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ANALYSIS OF LAND USE FACTOR ON LANDSLIDE USING MODIFIED FREQUENCY RATIO

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ABSTRACT

Landslide is one of the most hazardous in Semarang Regency. This study was conducted to develop landslide susceptibility mapping (LSM) and analyzes land use and land cover (LULC) with other factors to landslide. Land use, ground motion, elevation, slope, soil type, rainfall, and Normal Difference Vegetation Index (NDVI) were used for landslide causative factor. 303 landslide data used for landslide inventory was randomly divided into data training (70%) and data validation (30%). Landslide inventory and landslide causative factors were performed using Geographic Information System (GIS) with method Modified Frequency Ratio. The result of Modified Frequency Ratio analysis for the highest value for each class factor was 3500-4000mm/year (rainfall): 1500-2000m (elevation), mid (ground motion): Settlement (LULC): Andosol (soil): 0 - 0.25 (NDVI): 15-25% (Slope). The highest value for Prediction rate was LULC. Landslide susceptibility was evaluated with the area under curve (AUC): the value showed 0.957 excellent analysis. LULC class settlement showed the highest landslide susceptibility in Semarang Regency.

Keywords: Semarang Regency, landslide, land use, modified frequency ratio

INTRODUCTION

Landslide can be defined as the mass movement of soil or rock that contribute to landscape change (Campforts et al., 2022). It is one of the natural disasters that occur on steep slopes under the force of gravity (Thapa & Bhandari, 2019). In Semarang Regency, Landslide is one of the most natural occurrences that cause damage to casualties, economic, and infrastructure. This Natural hazard was influenced by highly complex geomorphology factors, climate rainfall, and unplanned land use practice (Wubalem, 2021).

Land use and land cover (LULC) was considered as an important factor in landslide (Meneses et al., 2019). Many uncontrolled land use changes are due to population growth and urbanization (Selamat et al., 2022). Deforestation, expanding agricultural land in forest land, and development of settlement areas in steep terrain trigger landslide occurrences (Chen et al., 2019). Specific area LULC has a positive and negative effect due to influencing landslides (Bahrami et al., 2021). Vegetation land/ forest land has a major role in preventing downslope movement. There is a relationship between vegetation land and slope stability for influencing landslides. Vegetation enhances slope stability against erosion and landslide than barren land and cultivated land in steep terrain (Achour et al., 2017; Ajin et al., 2022).

Landslide susceptibility is an essential tool for landslide hazard management and mitigation. It is used for sustainable land use spatial planning and providing potential local mitigation techniques to reduce the impact on society in steep terrain environmental. It is based on combining Geographic Information System (GIS) and remote sensing data, which delineate areas where landslides are likely to occur based on local geomorphology and other environmental conditions.

This paper focuses on developing a landslide susceptibility map using modified frequency ratio in Semarang Regency. This paper will investigate the landslide causative factor that most influence to bring landslide. The main objective is to produce a landslide susceptibility map in Semarang Regency and describe the most influential landslide causative factor. The accuracy of the result LSM will be evaluated using Area Under Curve (AUC). Lastly, LULC will be linked with other landslide causative factor to investigate the correlation to landslide occurrence.

