Detection of satellite data-based flood-prone areas using logistic regression in the central part of Java Island

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Abstract. The history of natural disasters recorded in BNPB (2019) explains that the total number of natural disaster events in the central part of Java (Central Java Province and Special Region of Yogyakarta Province) ranks highest in terms of the number of frequency of occurrences nationally. Of the total natural disasters that have occurred in Central Java, the number of floods is ranked third after the landslide and tornado disaster, which is around 1500 disasters. Various factors that can cause flooding cannot be eliminated. However, what is more, necessary is how to control the impacts caused by floods so that they can be managed and monitored appropriately. One effort to overcome the problem of the threat of flooding is to develop a detection model for flood-prone areas. In this study, the detection of flood-prone areas was carried out by using a logistic regression method that takes into account the variables that cause flooding such as elevation, land slope, river distance, flow accumulation, rainfall, and runoff coefficients. The results of the modelling, obtained coefficients of the variables/parameters mentioned earlier, namely intercept (5.05766 – 16.13210), rainfall (-0.01547 – 0.04075), elevation (-0.02173 – -0.00592), slope (-0.28108 – -0.01940), runoff coefficient (-9.10476 – 7.15039), river distance (0.00038 – 0.00783), and flow accumulation (-9.26342E-06 – 0.00309). The level of success in this modelling testing was 93.47826% - 98.26087% of 329 flood event data points and not floods.

1 Introduction

The history of natural disasters recorded in the National Disaster Management Agency (BNPB) explains that the total number of natural disasters in the central part of Java island (Central Java Province and Special Region of Yogyakarta Province, DIY) rank highest in terms of the number of occurrences of frequency nationally. More than 7000 recorded various natural disasters ranging from floods, landslides, tornadoes, earthquakes, tsunamis, forest fires, droughts, and other natural disasters, which have occurred in this area in the period up to 2019. This indicates that Central Java has a very high level of vulnerability to the threat of natural disasters.

According to the BNPB, natural disasters that occurred in the central part of Java Island were dominated by floods, landslides, and tornadoes. From the total natural disasters that have occurred in those regions, the number of floods occurred in third place after landslides and tornadoes, which were around 1500 disaster events as can be seen in table 1. Furthermore, there are more than 25 districts/cities in the provinces of Central Java and DIY that are vulnerable to flood hazards due to occurring every year during the rainy season [1].

Journal of Physics: Conference Series **1367** (2019) 012086 doi:10.1088/1742-6596/1367/1/012086

Table 1. Frequency of natural disasters in the central part of Java Island (1815-2019).

No	Type of Disaster	Central Java	Special Region of Yogyakarta
1	Floods	1429	68
2	Landslides	2098	124
3	Floods and Landslides	1	0
4	Tidal / Abrasion Wave	23	9
5	Tornado	1961	177
6	Drought	433	48
7	Forest and Land Fires	88	1
8	Earthquake	35	14
9	Tsunami	7	0
10	Volcanic Eruption	28	15

A flood is an event or situation, in which an (urban) area is submerged since the water level in the rivers increase and overflow to plains around the river due to heavy rainfall intensity [2]. Recently, there is an increase in extreme rainfall resulting from global warming phenomena, namely increased in the surface temperature of the earth leading to climate change. The United Nations Office for the Coordination of Humanitarian Affairs report states that Indonesia is one of the countries most vulnerable to extreme climate-related disasters [3].

In addition to extreme rainfall factors, the cause of the increase in floods is human activities because of increasing population growth and rapid infrastructure developments [4]. It is a logical consequence that the many development activities will have an impact on changes in land use from infiltration areas to build areas reducing the flood retention capacity.

Various factors that can cause flooding cannot be completely eliminated. However, what is more, necessary is how to control the impacts of floods so that they can be managed and monitored appropriately. One effort to overcome the problem of the threat of flooding is to develop a model that can detect flood-prone areas. Accurate detection of flood-prone areas can strengthen the flood disaster early warning system so that it can minimize both material and non-material losses caused by floods. This study aims to develop a model for flood prediction using logistic regression.

