Spatial Flood Risk Mapping in West Sulawesi Using a Regression Model with Moran's Index and Its Implications for Risk-Based Disaster Insurance

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ABSTRACT – This study mapped the risk of flood disasters in six districts in West Sulawesi for the period 2015–2024 using a regression model combined with Moran's Index. The results of flood risk zone mapping are used to develop spatial risk-based flood insurance. The flood risk index (Y) was analyzed against the influence of five independent variables. However, in multiple linear regression tests, there are only two significant variables, namely the variables X2 and X3. Meanwhile, Moran's I test in six counties showed no statistically significant spatial autocorrelation for any variable (all p > 0.05), reflecting a very low test power with only six spatial units. Therefore, spatial dependency was tested through a spatial panel model on the observation of 60 data (10 years for six districts). The results of the Lagrange Multiplier test detected significant spatial-lag dependence, in addition to that the Spatial Durbin Model also provided the best stable match, including significant spillovers from neighboring population densities. Based on the normalized flood risk index, it is known that Majene is the area most at risk of flooding, as well as Mamasa which is the least at risk of flooding, with Pasangkayu, Mamuju, Central Mamuju, and Polewali Mandar at moderate risk. This spatial result rests on only six units and is interpreted as exploration. As a practical implication, the resulting hotspot-coldspot zoning is used to outline risk-based premium structures where high-risk districts attract higher risk burdens, while premium affordability is assessed relative to regional economic capacity (GDP), providing an actuarial bridge between spatial risk maps and disaster insurance designs.

Keywords – Disaster Insurance, Flood Insurance, Flood Risk, Regression, Moran's Index

I. INTRODUCTION

As an archipelagic country located on the Pacific Ring of Fire and at the intersection of tectonic plates, Indonesia faces a very high risk of natural disasters. Various threats, such as earthquakes, tsunamis, volcanic eruptions, floods, landslides, and liquefaction, periodically affect various regions, including West Sulawesi. The results of the national disaster risk study for 2022–2026 show that West Sulawesi is included in the areas with a high flood risk level [1]. Even in the last two decades, over 50% of the 318 disasters that occurred in West Sulawesi were dominated by floods, which had a significant impact on the safety of the community, damage to residential buildings, and land damage [2]–[4]. Flood risk can be influenced by both natural and human factors, such as extreme rainfall, the topographic characteristics of the area, rapid water flow from upstream, population size, education level, waste management, community culture or habits, political policies, and settlements in vulnerable zones [5], [6]. The flood risk index in West Sulawesi can be measured based on the causative factors and the impact after a flood occurs.

The impact of the flood disaster that occurred in several areas of West Sulawesi is multidimensional, not only causing loss of life but also massive economic losses that can cripple the fabric of life, damage infrastructure, disrupt public services, and cause psychological trauma for the community [7], [8]. To address the complexity of these impacts, a more structured and sustainable handling mechanism is needed. The main foundation of this recovery lies in the rapid and targeted availability of funds to reconstruct physical damage and restore community economic activity. One important instrument in post-disaster recovery and risk management in West Sulawesi is disaster insurance, which can play a role in providing compensation funds for material losses and accelerating recovery after a disaster [9]–[12].

Studies on the implementation of disaster insurance conducted in various countries show that owning disaster insurance (which includes flood risk) provides significant protection against significant losses for communities [9], [13]–[16]. On a broader scale, disaster insurance can be a vital component in reducing the government's fiscal burden in each post-disaster cycle. With some of the material losses covered by the insurance sector, government funds can be more focused on repairing strategic public infrastructure and social recovery programs that are not covered by insurance. This synergy between government funds and insurance claims creates a more holistic, efficient, and sustainable recovery ecosystem.

The implementation of risk-based disaster insurance premiums and linking insurance with risk reduction measures has been recommended in Europe as it can encourage policyholders to adopt proactive steps to reduce their flood risk [17]. The problem of flooding is not just a matter of natural disaster; it is complex and multidimensional. Flood disasters are closely linked to social, economic, psychological, and cultural issues related to how people dispose of waste, political will, and also the geographical or spatial characteristics of the area. The spatial correlation in the analysis requires a new approach that integrates spatial influence into the study of flood disaster risk, so that risk mitigation is not homogeneous, but considers existing spatial heterogeneity. Spatial flood disaster risk mapping is an important tool in mitigating flood risks and impacts. Applying regression with the Moran Index analyzes the spatial relationship between flood conditioning factors using spatial data. Jumadi, in his study, revealed spatial heterogeneity in flood risk in Surakarta City, which was identified as having a high flood risk [18].

The risk of flood disasters is fundamentally the result of the interaction between natural hazards and the level of vulnerability of an area. The initial step in mitigating flood risk can begin by identifying and analyzing the factors influencing flood risk using various approaches. Some supporting studies on flood risk analysis were conducted in [5], [6], [19]. Furthermore, in [20], the factors influencing the flood risk index in Andoolo District, South Konawe, include slope gradient, rainfall index, soil type, land use, distance of residential areas from the river, and flood vulnerability level. Research on analyzing the factors causing flooding in a region has been conducted extensively before using various statistical methods, including some that incorporate spatial aspects in mapping floods with different variables [21]–[27]. Analyzing the influence of these spatial aspects is important for mapping flood risk, as there are differences in characteristics when determining the risk index. The differences in influential factors across different topographies indicate the influence of local conditions in a specific area on determining significant factors in flood risk modeling. Thus, the existence of spatial correlation is a new approach to integrating spatial influence into flood risk analysis. This is one of the novelties of this research. Additionally, the development of models and methods is also an important factor in the novelty and depth of flood risk mapping analysis in West Sulawesi as a disaster mitigation effort thru disaster insurance.