METHODOLOGY

1. Area of study

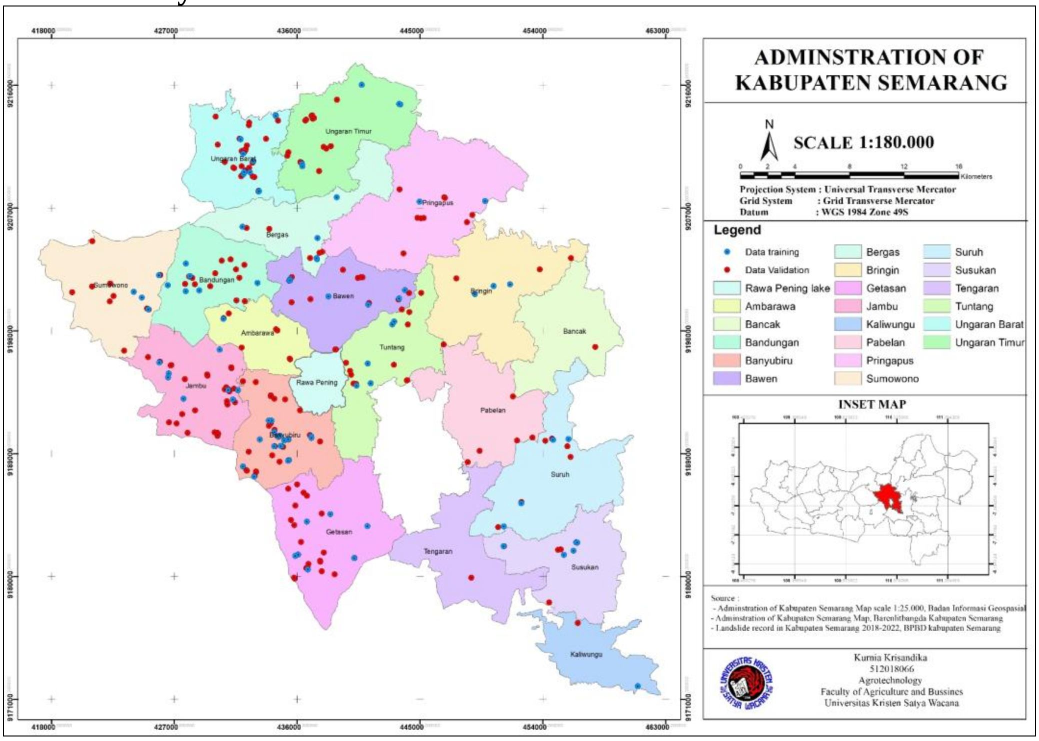

Figure 1. Administration of Semarang Regency

Semarang Regency is located in Jawa Tengah Province, Indonesia. It lies within longitude 110°14’54,75’’ E - 110°39’3’’ E and latitude 7°3’57” - S 7°30’ S. Semarang Regency is surrounded by a few mountains and a steep area with elevation range between 46 Meters above sea level (MASL) and 3.097 MASL. Annual rainfall in Semarang Regency is between 3000mm/year until 4000mm/year. Landslides have become one of the most hazard natural disasters in Semarang Regency. 303 landslide occurrences were recorded in the last five years.

2. Methodology

This research is divided into three steps. The first step is data preparation, the second is Landslide susceptibility mapping, and the last is verification data. The first step, collecting data for landslide causative factor and landslide inventory. The second step, landslide susceptibility mapping (LSM) is generated by landslide causative factor and landslide inventory using modified frequency ratio model. The last step, Verification LSM with landslide data validation using Area Under Curve (AUC).