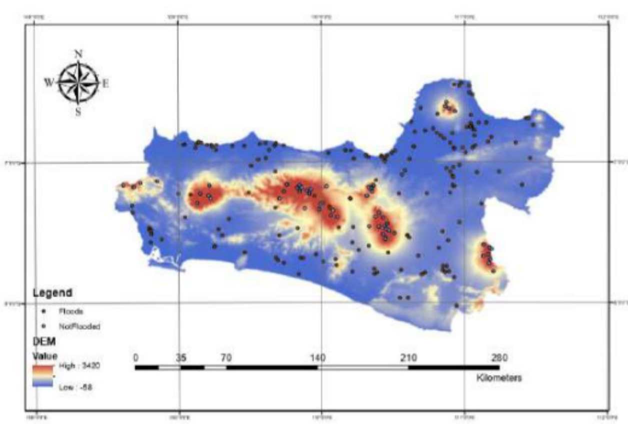

Figure 1. Map of Central Java and Special Region of Yogyakarta Provinces.

Journal of Physics: Conference Series **1367** (2019) 012086 doi:10.1088/1742-6596/1367/1/012086

2 Data and study location

2.1 Study location

The location of the study was conducted in the central part of Java, as shown in figure 1. Geographically, the Province of Central Java is located at 5° 40 "and 3° 30" South Latitude and between 108° 30 "and 111° 30" East Longitude (including Karimunjawa Island). The farthest distance from West to East 263 km and from North to South 226 km.

According to the Regional Disaster Management Agency (BPBD) in Central Java Province, a number of regions were listed as prone to flash flood. The area is on the banks of a large river. Areas prone to flooding include Banyumas, Purwokerto, Pati, Demak, Kudus, Brebes, Cilacap. Areas are prone to large rivers such as Karanganyar, Solo and Sukoharjo.

2.2 Data collection

The data needed in this study can be explained as follows:

2.2.1 Topographic data obtained from digital elevation model (DEM). This topographic data uses the most recent Shuttle Radar Topography Mission (SRTM) Data with the spatial resolution of 30m x 30m [5]. This DEM data will be processed to find out the slope and configure pixels where flow. The following is a map of Central Java DEM which can be seen in Figure 2. slope map in Figure 3., and flow accumulation map in Figure 4.

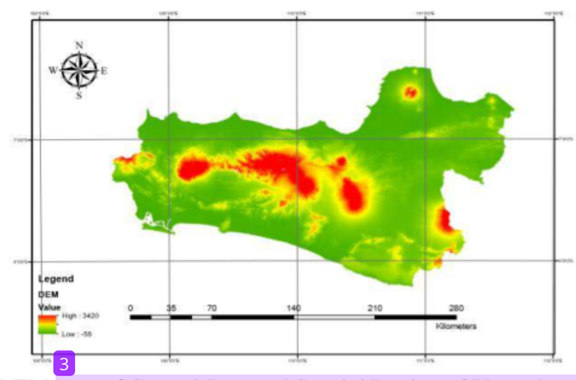

Figure 2. DEM map of Central Java and Special Region of Yogyakarta Provinces.

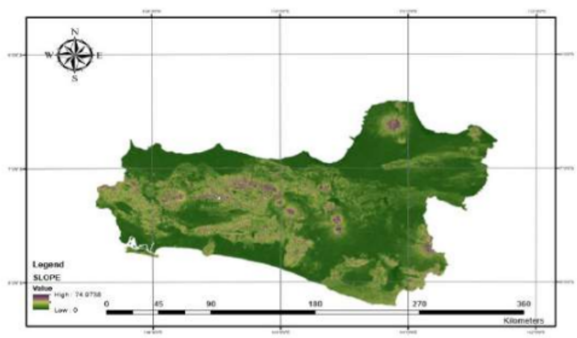

Figure 3. Slope map of Central Java and Special Region of Yogyakarta Provinces.