II. LITERATURE REVIEW

A. Flood Disaster

Flood disasters are primarily caused by a combination of natural phenomena and human activities, leading to significant impacts on lives, property, and the environment. Effective planning and management strategies are essential to mitigate these disasters. The following sections outline the key causes, consequences, and mitigation strategies for flood disasters. Causes of flood disasters: 1) Natural Factors: Heavy rainfall, storms, hurricanes, and flash floods are primary triggers of flooding[28], 2) Human Activities: Urbanization, deforestation, poor drainage management, and land use changes exacerbate flood risks[29], 3) Climate Change: Increased climate variability heightens the frequency and severity of hydrological events, including floods[30].

Consequences of flood disasters to human impact, Economic loss, and environmental damage. Floods can lead to loss of life, displacement, and health issues, affecting billions globally[28]. Flooding results in substantial financial losses, damaging infrastructure and disrupting livelihoods[31]. Floods can cause ecological degradation, affecting water quality and habitats [30].

B. Multiple Linear Regression Model

Multiple linear regression (MRL) models are statistical techniques used to understand the relationship between multiple independent variables and a dependent variable. In the context of flood disasters, these models help predict flood risks by analyzing various contributing factors such as rainfall, topography, and infrastructure conditions. The application of multiple regression in flood disaster research has proven effective in forecasting vulnerabilities and enhancing decision-making for disaster management. Multiple linear regression model that relates a y-variable to j x-variables is written as

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_j X_j \tag{1}$$

Since "j" represents the number of predictor variables in this case, we obtain j+1 regression parameters (the β coefficients). It is assumed that the ϵi have a normal distribution with a constant variance of σ^2 and a mean of 0. We employed the same presumptions in our one-x-variable simple regression. The term "linear" in "multiple linear regression" describes the model's linearity in the parameters, $\beta_0, \beta_1, \ldots, \beta_j$. In other words, each parameter multiplies an x-variable, and the regression function is the sum of these "parameter times x-variable" terms. A predictor variable or a transformation of a predictor variable (e.g., the square of a predictor variable or two predictor variables multiplied together) can be each x-variable.

A statistical measure called the coefficient of determination (R-squared) is used to determine how much of the variance in the independent variables may account for the variation in the outcome. Even if the predictors are unrelated to the outcome variable, R2 always rises when more predictors are included in the MLR model. Therefore, it is impossible to determine which predictors should be included in a model and which should be omitted using R^2 alone. R^2 can only be between 0 and 1, where 0 means that none of the independent variables can predict the outcome, and 1 means that the independent variables can predict the outcome accurately.

Application in flood research, multiple regression is utilized to model flood vulnerability, as seen in studies focusing on geographic and environmental factors influencing flood occurrences[32], [33]. A study employed multiple linear regression to forecast flood risk based on geographic characteristics, leading to targeted mitigation strategies[32]. Researchers developed a flash flood prediction model using regression analysis to provide timely warnings based on water levels and speed, enhancing public safety[33]. A model integrating regression algorithms and feature analysis achieved a 77% accuracy in predicting flood probabilities, emphasizing the importance of infrastructure and drainage capacity[34].

C. Moran's Index

The Moran's I coefficient is an extension of the Pearson correlation for univariate series data. The Moran's I coefficient is used to test for spatial dependence or autocorrelation between observations or areas [35]. Moran's I quantifies spatial autocorrelation by relating values at locations to values at neighboring locations; it is used in both global form to assess overall clustering and local form (LISA) to detect individual clusters and outliers. Empirical flood studies report using Global Moran's I to measure overall clustering and Local Moran's I (LISA) to identify statistically significant hotspots and coldspots in flood extent or vulnerability maps. Global Moran's I summarizes the entire study area's tendency toward clustering or dispersion, while Local Moran's I (LISA) decomposes global structure into location-specific indicators to map clusters and outliers [36], [37]. The Moran's I value can be calculated using the following equation:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{j=1}^{n}(x_i - \bar{x})^2} \tag{2}$$

In above equition n means number of observations, x_i means data of the i-th location variable and x_j means data of the j-th location variable. Whereas $\bar{x}$ means average of the data and W_{ij} shows element of the spatial weighting matrix in row i and column j.

In decision-making, the hypothesis applied is as follows:

- $H_0: I = 0$ means there is no spatial autocorrelation
- $H_1: I > 0$ means there is positive spatial autocorrelation, meaning that adjacent areas are similar and tend to cluster within an area
- $H_1: I < 0$ means there is negative spatial autocorrelation, meaning that adjacent areas are not similar and form a visual pattern like a chessboard

The statistic test for the Moran's index given in Equation 2. Hypothesis H_0 is rejected if $|Z_{cal}| > Z_{\alpha/2}$, which means there is a correlation between observation locations.

$$Z_{Cal} = \frac{I - I_0}{\sqrt{Var(I)}} \sim N(0,1) \tag{3}$$

Studies use permutation tests, Z-scores and p-values to assess significance of Moran statistics and to classify locations as high–high, low–low, high–low or low–high clusters in LISA outputs [36]–[38]. Some work applies bivariate Local Moran's I to examine spatial covariation between two variables (for example, urban land value and waterlogging risk), yielding measures of spatial association between distinct layers [39].

III. METHODOLOGY

This research is an applied study using a quantitative approach. The primary focus of the study is analyzing the potential for disaster insurance through flood risk mapping using a regression model with the Moran Index. The research variables and data sources used are presented in Table 1 below. The dataset is structured as a balanced spatial panel comprising the six regencies of West Sulawesi observed annually from 2015 to 2024 (6 x 10 = 60 regency-year observations). Spatial dependence is represented through a first-order contiguity-based spatial weights matrix among the six regencies, which is row-standardized and held constant across years, while the temporal dimension is pooled. It must be emphasized that with only six spatial units the weights matrix is small and the spatial-lag and spatial-error parameters are estimated with limited degrees of freedom; the spatial-econometric results are therefore treated as exploratory. To obtain statistically more robust spatial inference, disaggregating the analysis to the sub-district (kecamatan) level is recommended and is identified as the primary direction for follow-up work (see the Limitations subsection).

