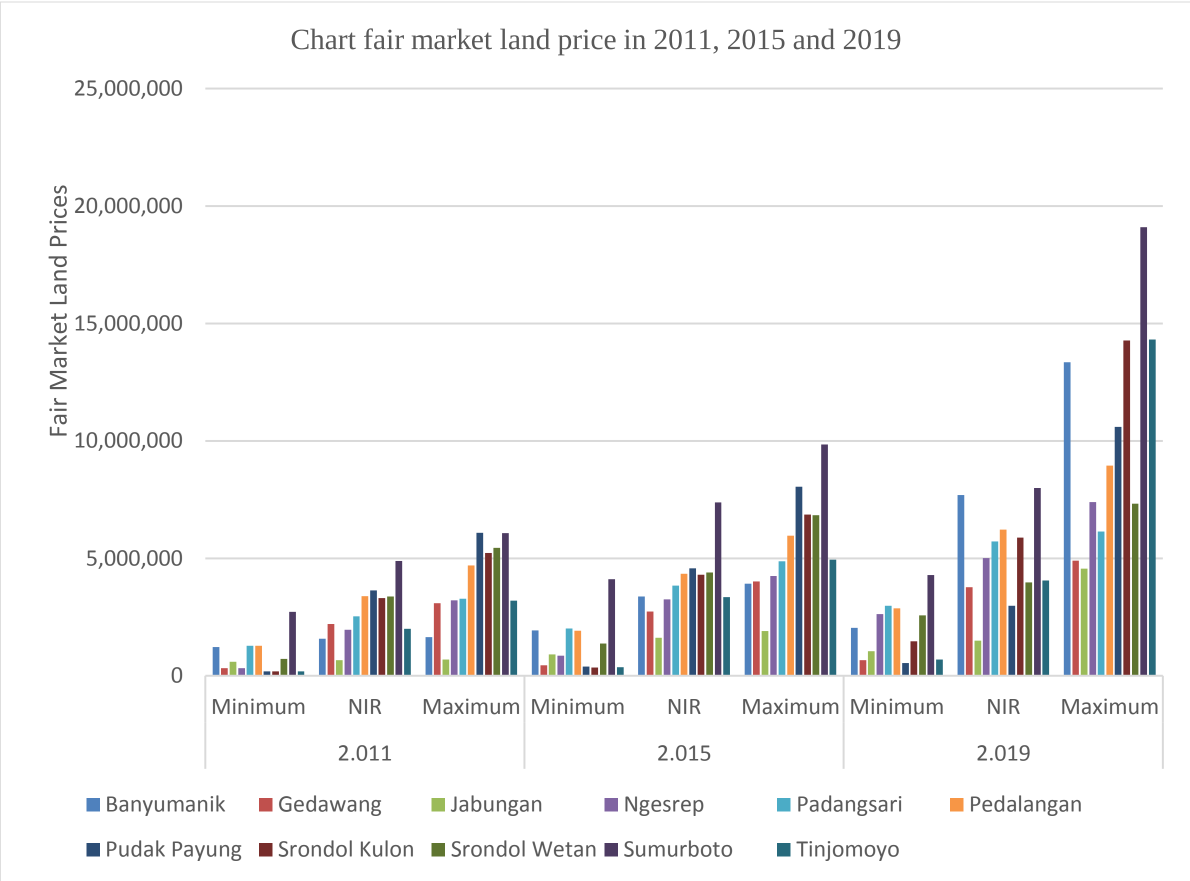

Figure 4. Chart fair market land price in 2011, 2015 and 2019.

c. The Driving variables and value testing testing the value of Cramer's V

Variables are tested for the value of Cramer's V. Cramer's V measures the relationship between one variable with each land use with a value range of 0-1, where 0 indicates no association, while value 1 indicates a close relationship between these variables and land use. The **Table 2** it can be seen that the variable has a Cramer's V value of more than 0.1 so that the variable can be entered into the model.