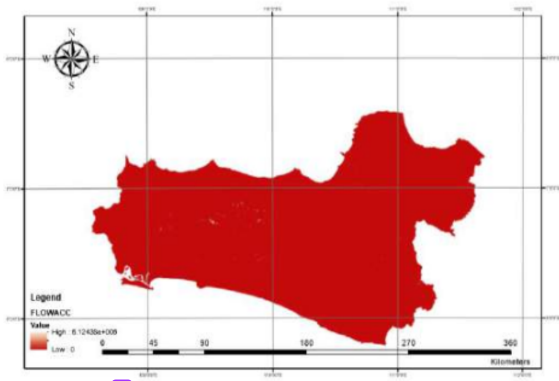

Figure 4. Flow accumulation map of Central Java and Special Region of Yogyakarta Provinces.

2.2.2 Precipitation data. Daily rainfall data used in this study is the TRMM (Tropical Rainfall Measuring Mission) satellite from the range of 1998 to 2018 [6], [7], [8]. The satellite data is processed using ArcGis, Microsoft Excel, and RStudio software. The following is an example of the TRMM rainfall map of Central Java Province on May 16, 2016, as can be seen in Figure 5.

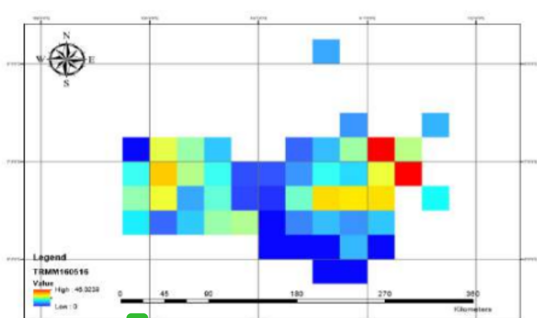

Figure 5. TRMM rainfall map of Central Java and Special Region of Yogyakarta Provinces.

2.2.3 Spatial data on flood events (historical flood)

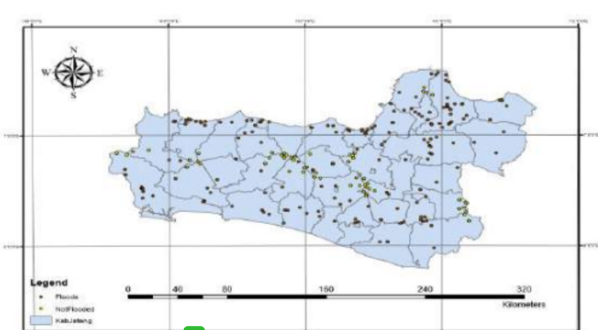

Figure 6. Historical flood map of Central Java and Special Region of Yogyakarta Provinces.

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The historical flood data used is flood data that has occurred in the Central Java and DIY provinces. The data is then combined with daily rainfall data, so that rainfall is known in the flooded area. Map of flood events in Central Java and DIY are shown in Figure 6.

2.2.4 Land use land cover data (LULC). LULC data was obtained from TERRA MODIS satellites and data were used from 2001 to 2017 [9]. The data will show changes in land use caused by development in the Central Java Province. The following is an example of the 2017 Central Java LULC map which can be seen in Figure 7.

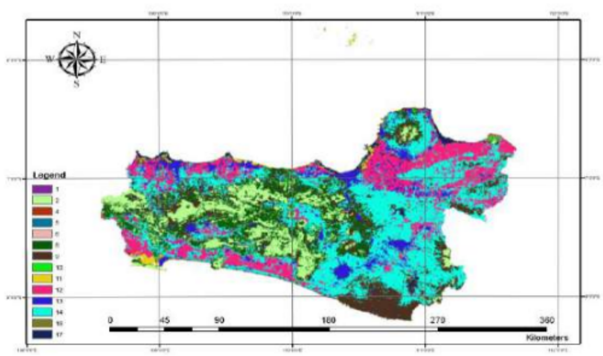

Figure 7. LULC map of Central Java and Special Region of Yogyakarta Provinces.