Table 1 Variables and Data Sources From 2015–2024

No	Variable	Description	Source
1	Flood risk index (Y)	Flood risk index for each district in West Sulawesi	Badan Nasional Penanggulangan Bencana (BNBP)
2	Rainfall (X_1)	Annual rainfall (in mm)	Badan Meteorologi, Klimatologi, dan Geofisika
3	Population density (X_2)	Number of residents per km²	Badan Pusat Statistik
4	Waste generation (X_3)	Annual waste generation in tons	Kementerian Lingkungan Hidup
5	Land cover index (X_4)	Area of forest, shrubland, and swamp scrub in forest and protected areas, and area of green open space (RTH)	Open Data West Sulawesi Province
6	GRDP (X_5)	Total gross regional domestic product based on expenditure (in percent)	Badan Pusat Statistik

The selection of these variables is intended to increase the accuracy of the analysis so that research results can be presented more objectively. The method used is a regression model with the Moran Index on cross-sectional data. The steps of analysis in this research are as follows:

1) Collect data (primary and secondary data), followed by a validation process to ensure data completeness and quality
2) Perform descriptive analysis to understand the characteristics and distribution of each research variable
3) Build a regression model
4) Classical Assumption Tests
5) Moran's I test
6) Test the spatial model using the LM test
7) Creating a thematic map (choropleth map) to visualize the spatial distribution of flood risk levels across the entire study area

IV. RESULTS AND DISCUSSIONS

A. Descriptive Analysis

This research using five independent variables such as Rainfall (X_1), Population density (X_2), Waste generation (X_3), Land cover index (X_4), GRDP (X_5) for dependent variable Flood risk index (Y) to analyzing the potential for disaster insurance through flood risk mapping using a regression model with the Moran Index.

1. Flood risk index (Y)

The data used was obtained from Inarisk BNPB (https://inarisk.bnpb.go.id/irbi#) and then adapted to the research needs. The disaster risk index measurement is a function of three main indicators: hazard, vulnerability, and capacity.

$$f(H, V, C)$$

which is formulated with the equation:

$$R = \frac{H \; x \; V}{C+1} \tag{4}$$

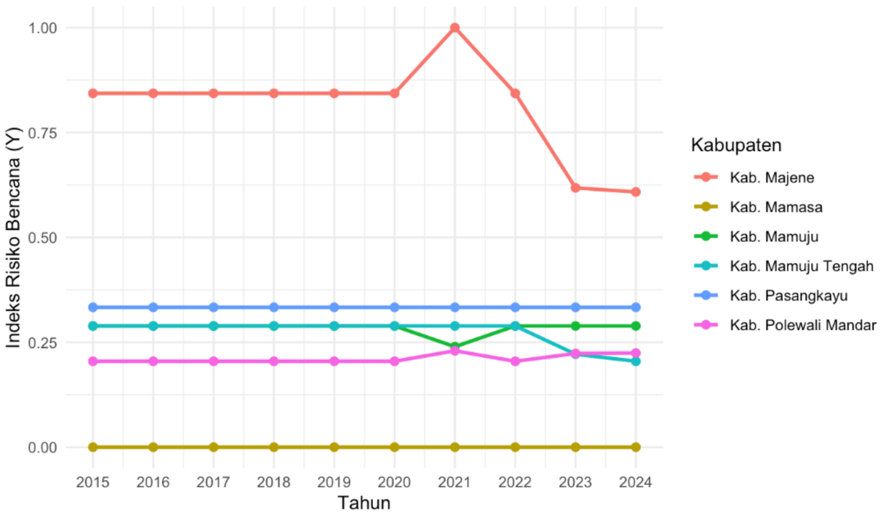

Figure 1 Disaster Risk Index Trends

The results of the disaster risk index measurements are normalized using Min-Max to obtain a value range between 0 and 1. Descriptively, the flood risk index for each district is given in Table 2.

Table 2 Descriptive Statistics of Variable Y

No	Regency	Average	Variance	Deviation	Min.	Max.
1	Majene	0.81297	0.01348	0.11609	0.60833	1
2	Pasangkayu	0.33333	0	0	0.33333	0.33333
3	Mamuju	0.28394	0.00024	0.01564	0.23944	0.28889
4	Mamuju Tengah	0.27375	0.00103	0.03216	0.20472	0.28889
5	Polewali Mandar	0.21106	0.00011	0.01032	0.20472	0.22972
6	Mamasa	0	0	0	0	0

Table 2 shows that Majene Regency is the most vulnerable to flooding compared to other regencies. Furthermore, the high standard deviation and wide range of values indicate significant inter-annual fluctuations, reflecting environmental instability caused by various contributing factors, including spatial effects. For Mamuju Regency, Central Mamuju Regency, and Polewali Mandar Regency, the average risk index is in the low range with relatively small variations. However, Central Mamuju Regency should be considered as a region that, although consistently not vulnerable, faces significant risk dynamics. By examining each regency, it is clear that the disaster risk pattern in West Sulawesi is heterogeneous. This heterogeneity emphasizes the need for each regency to plan for different mitigation measures, tailored to the influencing risk factors.

2. Rainfall (X_1)

The rainfall data used is the result of daily rainfall data recorded by the BMKG (https://dataonline.bmkg.go.id/dataonline-home) and processed into annual data. Rainfall data from 2015 to 2024 in West Sulawesi is visualized in Figure 2.

