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Flood Risk Spatial Modeling Based on Geographical Information Systems and Remote Sensing in the Pemangkat Regensi

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Abstract: Flood is a disaster that occurs every year in Indonesia with various risks. This study aims to create a spatial model of flood risk and determine the distribution of flood risk in Pemangkat, Sambas Regency. The method used is surveying and interpreting secondary data from the Digital Elevation Model, topographic maps, and land cover images. The data collected includes area, elevation, slope, distance from the river, land use, and rainfall. The tool used is a set of Geographic Information System tools, namely Arcgis 10.8. Data analysis using Weighted Sum for generated Flood risk map and Geographically Weighted Regression for flood risk spatial modeling. The results showed that the Pemangkat sub-district had flood risk classes, namely very low, low, moderate, high, and very high classes. Very high to high flood-risk classes are spread in the cities of Pemangkat and Sabatuan. In contrast, medium to deficient classes are spread in Jelutung, Gugah Sejahtera, Penjajap, Harapan, Lonam, and Parapakan. Very low flood risk area is 8.17 ha (8.16%), low 16.97 ha (16.97%, medium 28.17 ha (28.16%), high 32.28 ha (32.28%) and very high 14.41ha (14.39%). The values obtained from the analysis show that GWR modeling is excellent because R2 is relatively tiny, 0.39.

Keywords: Flood risk; GIS; Remote sensing; Spatial modeling

Introduction

Landforms have an essential role in studying flooding. They are a cross-sectional form for flowing water into the sea (Riadi et al., 2018). The areas most affected by flooding are areas with flat and sloping relief. That indicates a flood-prone landscape in the form of flood plains, sea terraces, swamps, and back swamps. Geomorphology Flooded areas are characterized by concave morphology or flat landforms associated with rivers, with winding and or meandering flow patterns, as one of the areas with potential for flooding, and this area needs to be mapped (Pourali et al., 2016; Riadi et al., 2018).

Flooding is a problem for a country and has even become a global problem in various countries (Coumou & Rahmstorf, 2012; Hu & Demir, 2021). Floods are one of the most damaging natural disasters and phenomena that occur in both rural and urban areas (Gianotti et al., 2018; Hlodversdottir et al., 2015; Z. Li et al., 2020a; Morris et al., 2016; Zhou et al., 2019) even in coastal areas. Various losses were caused by flooding, including losses in the monetary and demographic fields (Z. Li et al., 2020a; Sayama et al., 2015), social and economic, as well as education.

Flood risk is analyzed for spatial aspects emphasizing spatial aspects, including location and flood coverage. Flood modeling can be done conceptually based on processes and models according to data availability (data-driven model). Flood risk assessment is carried out by identifying three components, namely vulnerability, hazard, and exposure to floods (Agus, 2006; Riadi et al., 2018). The importance of risk spatial modeling and predicting flood inundation can be used as important information for flood mitigation (Bhola et al., 2018; Hu & Demir, 2021; Tadesse & Fröhle, 2020), preparedness (Arrighi et al.,

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2019; Hu & Demir, 2021), and planning and response efforts (Bhatt et al., 2017; Hu & Demir, 2021).

Spatial modeling of floods can facilitate understanding of potential flood risks and damage impacts (Singh et al., 2017; Yildirim & Demir, 2021), supporting flood mitigation and planning (Hu & Demir, 2021; Yildirim & Demir, 2021). Accurate information on flood-affected areas to prioritize relief efforts and plan damage mitigation measures (Rosser et al., 2017). Many factors cause flooding such as high rainfall (Dettinger, 2011; Hu & Demir, 2021), surface runoff, flow patterns (Dettinger, 2011; Hu & Demir, 2021), and other problems that affect flooding significantly (Dettinger, 2011; Hu & Demir, 2021), such as human behavior in managing the environment. Therefore, flood prediction is very complex (Di Baldassarre & Uhlenbrook, 2012; Hu & Demir, 2021), because it must involve many parameters that cause flooding (Xiang & Demir, 2020).