2.2.5 River network data. River network data is obtained from http://tanahair.indonesia.go.id_per district of Central Java. This data will configure the river network in Central Java and display the distance of flood-prone areas with the river network. Map of the river network in Central Java Province can be seen in Figure 8.

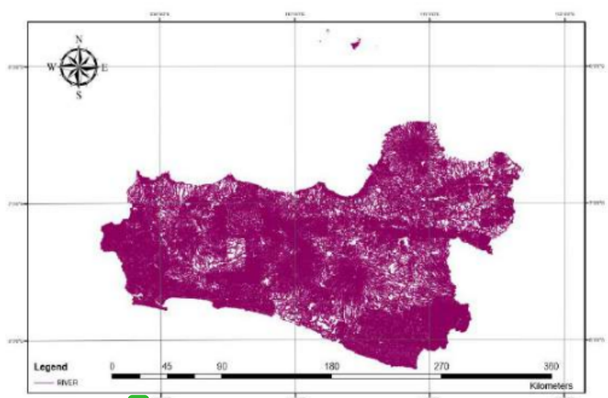

Figure 8. Stream map of Central Java and Special Region of Yogyakarta Provinces.

The data that has been mentioned, will later be used for data processing as a logistic regression modeling factor. The following is a summary of the data types that will be used in Table 2.

Tabel 2. The data layer of study area.

Parameter	Sub-Classification	Data Type	Scale
Historical Flooded Area	Flood Extent	Point	-
	Topographic Map in meter	Grid	30 m x 30 m
DEM	Slope in degre	Grid	30 m x 30 m
	Flow Accumulation	Grid	30 m x 30 m
TMPA	Precipitation in mm	Grid	27.5 km x 27.5 km
MODIS	Land Cover	Grid	500 m x 500 m
Stream Map	Distance from the Nearest Stream	Grid	15 x 15 m

Method
As mentioned above, the purpose of this study is to predict or detect flood-prone areas in Central Java and DIY using data from certain agencies and satellites and logistic regression models. The stages of data analysis and processing to be carried out are as follows:

3.1 Data processing

3.1.1 Flood record point data analysis (historical flood). Data on flood events are the main data in this study. The data was obtained from the BNPB (National Disaster Management Agency) from 2011 to 2018. For data on flood recording points that occurred in Central Java and DIY provinces, there were 215 data on flood events with 9 flood events in 2011 floods, in 2012 there were 16 floods, in 2013 there were 49 floods, in 2014 there were 49 floods, in 2015 there were 23 floods and 2018 as many as 69 floods.

3.1.2 Analysis of TRMM daily rainfall data . TRMM rainfall data was obtained after knowing the location of the flood event through historical flood data. Before data processing is carried out, the thing that needs to be done is the time adjustment of the historical flood data. Because TRMM data uses time with the format GMT + 0, then the time of the historical flood data needs to be changed first by reducing 6 hours from the original time.

3.1.3 Elevation data analysis. In this study, elevation data were obtained from the DEM (Digital Elevation Model) data obtained from the Indonesian Geospatial Information Agency (http://tanahair.indonesia.go.id). DEM data is in the form of pixels and can be processed with ArcGIS software. The elevation obtained refers to data on flood recording points. After processing it in ArcGIS software, the output that is produced is the elevation data in meters at each coordinate data point of the flood record.

3.1.4 Slope data analysis. Like elevation data, slope or slope data is also obtained from DEM data. DEM data is processed into land slope data using ArcGIS software. The output produced is the magnitude of the slope of the land in Central Java Province and DIY in the form of a percentage (%).

3.1.5 Analysis of LULC data. LULC data obtained from TERRA MODIS satellites were processed using ArcGIS software to obtain the type of land use at flood recording points in Central Java and DIY Provinces. Land use classification uses land use classification data from the Earth Observation and Modelling Facility (EOMF) which can be accessed at http://www.eomf.ou.edu/. This land use classification is obtained from the International Geosphere-Biosphere Program (IGBP) which is a research program that studies the phenomenon of global change that took place from 1987 to

2015.After obtaining LULC data, then the classification is changed according to the run-off coefficient of each flood point.