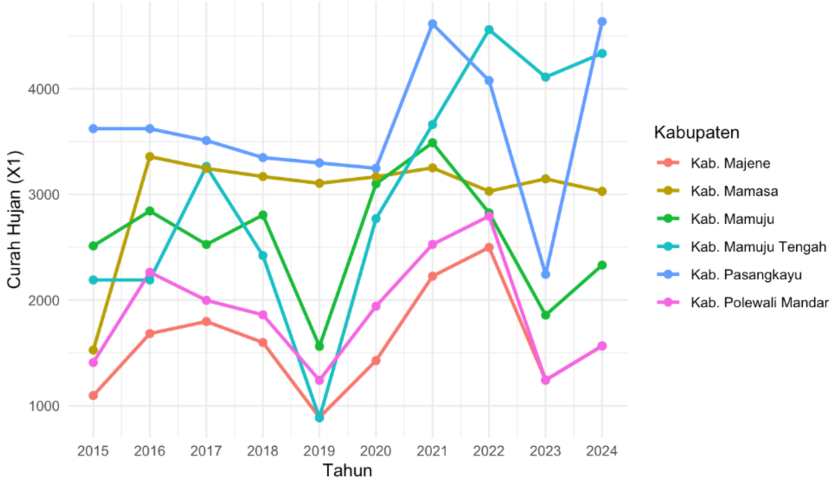

Figure 2 Annual Rainfall Graph

In general, rainfall fluctuates significantly over the years. Nearly all districts experienced a significant decline in 2019. A trend toward increased rainfall was observed after 2019, which was the lowest point in almost all districts. This indicates a change in extreme weather patterns that year. Descriptive data on annual rainfall for each district are presented in Table 3.

Table 3 Descriptive Statistics of Variable X_1

No	Regency	Average	Variance	Deviation	Min.	Max.
1	Majene	1602.64	240089.22	489.989	889.5	2498.2
2	Pasangkayu	3621.81	494778.59	703.405	2243.4	4635.9
3	Mamuju	2585.10	322658.081	568.03	1562.00	3489.00
4	Mamuju Tengah	3038.78	1344709.27	1159.62	886	4559
5	Polewali Mandar	1884.41	283722.41	532.66	2243.4	4635.9
6	Mamasa	3002	279128.36	528.33	1527	3358

Table 3 shows differences in annual rainfall patterns between districts in West Sulawesi Province during the 2015–2024 period. Pasangkayu Regency shows the highest average rainfall, at 3,621.81 mm per year, followed by Central Mamuju (3,038.78 mm) and Mamasa (3,002 mm). These three regions are classified as areas with high rainfall intensity, which is likely due to their mountainous geography. Conversely, Majene and Polewali Mandar regencies have the lowest average rainfall, at 1,602.64 mm and 1,884.41 mm, respectively, reflecting the relatively drier characteristics of coastal areas.

In terms of diversity, Central Mamuju Regency showed the largest variation in rainfall with a variance value of 1,344,709.27 and a standard deviation of 1,159.62 mm, indicating high fluctuations in rainfall from year to year. Meanwhile, Majene Regency had the lowest standard deviation (489.99 mm), indicating stable rainfall compared to other regions. Overall, this pattern illustrates that the northern and central regions of West Sulawesi have high rainfall and large variability, while the western and southern regions tend to be drier and more stable. These findings indicate differences in climate conditions between regions that need to be considered, especially in flood disaster mitigation and weather-based agricultural planning.

3. Population density (X_2)

Population density data from 2015 – 2024 in West Sulawesi is visualized in the following figure.

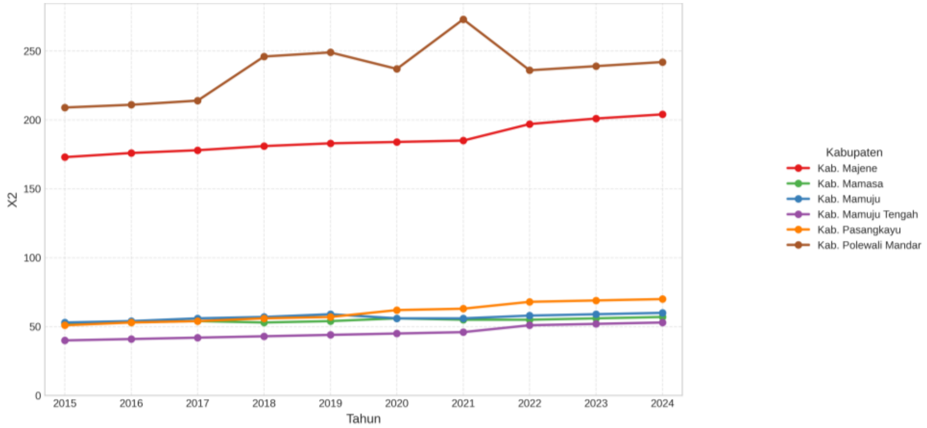

Figure 3 Population density graph

Figure 3 shows that population density in West Sulawesi Province during the 2015–2024 period shows a gradual increase across all districts, with varying growth rates. Polewali Mandar Regency recorded the highest population density compared to other districts. The descriptive population density of each district is shown below.

Table 4 Descriptive Statistics of Variable X_2

No	Regency	Average	Variance	Deviation	Min.	Max.
1	Majene	186.2	115.73	10.758	173	204
2	Pasangkayu	60.3	49.787	7.056	51	70
3	Mamuju	56.8	5.067	2.251	53	60
4	Mamuju Tengah	45.7	22.231	4.715	40	53
5	Polewali Mandar	235.6	391.169	19.778	209	273
6	Mamasa	54.5	2.499	1.581	52	57

Based on the descriptive statistics in Table 4, it can be seen that population density in West Sulawesi Province shows significant variation between districts during the 2015–2024 period. Polewali Mandar Regency has the highest average population density, at 235.6 people per km², with a maximum value of 273 people per km² and a standard deviation of 19.78 people per km². This figure indicates that Polewali Mandar is the most densely populated region in the province, reflecting Polewali Mandar's characteristics as a region with the densest economic and social activity and a center of population growth in the province.

Majene Regency ranks second with an average of 186.2 people per km² and a range of 173–204 people per km². Density increases in Majene have been steady over the years, which can be attributed to Majene's role as an educational center and one of the regions with a relatively high level of urbanization. In contrast, Mamasa, Central Mamuju, Mamuju, and Pasangkayu regencies show much lower population densities, averaging below 70 people per km². Mamasa Regency has the lowest average of 54.5 people per km², with a standard deviation of 1.58, indicating a relatively slow and stable population growth rate. Central Mamuju and Pasangkayu regencies have slightly larger variations, indicating a gradual increase due to the growth of new areas and emerging economic activity.