Table 2. The value of testing physical and social variables with the Cramer's V value test

Cramer's Distance to		(1)	(2)	(3)	(4)	(5)	Overall V
Agricultural Land	Cramer's V	0	0,1669	0,112	0,0974	0,2098	0,2258
	P Value	1	0	0	0	0	0
Elevation	Cramer's V	0	0,1261	0,1219	0,2498	0,1242	0,1556
	P Value	1	0	0	0	0	0
	Cramer's V	0	0,0979	0,14	0,2354	0,1003	0,1381

Fair Market Land Price	P Value	1	0	0	0	0	0
Land Movement	Cramer's V	0	0,0601	0,049	0,0343	0,0826	0,044
	P Value	1	0	0	0	0	0
Main Road	Cramer's V	0	0,0953	0,1018	0,2533	0,1158	0,1581
	P Value	1	0	0	0	0	0
Population Density	Cramer's V	0	0,0601	0,049	0,0343	0,0826	0,044
	P Value	1	0	0	0	0	0
Rainfall	Cramer's V	0	0,0601	0,049	0,0343	0,0826	0,044
	P Value	1	0	0	0	0	0
River	Cramer's V	0	0,0155	0,0241	0,0256	0,0126	0,0173
	P Value	1	0,1891	0,0007	0,0002	0,4972	0,0027
Tol Road	Cramer's V	0	0,184	0,0973	0,146	0,1459	0,1179
	P Value	1	0	0	0	0	0
Type of Soil	Cramer's V	0	0,0601	0,049	0,0343	0,0826	0,044
	P Value	1	0	0	0	0	0
Vacant Land	Cramer's V	0	0,1286	0,1393	0,1042	0,1489	0,1072
	P Value	1	0	0	0	0	0

4.2. Land Use Area Predict in 2027

Field validation for land use surveys and fair market land prices is carried out simultaneously and can been show in **Figure 1b**. The availability of vacant land that reduced is biger due to the transition of vacant land to settlements. One example of changing vacant land into housing use is shown **Figure 5**.

Figure 5. The result of validation changes in the use of vacant land into settlements in the Pedalangan Sub-district : (a) the imagery of the year 2010 (b) the imagery of the year 2015 (c) 2019 imagery in period.

Based on the classification results has 5 land use classes namely Settlement, Vacant Land Allocated, Vacant Land Not Allocated, Vegetation and Shrub. The results classify land use categories using the Markov Chain prediction method. Predicted land use can be seen in the **Figure 6.**

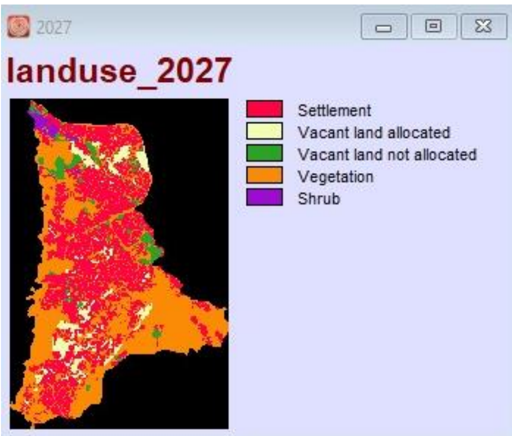

Figure 6. Landuse predictions for projections in 2027.

The area of each land use can be seen in **Table 3**. Sub-District names are replaced with the following gridcode: Banyumanik (A), Gedawang (B), Jabungan (C), Ngesrep (D), Padangsari (E), Pedalangan (F), Pudak Payung (G), Srondol Kulon (H), Srondol Wetan (I), Sumurboto (J), Tinjomoyo (H). Cover Land Code: Settlement (1), Vacant Land Allocated (2), Vacant Land Not Allocated (3), Vegetation (4), Shrub (5).

Tabel 3. Land Use Area Predict 2027.

	Physical Variable					Social Variable					Physical & Social Variable				
	Gridcode					Gridcode					Gridcode				
Sub-District	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
A	87,7	12,8	7,9	43,6	5,3	96,4	12,9	8,1	45,1	10,3	104,2	12,7	9,9	45,1	6,3
B	95,7	24,6	2,9	197,2	7,4	105,1	26,0	3,0	197,1	6,4	112,8	26,0	4,8	153,3	9,4
C	39,2	7,8	5,1	303,8	10,5	43,1	6,8	5,2	303,2	8,5	52,8	4,6	7,0	259,4	7,5
D	142,7	42,2	12,1	55,2	0,2	148,7	41,9	12,4	59,9	0,2	158,8	39,4	14,2	59,9	0,2
E	42,8	1,6	11,1	43,3	0,2	51,9	1,3	11,2	44,6	0,3	59,1	1,7	8,0	44,6	0,3
F	152,7	0,6	41,4	54,8	0,1	156,8	1,6	42,1	58,9	0,1	157,2	10,0	43,9	58,9	0,1
G	214,2	69,3	2,5	363,3	8,3	224,6	67,0	2,6	315,5	9,0	241,7	77,5	4,4	321,7	6,0
H	103,9	1,3	2,8	140,6	0,4	106,3	8,4	2,9	141,6	0,5	122,2	0,1	4,7	97,8	0,5
I	144,2	6,6	2,8	38,6	10,5	148,0	9,0	2,9	42,9	5,5	146,6	10,0	4,8	42,9	7,5
J	118,9	0,8	9,6	36,1	6,3	123,8	2,8	9,9	39,3	10,3	133,0	1,2	11,8	39,3	5,3
K	105,4	14,5	67,0	135,5	35,3	114,5	14,0	67,3	88,0	25,4	114,7	31,4	69,1	94,2	30,4