3.1.6 River network data analysis. River network data is obtained from the Geospatial Information Agency (BIG) and is used to identify river networks in Central Java and DIY Provinces. This data will result in the distance of the nearest river network to flood recording points in Central Java and DIY Provinces. Following 8 a summary of some data samples or parameters that will be used to do logistic regression modelling can be seen in Table 3.

Table 3. Sample of logistic regression parameter data.

No	Disaster	Long	Lat	Precipitation (mm)	Elevation (m)	Slope (%)	LULC	*C*
55	Flood	110.201	-7.25961	0.000000	650	3.409910	9	0.45
121	Flood	110.201	-7.25961	0.000000	650	3.409910	9	0.45
226	Flood	111.073	-6.88254	9.389348	49	3.607020	14	0.175
239	Flood	111.097	-6.72001	3.904148	6	1.033940	12	0.175
243	Flood	111.058	-6.89586	5.830828	45	3.985060	14	0.175
286	Flood	110.201	-7.25961	11.828920	650	3.409910	9	0.45
293	Flood	110.986	-6.89914	50.459920	20	3.011980	14	0.175
305	Flood	111.038	-6.74867	47.854560	14	0.462433	13	0.5
306	Flood	111.038	-6.74867	47.854560	14	0.462433	13	0.5
307	Flood	110.924	-6.89947	52.878580	5	1.178840	12	0.175
309	Flood	111.046	-6.74496	2.456600	13	1.178840	13	0.175
498	Flood	109.692	-7.69878	0.000000	19	5.551110	12	0.175
500	Flood	110.959	-6.45553	80.877680	52	8.068660	14	0.5
503	Flood	110.834	-6.81191	52.647260	19	3.807780	13	0
504	Flood	110.510	-6.92071	18.382400	0	0.000000	17	0.5
505	Flood	109.200	-6.87534	60.252830	3	1.906000	13	0.175
509	Flood	109.634	-6.91320	24.360450	10	2.287760	12	0.45
511	Flood	109.462	-7.64387	7.204940	122	17.299000	9	0.175
536	Flood	108.677	-7.30763	18.757860	140	8.854100	14	0.175
537	Flood	108.807	-7.48678	43.601220	6	1.906000	12	0.175
542	Flood	109.250	-7.60460	31.781600	7	1.178840	12	0.175

3.2 Logistic regression modelling

Logistic regression analysis is a regression method used to find the relationship between categorical response variables with the nominal, ordinal scale with one or more continuous and categorical explanatory variables [10]. The response variable (y) from binary logistic regression consists of two categories namely "success" and "failure", where the notation for the "success" category and for the "fail" category. So that the response variable follows the Bernoulli distribution for every single observation. The probability functions for each observation are as follows:

$$f(y) = \pi^{y}(1-\pi)^{1-y} \; ; y = 0{,}1 \tag{1}$$

where if y = 0 then f (y) = 1-π and y = 1 then f (y) = π, so that the logistic regression function is obtained as follows:

$$f(z) = \frac{e^z}{1+e^z}; \; z = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p \qquad (2)$$

where p is many predictor variables. The value f (z) is between 0 and 1 for each z value given because the value of z itself is between-antara and ∞. The logistic regression model actually describes the probability of an object. The logistic regression model is as follows:

$$f(z) = \frac{e^z}{1+e^z}; \; z = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p \qquad (3)$$

The function π (x) is a nonlinear function so it needs to be transformed by using logic transformations to obtain linear functions in order to see the relationship between the response variable y and the predictor variable [11].

$$\begin{aligned} g(x) &= logit\,\pi(x) \\ &= log\,log\,\frac{\pi(x)}{1-\pi(x)} \\ &= \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p \qquad (4) \\ &= \beta_0 + \sum_{i=1}^{p} \beta_i x_i \\ &= X\beta \end{aligned}$$

4 Results and discussion

4.1 Model fitting

Development of a logistic regression model was carried out with Rstudio software using a file that has a .csv format that contains Flood data (rainfall, elevation, slope, run-off coefficient, distance to the river). Flood event data was used as non-independent variables and the Flood event data used for this modeling was 70% of the randomized Flood occurrence data.