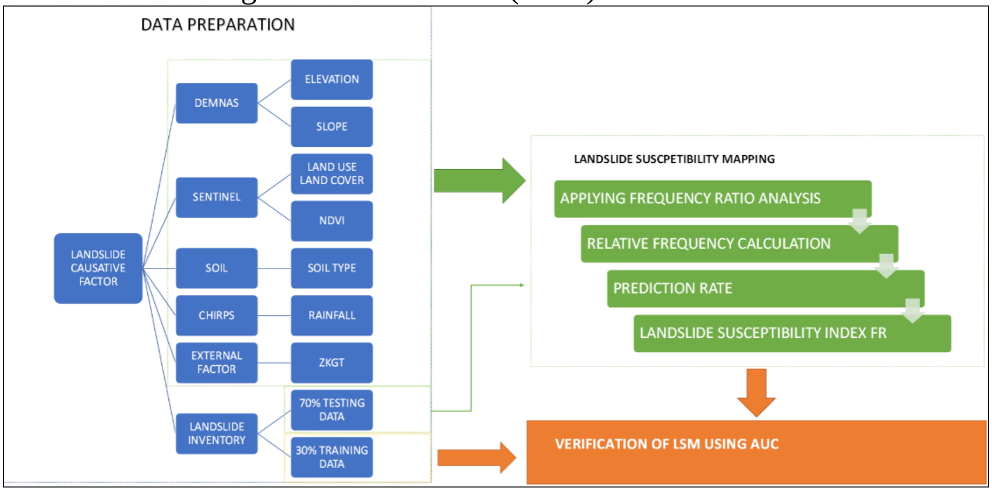

Figure 2. Flow chart showing research step-step of this study

2.1 Data Preparation

a. Landslide causative factor

Various landslide causative factors have appeared in recent literature, but no specific assured factors produce the optimal result for an area under analysis. There are no definite guidelines for the selection of landslide causative factors. It should be based on previous factors, data research literature, or USLE factors influencing landslides. There are two factors that should have in landslide causative factor, Intrinsic controlling factor and external triggering factor (Hamza,2016; Makealoun et al., 2014). This paper used seven causative factors, i.e., Land use and land cover (LULC): Normal Difference Vegetation Index (NDVI): Slope, Elevation, and soil, as intrinsic controlling factors. Ground motion and Rainfall as external triggering factors.

b. Landslide Inventory Mapping

Landslide inventory obtained from BPBD Semarang Regency. Total 303 landslides have been identified in the last 5 years (2022-2017). It was randomly divided into two groups for training data and validating data. 213 landslides were used for training data and the other 90 for validating data.

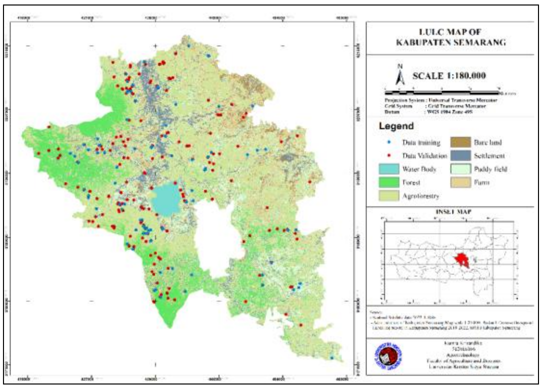

Figure 3. Land Use Land Cover Map

Landuse Land Cover map has 6 classifications. Paddy field (17.528%), Farm (8.265%), Agroforestry (37.474%), Forest (15.405%), Settlement (15.821%), Bare land (3.697%), and water body (1.809%).

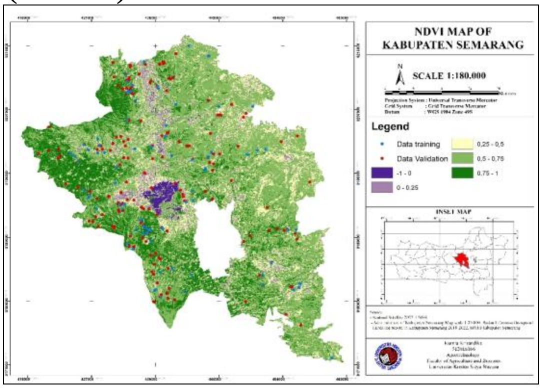

Figure 4. NDVI Map

NDVI map has 5 classifications. -1 – 0 (1.134%), 0 – 0.25 (5.101%), 0.25 – 0.5 (17.044%), 0.5 – 0.75 (56.461%), 0.75 – 1(20.26%).

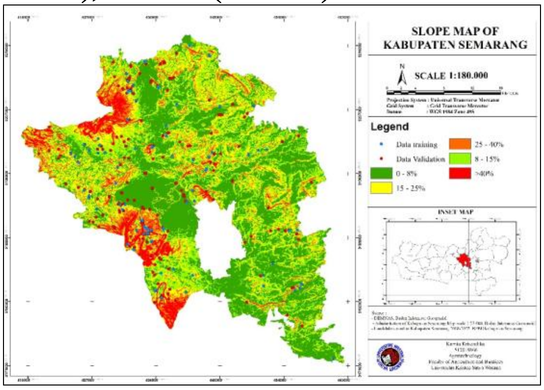

Figure 5. Slope Map

Slope map has 5 classifications. 0-8% (40.496%), 8% – 15% (24.295%), 15% - 25% (20.240%), 25% - 40% (10.031%), and >40%(4.938%).