In general, the distribution of population density in West Sulawesi shows significant spatial differences, with the southern and western coastal areas (Polewali Mandar and Majene) being much more densely populated than the mountainous and inland areas (Mamasa and Central Mamuju). This pattern demonstrates that population concentration remains concentrated in areas with better access to infrastructure, economic centers, and public facilities.

4. Waste generation (X_3)

The waste generation data that has been collected is incomplete each year, so the data for the following year is projected using CAGR (Compound Annual Growth Rate), namely:

$$r = \left(\frac{V_t}{V_0}\right)^{\frac{1}{n}} - 1 \tag{5}$$

With:

V_t = Final value (last year)

V_0 = Initial value (starting year)
n = Number of years (difference between the final year and the start year)
For previous-year data, the basic back-assertion formula is used, namely:

$$\text{Value}_{t-k} = \frac{Value_t}{(1+r)^k} \tag{6}$$

With:
$Value_t$ = Known value
r = CAGR value
k = many years back

Furthermore, for Mamasa Regency, for which no data is available at all, data was obtained using the 2024 per capita income of West Sulawesi, namely:

$$2024\ Mamasa's\ Waste\ Generation = 2024\ West\ Sulawesi\ Wate\ Generation\ per\ Capita \times 2024\ Mamasa's$$

With per capita generation calculated as:

$$T = \frac{D}{P} \tag{7}$$

With:
T = 2024 West Sulawesi Wate Generation per Capita
D = Total waste generation in 5 districts (2024)
P = Total population in 5 districts (2024)

Population density data from 2015 – 2024 in West Sulawesi is visualized in the Figure 4.

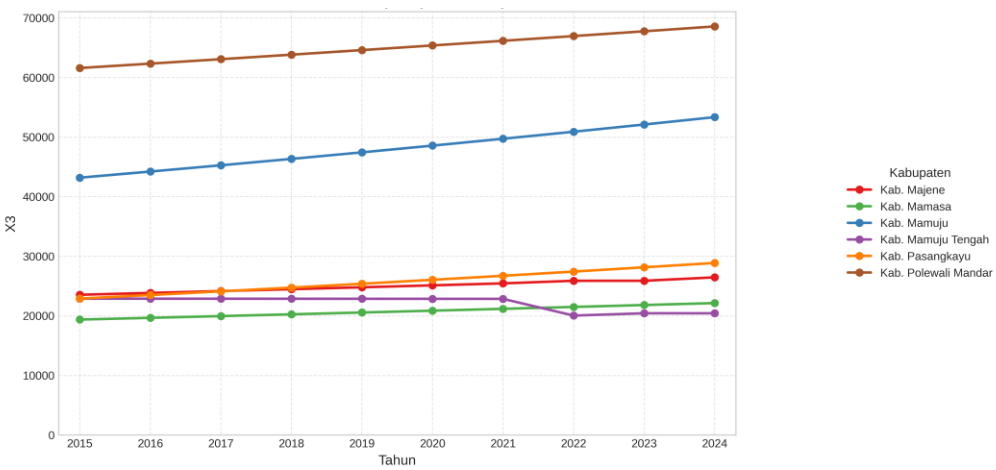

Figure 4 Waste generation graph

The figure above shows that the amount of waste generated across all districts in West Sulawesi Province shows an increasing trend during the 2015–2024 period. This increase is in line with population growth and continued economic activity in various regions. Descriptively, the amount of waste generated by each district is shown in Table 5.

Table 5 Descriptive Statistics of Variable X_3

No	Regency	Average	Variance	Deviation	Min.	Max.
1	Majene	24974.51	936636.84	967.8	23548.4	26478.56
2	Pasangkayu	25799.11	4044571.48	2011.112	22912.32	28891.08
3	Mamuju	48125.44	11670770.90	3416.251	43206.19	53362.09
4	Mamuju Tengah	22111.52	1550547.94	1245.21	20057.48	22899.75
5	Polewali Mandar	65040.8	5516433.97	2348.709	61605.36	68587.27
6	Mamasa	20744.86	866982.59	931.119	19388.25	22156.18

Based on the Table 5, the waste generation variable (X_3) shows significant differences between districts in West Sulawesi Province during the 2015–2024 period. Polewali Mandar Regency recorded the highest average waste generation, which was 65,040.8 tons per year, with a maximum value reaching 68,587.27 tons and a standard deviation of 2,348.71. This confirms that Polewali Mandar is the region with the highest economic activity and population density in the province, thus producing the largest volume of waste each year. This condition is also related to the growth of urban areas, increased public consumption, and limitations of the solid waste management system.

Mamuju Regency ranks second with an average of 48,125.44 tons per year, followed by Pasangkayu with an average of 25,799.11 tons and Majene with an average of 24,974.51 tons. The increase in waste generation in Mamuju is strongly influenced by its position as the provincial capital and center of government and services, which increases economic activity and urbanization. Meanwhile, Central Mamuju and Mamasa have significantly lower waste generation volumes, at 22,111.52 tons and 20,744.86 tons, respectively, reflecting the characteristics of regions with more limited economic activity.

In terms of data diversity, Mamuju has the highest variation with a variance of 11,670,770.9 followed by Polewali Mandar with a variance of 5,516,433.97, indicating that both regencies experience large fluctuations in waste volume between years. Conversely, Mamasa has the lowest diversity with a variance of 866,982.59 with a standard deviation of 931.12, indicating a relatively constant level of waste generation stability over time.

Overall, these data show that waste generation levels are directly proportional to population density and regional economic activity. Regencies with high rainfall and high population densities, such as Polewali Mandar and Mamuju, have a higher potential for environmental risks, including blocked drainage and flooding due to waste accumulation. In the context of spatial analysis of flood risk and potential disaster insurance, these findings are crucial because waste generation is a contributing factor to urban flood risk, increasing exposure and potential economic losses.