Spatial information related to the risk of flooding is a flood risk map (Hu & Demir, 2021; Lamichhane & Sharma, 2017; Sermet & Demir, 2019) and a new communication system about flooding (Sermet, Demir, et al., 2020). Flood risk maps are an essential resource for reducing flood damage that can be integrated into decision-making processes (Z. Li et al., 2020a, 2020b; Sermet, Demir, et al., 2020; Sermet, Villanueva, et al., 2020; Xu et al., 2020), especially in collaborative processes.

Flood risk modeling can be made by utilizing currently developing technology. Some of the models used are based on models that combine Remote Sensing, social media (Seo et al., 2019), topographical data sources (Seo et al., 2019), observation (Sermet, Villanueva, et al., 2020). However, modeling requires intensive computational requirements, large amounts of complex data, and calibration needs from experts (Mosavi et al., 2018; Teng et al., 2017; Tewari et al., 2021), which ,becomes an obstacle in the modeling process.

Under these conditions, the need for a model that is easy to implement leads to the development of a simplified conceptual model. The model is in digital data form (Z. Li et al., 2020a; McGrath et al., 2018), making it a preferred choice. One relatively simple model is spatial modeling which emphasizes the risk of flood disasters by utilizing Geographic Information Systems and Remote Sensing technologies (Purwanto et al., 2022).

The high intensity of rain in mountain areas causes flooding in residential areas under the mountain, and the water reservoirs in Mount Gajah burst. The shelter has experienced siltation. Mud and trash have piled up, and the shelter is decades old. The peak occurred on March 3, 2023, with flooding in the Pemangkat sub-district area. In addition to these factors, the flooding was also caused by a large amount of mud and garbage, causing siltation and flooding (PPID, 2023).

The provision of geospatial data on the flooding risk in this study was used to achieve the Sustainable Development Goals (SDGs), which require coordination between national, provincial, and district/city planning initiatives. This research is very important in supporting flood risk management and planning. Flood hazard maps and other outputs from flood risk spatial modeling can be used to inform a variety of flood risk management and planning activities, such as: identifying and prioritizing areas for flood protection measures, developing early warning systems and evacuation plans, assessing the potential economic and social impacts of flooding Making informed decisions about land use and development. This study aims to create a spatial model of flood risk and determine the distribution of flood risk in Pemangkat, Sambas Regency.

Method

Study Area

The research area is located in Pemangkat District, Sambas Regency, which is located at 108^0 54' 01" - 109^0 04' 49" E and 1^0 05' 01" - 1^0 12'14 N. Pemangkat sub-district is in Sambas Regency consisting of the villages of Penjajap, Rapakan Besi, Harapan, Parit Baru, Sungai Toman, Serunai, Jelutung and Pemangkat Kota. The area of Pemangkat District is 8.247.05 Ha. For more details, the area of the research location can be seen in Figure 1.

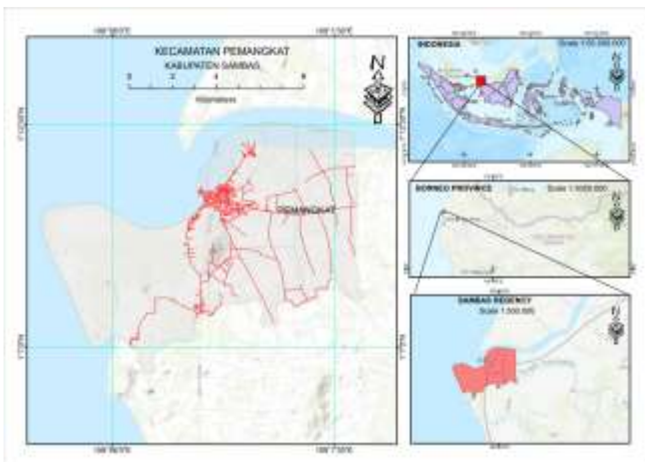

Figure 1. Study area

Study Method

Flood risk spatial modeling is a process to predict and visualize areas vulnerable to flooding. This method uses spatial data such as maps, satellite imagery, topographical data, and hydrological data such as rainfall and river flow to identify areas that can potentially experience flooding. The method used in this study is the interpretation of primary and secondary data. The flood risk map is generated from the Digital Elevation Model (DEM) and vector data from the Indonesian Topographical Map. DEM data was obtained from ALOS PALSAR image data with a resolution of 12.5 meters. DEM displays altitude or elevation information in the research area (Demirkesen et al., 2007; Kresch et al., 2002; Marfai et al., 2017). This DEM data is the primary data to create a spatial flood risk model in the study area. DEM is derived from ground-level points from the ALOS PALSAR image field measurements, which are then interpolated.