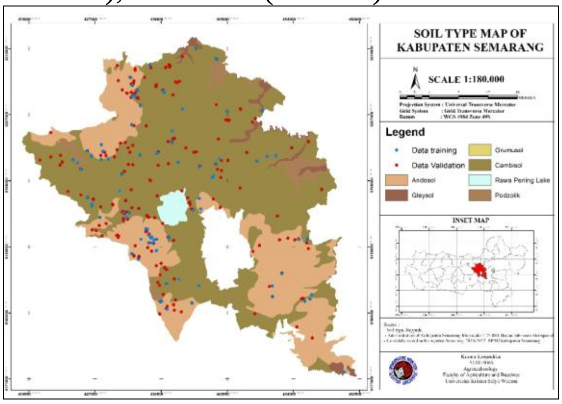

Figure 6. Soil Map

Soil type Map has 6 classifications. Andosol, Gleisol, Grumusol, Kambisol, Podsolik, and Rawa Pening lake.

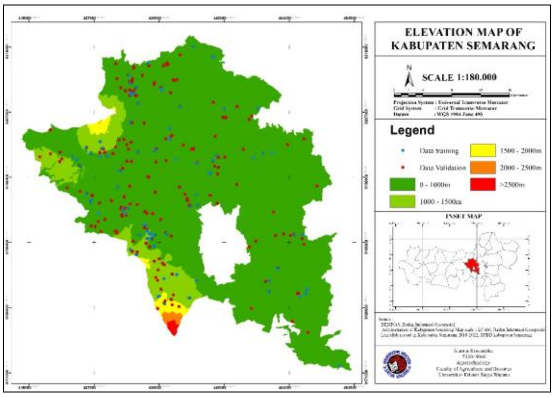

Figure 7. Elevation Map

The elevation map has five classifications. 0-1000m (89.346%), 1000m-1500m (8.719%), 1500m – 2000m (1.353%), 2000m – 2500m (0.362%), and >2500m (0.219%).

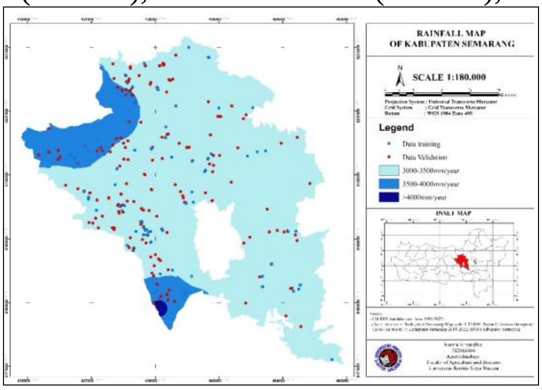

Figure 8. Rainfall Map

The rainfall map has 3 classifications. 3000 – 3500mm/year (87.096%), 3500–4000mm/year (12.611%), and >4000mm/year (0.293 %).

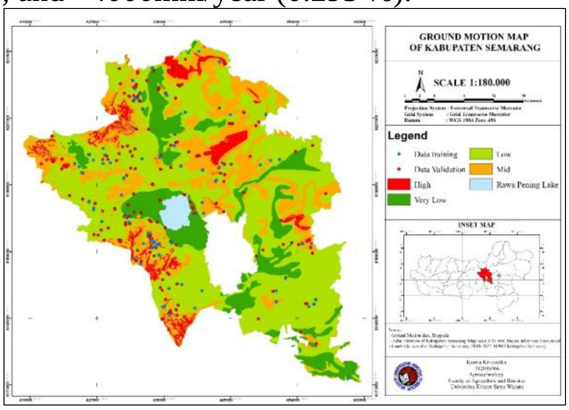

Figure 9. Ground motion Map

Ground Motion map has 5 classifications. Rawa Pening Lake (1.487%), Very low (15.405%), low (53.781%), mid (24.427%), and High (4.901%).