The data used in logistic regression modeling are 215 Flood record coordinate data and regional coordinate points which have a low probability of 114 data floods. Then the amount of data used in this modeling is 230 data taken randomly. After randomly collected data, the coefficients of logistic regression were obtained. In this study, the modeling that has been done is 500 times modeling to find out the range of the coefficients of logistic regression. The following coefficients from the logistic regression generated from the modeling are shown in Table 4.

Tabel 4. Coefficient of logistic regretion to flooded areas.

Parameter	Coefficient of Logistic Regression			
	5%	**50%**	**95%**	**Average**
(Interception)	5.05766	7.5110	16.13210	9.56692
Precipitation	-0.01547	0.01210	0.04075	0.01246
Elevation	-0.02173	-0.00831	-0.00592	-0.01199
Slope	-0.28108	-0.10251	-0.01940	-0.13433
Coefficient Runoff	-9.10476	-0.38548	7.15039	-0.77995
DNS	0.00038	0.00423	0.00783	0.00415
Flow Accumulation	-9.26342	0.00137	0.00791	0.00309

4.2 Model validation

In logistic regression modeling validation, the data used is all data minus data that has been used for logistic regression modeling or 30% of all data. The data used in the validation is 99 data. Logistic regression modeling validation aims to determine the reliability of the model that has been done. So that it will be known how much success is obtained and the value of reliability from the modeling itself.Of the 500 experiments that have been conducted, data that deviate approximately 4 data from 99 validation data are generated. And it can be concluded that the accuracy for the validation of logistic regression modeling is 93.47826% -98.26087%.

4.3 Prediction of flood prone areas

After finding out the coefficients of each flood parameter, the next step is to map flood-prone areas in Central Java and DIY Provinces. The mapping of flood-prone areas was made based on the results obtained from logistic regression modeling by mapping the results of binary numbers, namely 1 means flooding and 0 means no flooding in Central Java and DIY. By changing the map of Central Java and DIY into a grid size of 1000 m x 1000 m, the results obtained can be seen in table 5, below.

Table 5. Area of flood-prone areas in Central Java and DIY Provinces

Districts	**Capital City**	**Province**	**Area (km^2)**	**Area of Flood (km^2)**	**Area of Not Flood (km^2)**
Banjarnegara	Banjarnegara	Central Java	1160	904	256
Bantul	Bantul	Special Region of Yogyakarta	490	24	466
Banyumas	Banyumas	Central Java	1413	1133	280
Batang	Batang	Central Java	742	265	477
Blora	Blora	Central Java	1975	1402	573
Brebes	Brebes	Central Java	1726	1160	566
Cilacap	Cilacap	Central Java	2314	1623	691
Demak	Demak	Central Java	955	653	302
Grobogan	Purwodadi	Central Java	2024	1742	282
GunungKidul	Wonosari	Special Region of Yogyakarta	1460	177	1283
Jepara	Jepara	Central Java	1048	411	637
Boyolali	Boyolali	Central Java	1060	917	143
Karanganyar	Karanganyar	Central Java	833	569	264
Kebumen	Kebumen	Central Java	1305	1094	211
Kendal	Kendal	Central Java	1012	366	646
Klaten	Klaten	Central Java	660	351	309
Magelang City	Magelang	Central Java	13	4	9
Pekalongan City	Pekalongan	Central Java	77	63	14
Salatiga City	Salatiga	Central Java	17	13	4
Semarang City	Semarang	Central Java	380	187	193
Surakarta City	Surakarta	Central Java	56	24	32
Tegal City	Tegal	Central Java	42	34	8
Yogyakarta City	Yogyakarta	Special Region of	32	1	31