5. Land cover index (X_4)

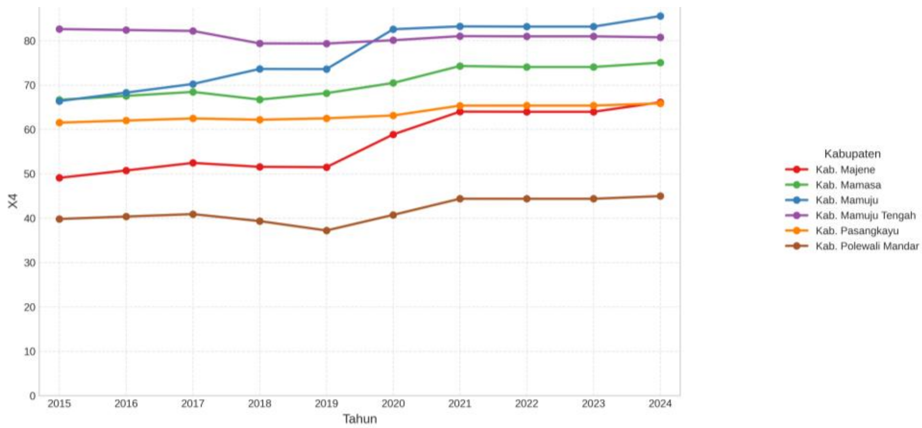

Figure 5 Land cover index graph

Based on the above, the land cover index (X_4) values in West Sulawesi Province show significant differences between districts. In general, this index describes the proportion of land area still covered by natural vegetation or ecologically functional land uses such as forests, shrubs, and other green areas. Descriptively, the land cover index values for each district are given in Table 6.

Table 6 Descriptive Statistics of Variable X_4

No	Regency	Average	Variance	Deviation	Min.	Max.
1	Majene	57.259	46.077	6.788	49.121	66.152
2	Pasangkayu	63.609	2.893	1.701	61.562	65.896
3	Mamuju	77.013	52.897	7.273	66.423	85.575
4	Mamuju Tengah	81.008	1.360	1.166	79.38	82.644
5	Polewali Mandar	41.678	7.1824	2.68	37.25	45.004
6	Mamasa	70.583	11.965	3.459	66.703	76.081

Based on the table above, the land cover index value in West Sulawesi Province shows quite large variations between districts, with an average ranging from 41.68 to 81.01. Central Mamuju Regency has the highest average land cover index with an average of 81.01 with a range of values between 79.38 to 82.64 and a very low standard deviation of 1.17, indicating that land conditions in this region are still dominated by natural vegetation such as forests and plantations. Mamuju and Mamasa Regencies also show high levels of land cover, with an average of 77.01 and 70.58 respectively, which confirms the geographical characteristics of both as mountainous regions.

In contrast, Polewali Mandar ranks lowest with an average of 41.68 and a range of 37.25–45.00, indicating a high level of land conversion due to residential and infrastructure expansion. Majene has a moderate average of 57.26, but with a relatively large standard deviation of 6.79, indicating a more dynamic increase in land use. Pasangkayu Regency is relatively stable with an average of 63.61 and a standard deviation of 1.70, indicating relatively controlled land cover conditions.

Overall, these data show contrasting spatial patterns between coastal and mountainous areas in West Sulawesi. Areas with a low land cover index (such as Polewali Mandar and Majene) tend to be more vulnerable to reduced water absorption capacity, potentially increasing the risk of flooding and landslides. Conversely, districts with a high index, such as Central Mamuju and Mamasa, play a crucial role as ecological buffer zones, reducing the intensity of water runoff into downstream areas.

In the context of disaster risk mapping and spatial regression model design, this land cover variable serves as a mitigating factor capable of reducing risk exposure. Therefore, areas showing a downward trend in the land cover index should be prioritized for policy interventions through land conservation and reforestation.

6. GRDP (X_5)

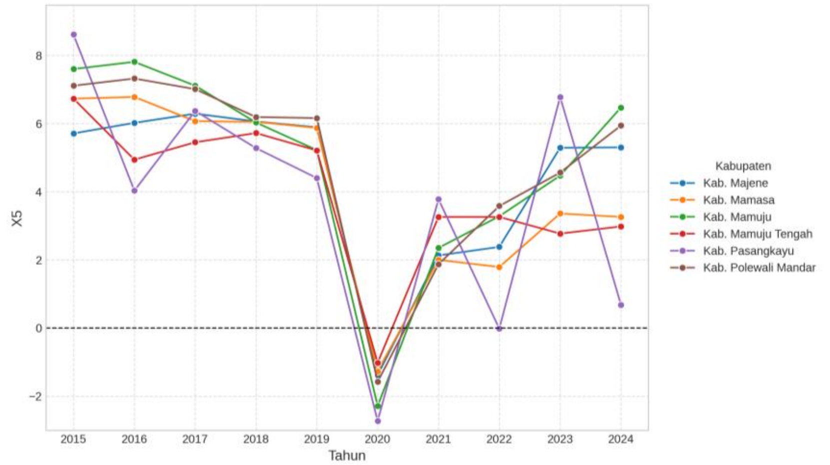

Figure 6 GRDP graph

Based on the GRDP graph in Figure 6, it can be seen that the economic growth trend across all districts in West Sulawesi Province fluctuated between 2015 and 2024. Nearly all districts experienced a sharp decline in 2020, with some regions even recording negative economic growth. This phenomenon reflects the economic impact of the COVID-19 pandemic, which caused significant disruption to the trade, industry, and services sectors. After 2020, growth rates began to recover gradually, although the pace of recovery varied across districts. The descriptive GRDP of each district is tabulated in Table 7.