2.2 Landslide susceptibility mapping

a. Frequency Ratio (FR)

Frequency ratio is a statistical analysis that evaluates the likelihood of a certain phenomenon by measuring the ratio between the density of phenomena in a given class and the density of the same class. FR can represent the influence of the categories of each controlling factor due to landslide occurrences. FR is slightly more convenient to interpret and understand than the other methods (Baral, 2021).

$$FR = \frac{= \% \, LSij}{\% \, Dij} \quad (1)$$

Where %Lsij is the percentage of landslides in a causative factor class, % Dij is the percentage area of the causative factor class of the entire map.

b. Relative Frequency (RF)

RF for calculating every causative class index. Every score class factor will divide by the total score causative factor.

$$RF = \frac{FRij}{\sum FRij} \quad (2)$$

Where Frij is the value FR class causative factor. ∑Frij is Total value FR causative factor

c. Prediction rate (PR)

PR use to score landslide causative factor.

$$PR = \frac{RFMax - RFMin}{(RFMax - RFMin)Min} \quad (3)$$

Where RFMax-RFMin is the maximum Relative Frequency among the classes of causative factors. (RFmax – RFmin)min is the minimum value among all the causative factors.

d. Landslide susceptibility index (LSI)

Every landslide causative factor (PR) and class factor (FR) that has a score will be combined by LSI.

$$LSI = \sum FRjxPRj \quad (4)$$

Where FRj is value FR causative factor. PRj is value PR class factor.

RESULTS AND DISCUSSION

The FR model in Table 1 shows the relationship value of each classification causative factor and landslide inventory. The highest value means a high likelihood of landslide occurrences. LULC map and NDVI map have the highest value of FR method. These two is the most important controlling factor for landslide occurrence.

Table 1 Modified Frequency Ratio Result

Factor	**Class**	**% Class pixel (%)**	**% Landslide pixel (%)**	**FR**	**RF**	**(max-min)**	**(max-min)*min**	**PR**
Rainfall ($^{mm}/_{year}$)								
	3000 - 3500	87.096	79.812	0.916	0.162	0.406	0.297	1.366
	3500 - 4000	12.611	19.249	1.526	0.270			
	>4000	0.293	0.939	3.208	0.568			
Total		100	100	5.650	1			
Elevation (m)								
	0 - 1000m	89.346	82.629	0.925	0.186	0.489		1.647

	1000 - 1500m	8.719	14.085	1.615	0.325		
	1500 - 2000m	1.353	3.286	2.429	0.489		
	2000 - 2500m	0.362	0	0	0		
	>2500m	0.219	0	0	0		
Total		100	100	4.969	1		
Ground Motion							
	Rawa Pening Lake	1.487	0	0	0	0.353	1.189
	Very Low	15.405	8.451	0.549	0.146		
	Low	53.781	54.930	1.021	0.272		
	Mid	24.427	32.394	1.326	0.353		
	High	4.901	4.225	0.862	0.229		
Total		100	100	3.758	1		
Land Use Land Cover							
	Forest	15.405	3.286	0.213	0.018	0.791	2.666
	Paddy field	17.528	1.408	0.080	0.007		
	Waterbody	1.809	0	0	0		
	Agroforestry	37.474	4.225	0.113	0.010		
	Settlement	8.265	76.056	9.203	0.791		
	Farm	15.821	9.859	0.623	0.054		
	Bare land	3.697	5.164	1.397	0.120		
Total		100	100	11.629	1		
Soil							
	Andosol	29.053	38.028	1.309	0.495	0.495	1.666
	Gleysol	1.983	0.469	0.237	0.089		
	Grumusol	0.018	0	0	0		
	Cambisol	64.374	61.033	0.948	0.358		
	Rawa Pening Lake	1.502	0	0	0		
	Podzolik	3.071	0.469	0.153	0.058		
Total		100	100	2.647	1		
Normal Difference Vegetation Index							
	-1	1.134	0	0	0	0.749	2.525
	0 - 0,25	5.101	43.662	8.560	0.749		
	0,25 - 0,5	17.044	42.254	2.479	0.217		
	0,5 - 0,75	56.461	9.859	0.175	0.015		
	0,75 - 1	20.260	4.225	0.209	0.018		
Total		100	100	11.423	1		
Slope (%)							
	0 – 8	40.496	20.188	0.499	0.099	0.297	1
	8 – 15	24.295	28.169	1.159	0.230		
	15 – 25	20.240	39.906	1.972	0.391		
	25 – 40	10.031	9.390	0.936	0.186		

	>40	4.938	2.347	0.475	0.094
Total		100	100	5.041	1

In the LULC map, the settlement area shows the highest landslide probability. It indicates that there needs to be more land use practices in the study area. The impact of human activities is essential to cause mass movement (Chen et al., 2019). Building area results overweight to the soil strength and slope instability (Medina et al., 2021). Although LULC is a significant causative factor, The other factor still influences the likelihood of landslide occurrences. Landslide happens not only by a single factor but by the combined results of external environmental factors (Meneses, 2019).