		Yogyakarta			
Kudus	Kudus	Central Java	419	361	58
KulonProgo	Wates	Special Region of Yogyakarta	600	46	554
Magelang	Mungkid	Central Java	1130	635	495
Pati	Pati	Central Java	1540	969	571
Pekalongan	Pekalongan	Central Java	965	816	149
Pemalang	Pemalang	Central Java	1127	964	163
Purbalingga	Purbalingga	Central Java	801	553	248
Purworejo	Purworejo	Central Java	1076	467	609
Rembang	Rembang	Central Java	1054	458	596
Semarang	Ungaran	Central Java	1050	851	199
Sleman	Sleman	Special Region of Yogyakarta	563	273	290
Sragen	Sragen	Central Java	971	911	60
Sukoharjo	Sukoharjo	Central Java	541	223	318
Tegal	Slawi	Central Java	987	893	94
Temanggung	Temanggung	Central Java	873	527	346
Wonogiri	Wonogiri	Central Java	1900	744	1156
Wonosobo	Wonosobo	Central Java	999	615	384

From the results obtained, the area is the area of the approach in grid units. For example, the area of Banjarnegara is 1160 grids, meaning that Banjarnegara has an area of 1160 grids with each grid having an area of 1,000,000 m2 and flood-prone areas which are predicted to have an area of 904 grids and non-flooded areas predicted to have 256 grids. For more details, the following map produced for mapping flood-prone areas can be seen in Figure 9.

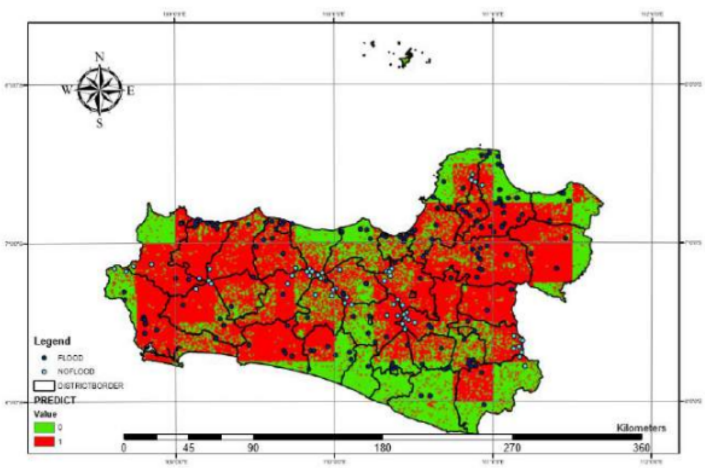

Figure 9. Mapping detection of flood-prone areas in Central Java and DIY Provinces.

8 Conclusions

Based on the results of the research that has been done, it can be concluded that the results obtained are as follows:

a. Parameter coefficients obtained from logistic regression modelling, each parameter has its own coefficients, namely intercept (5.05766 – 16.13210), rainfall (-0.01547 – 0.04075), elevation (-0.02173 – -0.00592), slope (-0.28108 – -0.01940), runoff coefficient (-9.10476 – 7.15039), river distance (0.00038 – 0.00783), and flow accumulation (-9.26342E-06 – 0.00309).

b. From the parameter coefficients obtained, it can be concluded that the greater the coefficient obtained the greater the chance for a Flood disaster.

c. Of the 500 experiments that have been conducted, data that deviate approximately 4 data from 99 validation data are generated. In addition, it can be concluded that the accuracy for the validation of logistic regression modelling is 93.47826% -98.26087%.

d. There are 25 districts that have the potential to be prone to flooding. This is concluded from the broader area 1 (flood prediction) than 0 (prediction of not flooding) from each district.

6 Acknowledgments

Financial support for completing this research is graciously provided by the Ministry of Research, Technology and Higher Education of the Republic of Indonesia with contact number: 176/SP2H/LT/DPRM/2019.

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