The following are general steps in flood risk spatial modeling: a) Data collection: Collect data required for modeling, such as topographical data, hydrological data (rainfall, river flow), and spatial data, such as maps and satellite imagery, b) Topographical analysis: Topographical analysis helps in understanding the slope of the land, water flow patterns, and drainage in the area to be modeled. This can be done using Geographic Information Systems (GIS) and Digital Elevation Model (DEM) data analysis, c) The hydrological analysis uses rainfall and river flow data to identify water flow patterns and predict potential flooding, d) Identification of flood-risk areas: Using topographical, hydrological, and other parameter data, identify areas potentially affected by flooding. This can be done by combining these data in a GIS analysis, e) Flood modeling: Use hydrological models and collected data to model flood behavior. Modeling can involve simulating water flow in rivers, raising water levels in flooded areas, and predicting the impact of flooding on residential areas or infrastructure, f) Visualization and evaluation: Visualization of modeling results using maps and other graphical representations. If available, evaluate model results by comparing them with historical flood data or by collecting field data to validate the model and, g) Risk analysis: Using modeling results, identify and analyze areas vulnerable to flooding, including areas with potential human loss, economic loss, or infrastructure damage.

Data collection techniques with image interpretation. The interpretation in this study is the interpretation of topographic maps and DEM images. The data collected includes area, elevation, slope, distance from the river, land use, and rainfall. The tool used is a set of Geographic Information System (GIS) tools, namely Arcgis 10.8. Data analysis using Weighted Sum for generated Flood risk map and Geographically Weighted Regression (GWR) for flood risk spatial modeling.

ArcGis 10.8 was used to explore the data, briefly, the steps in the research were carried out as follows:

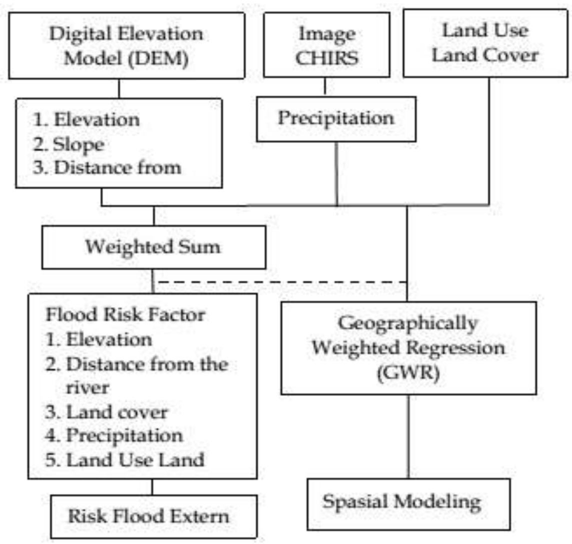

Figure 2. Research flowchart

In brief, the weight of the factors that affect flood risk can be seen in Table 2.

Table 1. Factors Used in Spatial Modeling for Flood Risk Assessment in the Study Area

Classification	Sub-classification	Source of data	Gis data type	Derived map
Flood event inventory	Flood inventory	Pemangkat Regional Water Authority Field surveys	Primary and secondary	-
	Altitude	DEM	GRID	Elevation
DEM	Slope angle	DEM	GRID	Slope angle
	Distance from river	DEM	Line coverage	Distance to river
Land use type	Land use	OLI * of Landsat 8 image	GRID	Land use
Precipitation	Rainfall	CHIRS 2022	GRID	Rainfall

GRID (graphic design); DEM (Digital Elevation Model) from ALOS PALSAR

Table 2. Flood Risk Factors and Weighted

Flood Risk Factors	Descriptive	Ranking	Reclasses	Influence (%)	Weighted
Elevation (m)	Very low	10	16 - 59		
	Low	8	59 - 120		
	Moderate	6	120 – 190	10	0.10
	High	4	190 - 274		
	Very High	2	274 - 403		