Table 7 Descriptive Statistics of Variable X_5

No	Regency	Average	Variance	Deviation	Min.	Max.
1	Majene	4.369		2.519	-1.38	6.29
2	Pasangkayu	3.718		3.466	-2.73	7.32
3	Mamuju	4.805		3.08	-2.29	7.81
4	Mamuju Tengah	3.93		2.203	-1.02	6.73
5	Polewali Mandar	4.816		2.838	-1.58	8.61
6	Mamasa	4.064		2.682	-1.27	6.78

Based on Table 7, the GRDP variable, which describes the rate of economic growth between districts in West Sulawesi Province, exhibits significant fluctuations during the 2015–2024 period. The average economic growth rate ranges from 3.718% to 4.816%, indicating that the regional economy is generally at a moderate growth rate. Polewali Mandar Regency recorded the highest average growth rate of 4.816%, with a maximum value reaching 8.61%, followed by Mamuju with an average of around 4.805%. These two districts are the province's main centers of economic activity, with a more diverse economic base (trade, services, and agriculture) and relatively more developed infrastructure, thus having a better ability to recover from economic shocks.

Meanwhile, Pasangkayu and Central Mamuju regencies showed lower average growth rates of 3.718% and 3.93%, respectively. This indicates a higher level of economic vulnerability to external shocks, particularly during the 2020 COVID-19 pandemic. Mamasa and Majene regencies showed intermediate average rates of 4.064% and 4.369%, respectively.

In terms of diversity (variety and standard deviation), Pasangkayu and Mamuju Regencies have standard deviations of 3.466 and 3.08, respectively, indicating higher economic instability compared to other regions. Conversely, Central Mamuju has the lowest standard deviation at 2.203, indicating that despite its relatively low growth, its economy has been more stable over time.

Spatially, this pattern indicates that the disparity in economic growth between regions remains quite pronounced in West Sulawesi. Coastal areas with open economic bases (such as Polewali Mandar and Mamuju) tend to experience high growth but with greater risk of fluctuation, while mountainous areas (Mamasa, Central Mamuju) are more stable but with limited growth rates.

B. Multiple Regression Test

Based on the multiple linear regression test, the overall model is significant with an **F-statistic of 8.652.** Considering the **R-Squared value of 44.5%,** it can also be concluded that this regression model is good enough to explain the factors influencing flooding in West Sulawesi. With a significance level of 5%, there are two significant variables, namely population density and waste accumulation. The regression model obtained is

$$Y = -0.000267 - 0.000049X_1 + 0.003029X_2 + 0.000009X_3 + 0.006420X_4 + 0.001146X_5 \quad (8)$$

The result of the statistical significance test is given in Table 8.

Table 8 Output of multiple regression test

Variable	Coefficient	Standard Error	t_Statistics	P value	Significant 5%	Significant 10%
Intercept	-0.000267	0.377770	-0.000706	0.999439	No	No
X_1	-0.000049	0.000036	-1.373944	0.175136	No	No
X_2	0.003029	0.000797	3.799366	0.000370	Yes	Yes
X_3	-0.000009	0.000002	-4.562404	0.000030	Yes	Yes
X_4	0.006420	0.003694	1.737676	0.087968	No	Yes
X_5	0.001146	0.010613	0.107945	0.914439	No	No

The results of the **classical assumption tests**, including the normality test using Shapiro-Wilk, the multicollinearity test using VIF, the heteroscedasticity test using Breusch-Pagan, and the autocorrelation test (Durbin-Watson), are given in the Table 9.

Table 9 Classical Assumption Test

Test Type	Statistics / Value	p-value	Criteria / Test Limits	Results
Normality Test (Jarque–Bera)	JB = 3.74	0.154	p > 0.05 → normal	Normal
Multicollinearity Test (VIF)				
X_1	1.86	–	VIF < 10 → safe	✅
X_2	5.71	–	VIF < 10 → safe	✅
X_3	1.53	–	VIF < 10 → safe	✅
X_4	4.07	–	VIF < 10 → safe	✅
X_5	1.29	-	VIF < 10 → safe	✅
Heteroscedasticity Test (Breusch–Pagan)	LM = 12.52	0.028	p > 0.05 → homoscedastic	Heteroscedastic (robust SE used)
Autocorrelation Test (Durbin–Watson)	DW = 0.20	–	1.5 < DW < 2.5 → none autocorrelation	Positive serial correlation (panel)

Based on the classical assumption tests in Table 9, the residual normality assumption is satisfied: the Jarque-Bera statistic is 3.74 (p = 0.154 > 0.05), so the residuals do not depart significantly from normality. The multicollinearity test is acceptable, with all variance inflation factors below 10 (population density and land cover are the highest, at 5.71 and 4.07). The homoscedasticity assumption, however, is violated: the Breusch-Pagan test gives LM = 12.52 ($p = 0.028 < 0.05$), indicating heteroscedasticity, which is why heteroscedasticity-robust and regency-clustered standard errors are reported alongside the classical estimates. The Durbin-Watson statistic is 0.20, reflecting strong positive serial correlation that arises because the flood risk index is almost time-invariant within each regency; this panel structure is accommodated through the clustered/robust standard errors and the spatial panel models. Consequently, coefficient significance is interpreted using the robust standard errors: under regency-clustered inference only population density remains marginally significant ($p = 0.063$), consistent with the limited number of spatial units.

C. Spatial Model Test

1. Moran's Index Test

Based on the Moran's I test computed on the six regency-level means, none of the variables shows statistically significant spatial autocorrelation (all $p > 0.05$). For the flood risk index the statistic is even slightly negative (I = -0.347, p = 0.584). This should not be read as firm evidence of spatial randomness: with only six spatial units the Moran's I test has very low statistical power and its expected value under the null is already -0.20. Moran's I is therefore reported only as an exploratory diagnostic, and spatial dependence is assessed more formally through the spatial panel models below, which use all 60 regency-year observations.