In the NDVI map, the 0 – 0.25 class has the highest landslide probability. This class generally corresponds to the settlement area. Area with low dense vegetation like settlement area has a higher likelihood of experiencing landslides (Simanjuntak & Tjahjono, 2022). The Root system from high dense vegetation area would reinforce the soil strength and stabilizes the slope (Soma, 2019). Canopy forests help decreasing erosive forces and reduce infiltration water (Hurlimann et al., 2021).

Class 15% - 25% in the slope map has the highest landslide probability. It is similar to Cellek (2020) stated that most landslides occurred in slope areas between 15% - 20%. Landslides occur in steep slope areas influenced by instability gravity force and high strength shear consolidated with existing land cover like settlements (Kornejady et al., 2017).

Class >4000mm/year in the rainfall map has the highest landslide probability. The relationship between rainfall and a landslide follows the general concept that the event's density positively correlates with increasing rainfall intensity (Priyono et al., 2020). Heavy rainfall mainly triggers landslides in areas with low dense vegetation like settlements (Karsli et al., 2008). Less intercepted precipitation promotes run-off that causes surface erosion. The rapid accumulation infiltration in certain soil layers in the settlement area will form underground run-off. The underground run-off will produce landslides (Zhang, 2020).

The Elevation map's FR value is increasing from 0-500m to 1500-2000m class. Class 1500-2000m has the highest probability of landslide occurrence with 2.429 FR. Class up to 2000m FR value is 0 because no record of landslide occurrence or social activity was found. The middle of mountainous areas from 1000 – 2000m are more susceptible to landslides (Liu et al., 2013). Some studies stated that elevation has no relationship to landslides, but it has a significant role in rainfall and land cover properties (Ding et al., 2017; Kavzoğlu et al., 2012; Dragicevic et al., 2015). Higher elevation influences heavy rainfall and can lead to runoff. Higher elevation also affects land cover from sparse vegetation to no vegetation like a settlement. Heavy rainfall in sparse vegetation or settlement gets much more precipitation, leading to decreased soil strength and landslides.

Class mid in the Ground motion map has the highest landslide probability. This causative factor influences slope instability and past occurrences that lead to a new landslide.

In the soil map, Andosol class is the highest probability of inducing landslide. Some studies stated that andosol soil is sensitive to natural change and prone to landslides (Vingiani et al., 2015; Sunarta et al., 2019). The soils derived from volcanic ash have low bulk density the characteristic of less soil compaction, wide range of pores, and high porosity soil structure and contain amorphous materials which may give potential for mass movement. When high rainfall, these soil can reach limit luqiud or water flow and become smeary to runoff

(Nurcholis et al., 2019). Andosol type with the land cover settlement is very susceptible to landslide (Diara et al., 2022).