Flood Risk Factors	Descriptive	Ranking	Reclasses	Influence (%)	Weighted
Slope (%)	Very low	10	0 - 2		
	Low	8	2 - 5		
	Moderate	6	5 - 10	15	0.15
	High	4	10 - 15		
	Very High	2	> 15		
Distance from drainage (m)	Very low	10	0 - 100		
	Low	8	100 - 200		
	Moderate	6	200 - 300	30	0.30
	High	4	300 - 400		
	Very High	2	> 400		
Rainfall (mm/hr)	Very low	10	> 2.620		
	Low	8	2.590 – 2.620		
	Moderate	6	2.570 -2.590	35	0.35
	High	4	2.550 – 2.570		
	Very High	2	2.523 – 2.550		
Land Use Land Cover	Very low	10	Waterbody		
	Low	8	Swam		
	Moderate	6	Settlement	10	0.10
	High	4	Ricefield		
	Very High	2	Vegetation		

Result and Discussion

Elevation is the most crucial factor affecting flooding. The effect of elevation on flood events in general, namely that flood events increase with decreasing elevation (Choubin et al., 2019; Mumbai, 2020). It is proven that places with low elevations often experience flooding every rainy season. The DEM in this study provides altitude information (Figure 3) and slope angle (Figure 4) processed in ArcGIS 10.8. The height factor and slope angle are classified into five classes (Althuwaynee et al., 2012; Bui et al., 2019). Flat areas with low slopes and low altitude classes have a higher potential for flooding. To create the elevation factor, the digital map of the elevations was edited using the reclassify command in ArcGIS 10.8. Subsequently, this layer was divided into five classes16-59, 59-120, 120-190, 190-274, and 274-403 m.

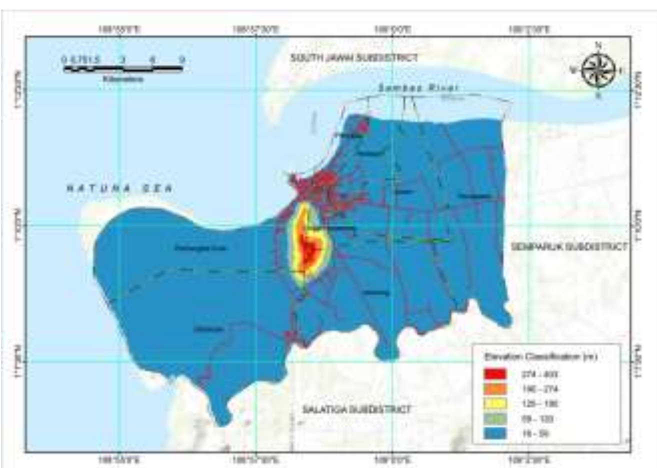

Figure 3. Elevation study area

The slope is the most significant factor in hydrology because it is directly proportional to surface runoff and, thus, influences floods (Meraj et al., 2015). The slope in percent for the study area was extracted from the processed ALOS PALSAR using the surface-slope tool under the spatial analyst tool in ArcGIS 10.8 and further reclassified into five classes (Figure 4).

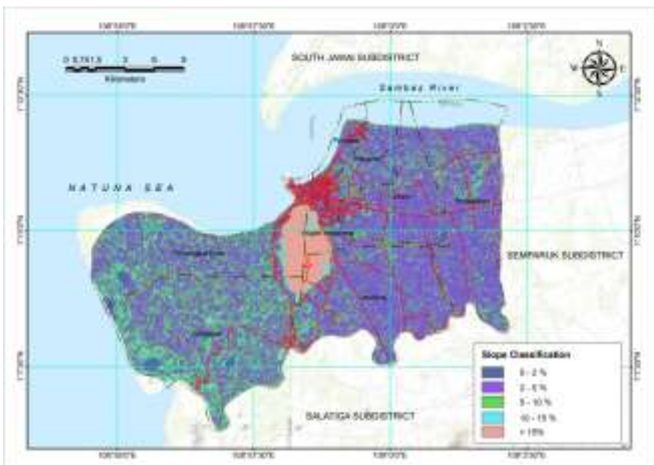

Figure 4. Slope of study area

Generally, the areas with low elevation have a gentle and, therefore, are more prone to floods and water-logging as steep slope generates more velocity than flatter or gentle slopes, and hence, can dispose of the runoff faster. For flat to gentle slopes, runoff gets stored over an area and disposed of gradually over time (Mumbai, 2020; Tehrany & Kumar, 2018). Therefore, low-gradient slopes at lower reaches are highly vulnerable to flood occurrence compared to high-gradient slopes. The elevation and the resulting slope both show a significantly lower spatial variation. The slope angle in this study was generated in percent units and classified into five classes, 0 – 2, 2 – 5, 5 – 10, 10 – 15, and >15.