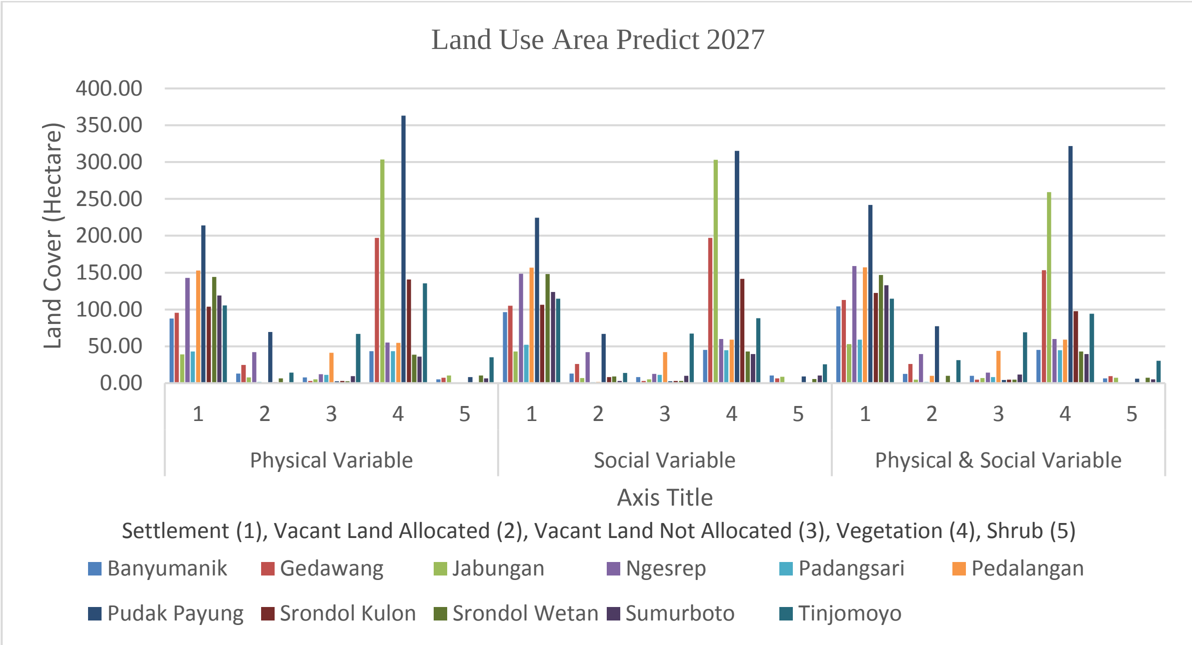

Figure 7. Land Use Area Predict 2027.

Table 4. Land use resulting from predictions with various driving variables.

	Physical Variable (PV)		Social Variable (SV)		Physical & Social Variable (PSV)		PV-PSV		SV-PSV	
LU Code	Area (Hektare)									
1	1.247,3	40,4%	1.319,1	42,7%	1.403,2	45,4%	155,9	12,5%	84,1	6,4%
2	182,1	5,9%	191,7	6,2%	214,6	6,9%	32,5	17,8%	22,9	12,0%
3	165,1	5,3%	167,6	5,4%	182,6	5,9%	17,4	10,5%	15,0	9,0%
4	1.411,8	45,7%	1.336,1	43,2%	1.217,1	39,4%	-194,8	-13,8%	-119,0	-8,9%
5	84,5	2,7%	76,4	2,5%	73,4	2,4%	-11,0	-13,0%	-3,0	-3,9%
Total	3.090,8	100%	3.090,8	100%	3.090,8	100%				