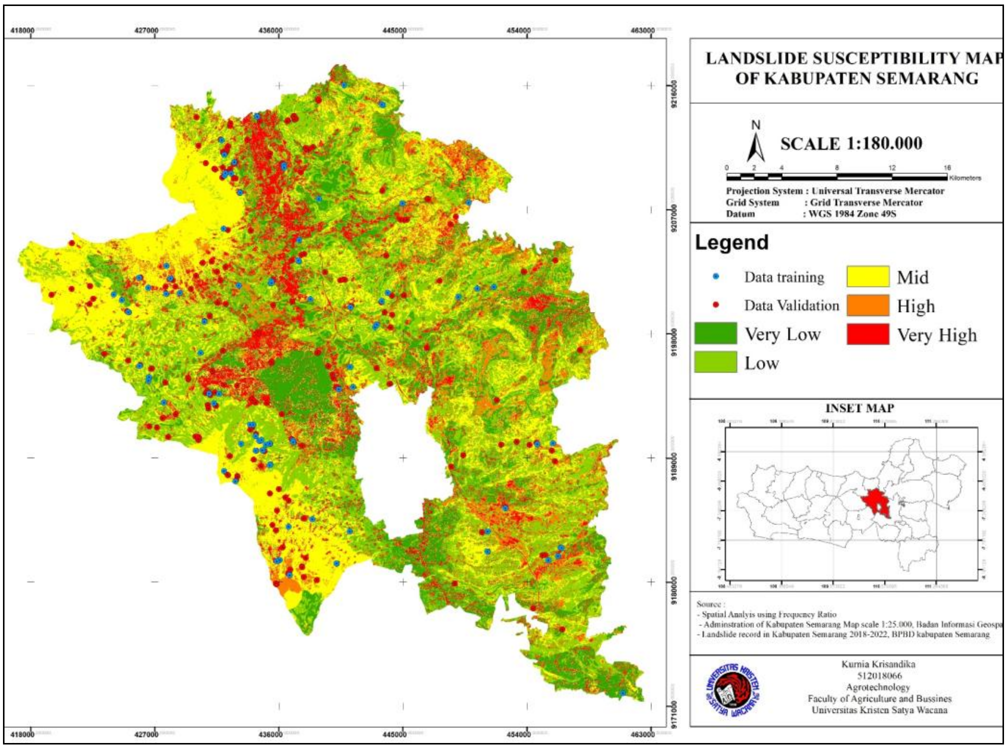

Figure 10 Landslide Susceptibility Map

The landslide susceptibility mapping developed using FR and PR is shown in Table 1. The result of landslide susceptibility is shown in Figure 3. LSM is divided into 5 classes, Very Low (15.977%), Low (33.322%), Mid (28.919%), High (11.643%), and Very High (10.137%).

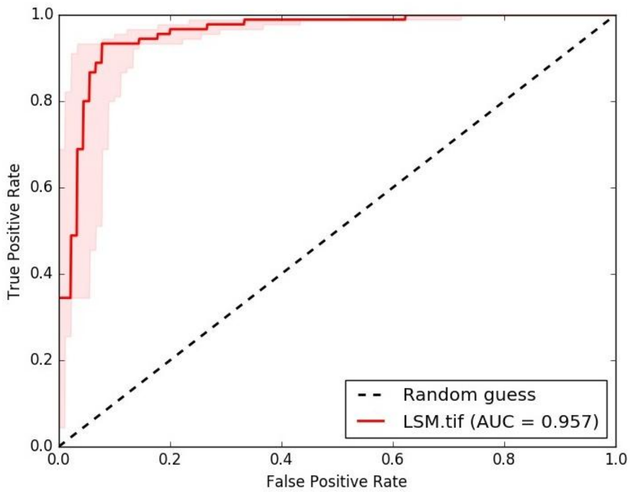

Figure 11. Area Under Curve of LSI in Semarang Regency

Validation of predictive landslides is important in assessing landslide susceptibility mapping (Rasyid et al.,2016). It is based on the causative factor and each class that influences the landslide event in the study area. The AUC value represents the performances of LSM. To classify the accuracy of the LSM, the value ranges from 0.50 to 0.60 (fail), 0.60–0.70 (poor), 0.70–0.80 (fair), 0.80–0.90 (good), and 0.90–1.00 (excellent). The threshold value For the AUC value is 0.6, so the parameters with an AUC value less than 0.6 will be ignored for determining the landslide susceptibility zone. The result verification of this LSM is 0.957 AUC. This result shows that the accuracy of the LSM is excellent classification (Arrisaldi et al., 2021).

CONCLUSIONS

The landslide causative factor with the highest value to prone landslide in Semarang Regency is LULC, with a 2.666 prediction rate value. The AUC value for Landslide susceptibility mapping is 0.957 showing excellent accuracy mapping. The result of landslide susceptibility mapping of Semarang Regency shows that area Very Low 15.977%, class Low 33.322%, class Mid 28.919%, class High 11.643%, and class Very high 10.137%. LULC, especially settlement class, is the main factor in prior landslides. Settlement area with high rainfall, steep slope, low dense vegetation, andosol type, and high elevation shows high landslide susceptibility.

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