Distance from River

Flood occurrences in the study area are frequent along the stream. Thus, distance from the river was considered another geomorphology-related conditioning factor. Subsequently, a distance from the river map was generated because the streams would disrupt the stability of the slopes either by toe undercutting or by saturating parts of the materials lying within the water level of stream ways (Mojaddadi et al., 2017). The proximity of rivers and drainages represents the distance from a river.

To create the layer for the distance from the river factor, the digital map of the river was edited using Euclidean with ArcGIS 10.8. Subsequently, this layer was divided into five classes: 100, 267, 410, 636, and > 1000 m. Distance from the river (or distance of the measurement points from the river) significantly affects the distribution and magnitude of floods in the area (Bui et al., 2019; Grayson & Ladson, 1991). Area with as a result of insufficient infiltration and percolation due to changes in soil characteristics, vegetation coverage, and ground surface slope, high-intensity rainfall events generate large amounts of runoff in the vicinity of the nearby river, causing catastrophic flood events in downstream areas with lower topographic gradients (Bui et al., 2019; Kia et al., 2012)

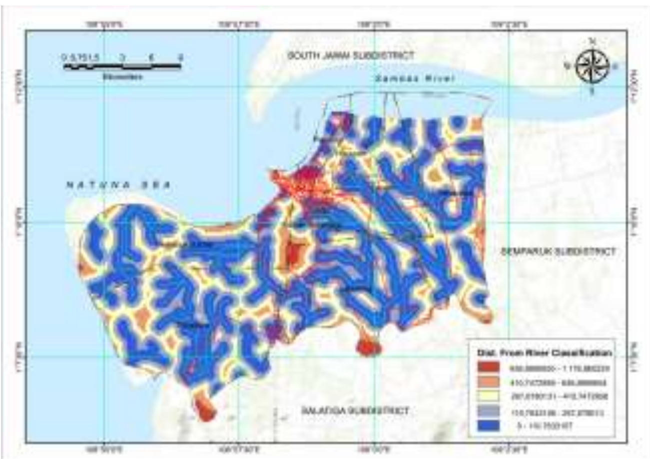

Figure 5. Distance from river study area

Rainfall

Rainfall affects the process of flooding and is a critical issue for flood risk reduction and water use in an area (Cheng et al., 2021). Rainfall is a source of flood discharge and is very important in predicting the peak discharge of a flood. Heavier-than-usual rainfall can cause a rapid decrease in the daily river flow (and water level) (Ronchail et al., 2018). Likewise, rainfall is a critical factor causing changes in monthly flood occurrence (Cheng et al., 2021; Ronchail et al., 2018). Extreme rainfall is the main factor triggering flooding in various regions. An increase in the intensity and duration of extreme rainfall is currently expected due to global climate change (Tunas et al., 2021).

The rainfall data inside and outside of the study area were used to generate an annual rainfall map. The rainfall data generate from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). The rainfall map generates with interpolation methods, Inverse Distance Weighting (IDW). The rainfall map of the study area was divided into five classes (Shafapour et al., 2014) (Figure 6).

Figure 6. Rainfall study area

Land Use Land Cover

LULC causes changes to natural drainage systems (Danandeh Mehr & Akdegirmen, 2021; Jaya, 2022), impacts surface runoff, and affects infiltration capacity (Danandeh Mehr & Akdegirmen, 2021). These factors are believed to be the cause of frequent flooding. Meanwhile, the available level of vegetation cover and absorption rates also change the evapotranspiration rate (Das et al., 2018). These factors change behavior and the balance that occurs between water evaporation (Jaya, 2022), water absorption (X. Li et al., 2021), and water distribution through rivers (Nahib et al., 2021; Sahoo et al., 2018).