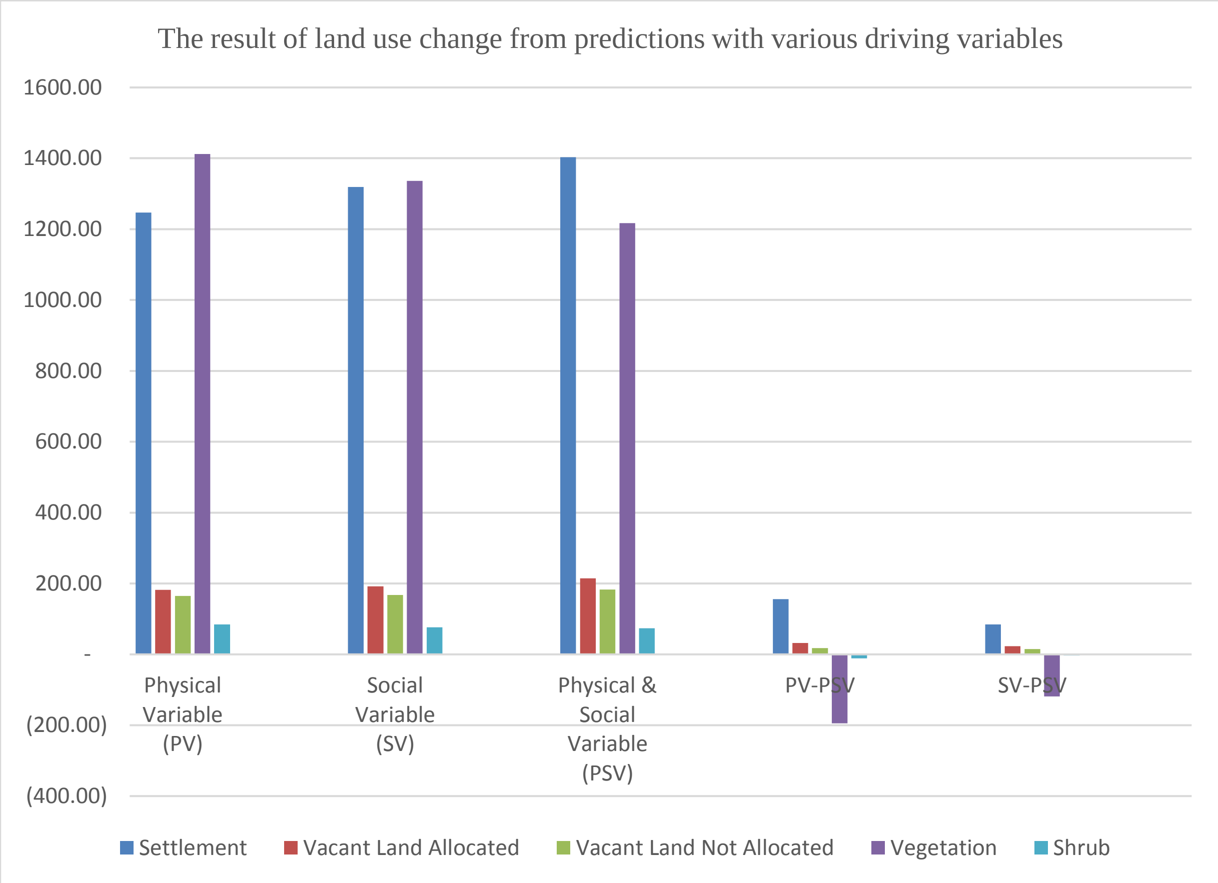

Figure 8. The result of land use change from predictions with various driving variables.

5. Conclusion

Land use changes that occurred in the period 2011-2015, and 2015-2019 were dominated by reduced vegetation area, shrubs and vacant land not yet allocated, and the increase in the area of settlements and vacant land has been allocated. Modelling of land use change using the MLP-ANN method at two years points (2011 and 2019) with driving variables namely physical and social-economic variables showing the results of the accuracy of the model is quite good (80%). Opportunities for vegetation, shrubs and vacant land have not been allocated to change into quite high settlements (0.95). While the land use projection with a combined scenario of two physical and economic social variables as drivers of land change shows the results of a better model accuracy (88%). Opportunities for vegetation, shrubs and vacant land have not been allocated to change into quite high settlements (0.99). With a combined variable indicates that settlements will dominate almost 56% of land use in Banyumanik Distric in 2027.

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