Another primary related factor that strongly contributes to flooding is LULC. A detailed understanding of LULC is essential for environmental and natural hazards (Rizeei et al., 2016). Vegetated areas are less prone to flooding because of the negative correlation between a flood event and vegetation density. However, urban areas typically comprise impermeable surfaces and bare lands, which increase stormwater runoff. In this research, a land-use map played a crucial role in flood hazard modeling as one of the conditioning factors and criteria for vulnerability assessment.

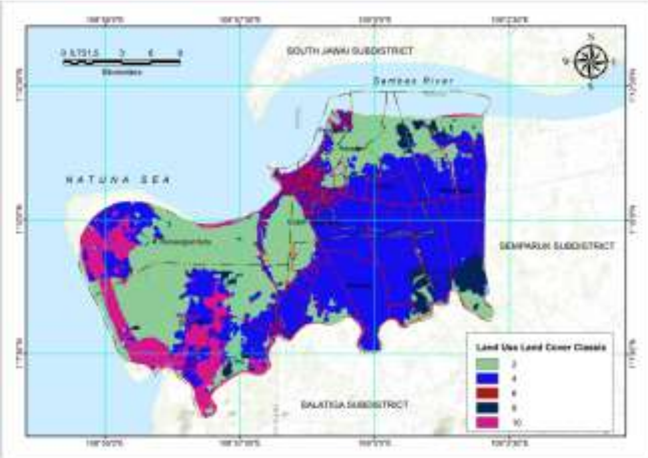

Figure 7. Land use land cover study area

The results showed that the Pemangkat sub-district had flood risk classes, namely very low, low, medium, high, and very high classes. Very high to high flood-risk classes are spread in the cities of Pemangkat and Sabatuan. In contrast, medium to very low classes is spread in Jelutung, Gugah Sejahtera, Penjajap, Harapan, Lonam, and Parapakan. Very low flood risk area is 8.17 ha (8.16%), low 16.97 ha (16.97%, medium 28.17 ha (28.16%), high 32.28 ha (32.28%)) and very high 14.41ha (14.39%). Flood risk classes and their distribution can be seen in Figure 8.

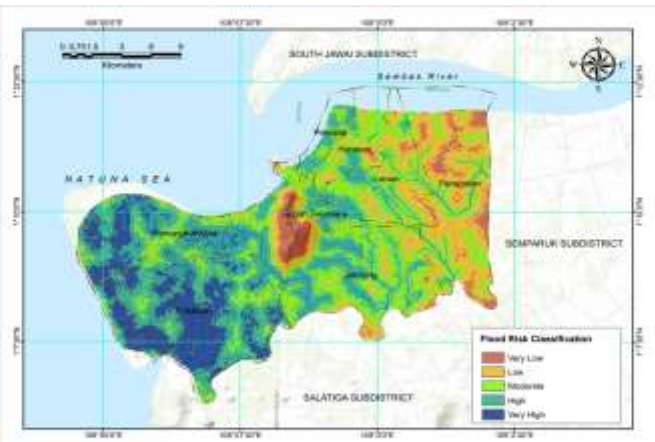

Figure 8. Flood risk map

Geographically weighted regression (GWR) to the geography literature to investigate the possibility of correlations in a regression model is spatially variable, or what is known as parametric nonstationarity (Brunsdon et al., 1996). GWR has been proposed as a technique to perform inference on spatially changing connections to extend the initial focus on prediction to confirmatory analysis, while the emphasis on conventional locally weighted regression in statistics has been on curvetting, that is, estimating or predicting the response variable (Isazade et al., 2023).

Although the model calibration sites are not limited to observation locations, any observation location in the dataset may have a regression model fitted using GWR. The weights that indicate the geographical dependency between observations are calculated using the inter-point distances obtained from the spatial coordinates of the data points. Geographically weighted regression forms separate equations with the participation of independent and dependent variables placed inside a "distance" bar of each phenomenon and also allows parameter values to change continuously in geographic space. Equation 1 shows the GWR model (Kim & Graefe, 2021; Kuo et al., 2017).

$$yi = \beta i0 + \beta i1 \times 1i + \beta i2 \times 2i + \ldots + \beta in \times ni + ei \quad (1)$$

where yi is the dependent variable, βi0 is the intercept, βi is the coefficient, and ei is errors at location (i) (Isazade et al., 2023). Geographically weighted regression (GWR) analysis uses ArcGIS using spatial statistical tools and modeling spatial relationships and the results are as follows:

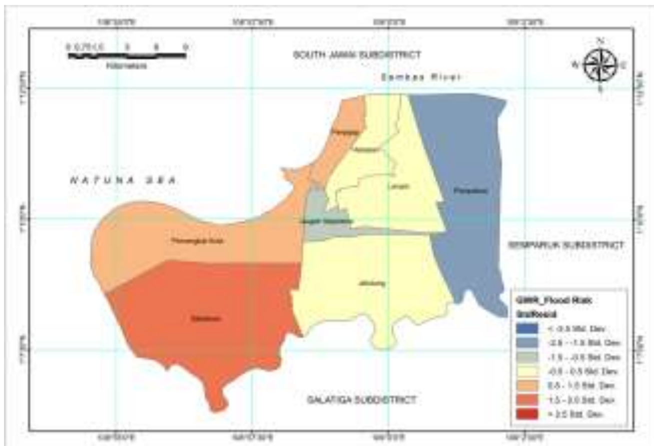

Figure 9. GWR flood risk

The results of calculations using Geographically weighted regression (GWR) obtained the following results:

Table 3. Results Obtained from the GWR Model for Indicators of Flood Risk

Records	Parameters	Amount of Parameters
1	Residual Squares	2.31
2	Effective Number	2.78
3	Sigma	0.67
4	AICc	28.09
5	R2	0.39
6	R2Adjusted	0.19

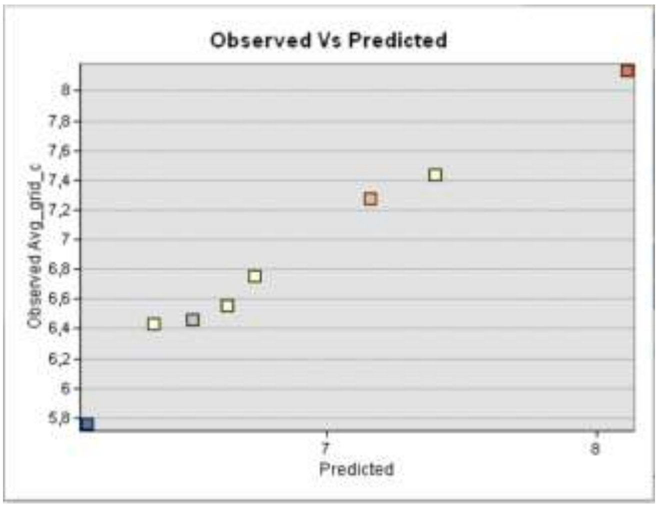

Figure 9. Scatterplot observed Vs predicted

The observed and predicted scatterplot results show a pattern of relationship between observed and predicted values indicating conditions that tend to be linear, so it can be concluded that the identical test is fulfilled. The model analysis results with GWR show a Residual Square with a small value of only 2.31, R2 0.39. In Geographically Weighted Regression analysis, the main thing that needs to be done is to identify a model based on the weighting function with the right side of the model's goodness. The goodness of the model being compared is AIC and AICc, which are seen from the smallest value, while the goodness of the R-square model is seen from the most significant value. The smaller the value of the model's goodness, the better the model. So that in the application of the GWR analysis, the model with the smallest AIC and AICc values is selected.

Conclusion

GIS approaches and remote sensing data are practical tools for mapping flood risk. In addition, GIS and remote sensing-based flood risk mapping is a valuable tool for estimating where flood risks will occur and assisting in making area-specific decisions when carrying out a more detailed flood hazard assessment. Geographic Information Systems and Remote Sensing as a tool for flood risk assessment and spatial modeling can minimize the risk of flooding that occurs. This is because this approach and model can predict places that have a high risk of flooding so that they can reduce property damage and even fatalities. Geospatial information obtained from remote sensing data, supported by GIS, is quickly applied and analyzed spatially. Therefore, mitigation efforts need to be carried out when managing risks that have the potential to become disasters or reduce their impact when they occur. From the facts above, Remote Sensing and GIS data need to be increased to support disaster management, especially floods.

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Author Contributions

Mr. Paiman has contributed to the mapping and rapid provision of flood inundation data on topographic conditions that are difficult to reach in the field.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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