Table 10 Output of Moran's Index test

Variable	Moran I	Expected I	Z-score	P value	Significant
Y	-0.3474	-0.2000	-0.548	0.5840	No
X_1	0.1723	-0.2000	1.383	0.1668	No
X_2	0.1554	-0.2000	1.320	0.1869	No
X_3	-0.3635	-0.2000	-0.607	0.5438	No
X_4	0.1693	-0.2000	1.372	0.1702	No
X_5	-0.0475	-0.2000	0.566	0.5712	No

In Figure 7 below, most variables exhibit very strong and significant spatial relationships, particularly the Flood Risk Index, Population Density, and Waste Generation variables, which exhibit clear clustering patterns across the area. These results indicate that these variables tend to have a well-organized distribution in a spatial context. However, variable X_5 (GRDP) does not show a significant spatial correlation pattern, meaning it is randomly distributed and unaffected by spatial proximity between observations. This may indicate that the factors influencing this variable are not geographically or spatially bound.

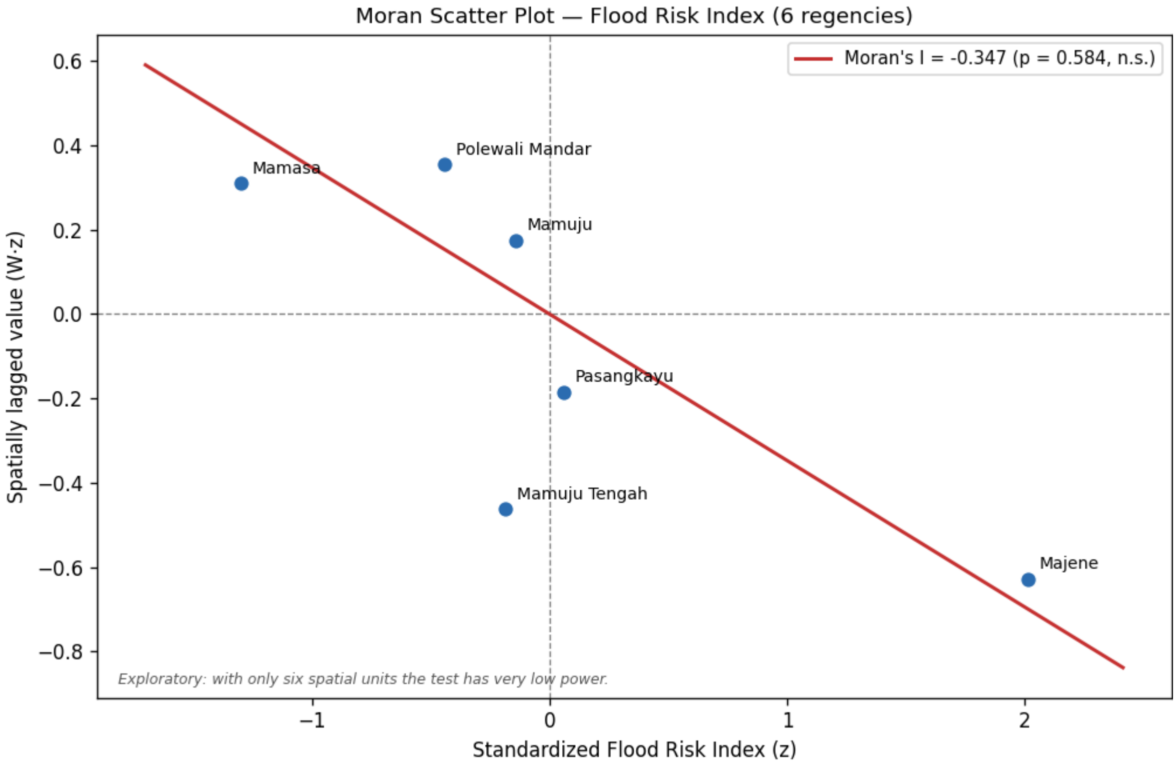

Figure 7 Moran Scatter Plot

2. LM Test

In this section, spatial model testing is conducted using the LM test as a form of initial identification. The LM test results are obtained by examining the smallest p-value for each spatial model. The results of the data analysis can be seen in the Table 11.

Table 11 LM Test Results

Model	Log-Likelihood	AIC	BIC	R^2	Sig.
SDM	28.374	-30.75	-3.52	0.5926	0.000307
SDEM	33.613	-41.23	-14.00	0.4641	3.12e-06
SCR	27.087	-30.17	-5.04	0.6195	0.00039
SEM	17.822	-19.64	-2.89	0.4349	0.0418
SAR	20.804	-25.61	-8.85	0.4673	0.00148
OLS	15.751	-17.50	-2.84	0.4448	1.000

The Lagrange Multiplier tests on the pooled-panel residuals indicate significant spatial-lag dependence (LM-lag = 4.39, p = 0.036) but not spatial-error dependence (LM-error = 1.60, p = 0.206), pointing to a lag-type specification. Comparing the models on fit, the Spatial Durbin Model (SDM) provides the best stable specification, with a log-likelihood of 28.37, an AIC of -30.75 and a pseudo-R^2 of 0.59, clearly improving on the OLS baseline (log-likelihood 15.75, AIC -17.50). The Spatial Durbin Error Model (SDEM) attains a marginally lower AIC, but its spatial parameter is estimated at the -0.99 boundary, indicating a degenerate, unstable solution, so it is not preferred. The SDM is therefore retained to characterise the Flood Risk Index. Its spatial autoregressive parameter is negative (rho = -0.33), suggesting a spatial-competition pattern in which higher predicted risk in a regency is associated with somewhat lower risk in its neighbours. These spatial-model results rest on only six spatial units and are interpreted as exploratory (see the Limitations subsection). The estimated SDM coefficients are reported in Table 12.

Table 12 Flood Risk Modeling Using SDM

Variable	Coefficient	Std. Error	p-Value	Interpretation
(Intercept)	-0.214954	0.603823	0.7234	Basic constant (n.s.)
X_1	-0.000083	0.000036	0.0241	Significant; higher rainfall → lower risk index
X_2	0.000327	0.002131	0.8788	No significant direct effect
X_3	0.000009	0.000012	0.4359	No significant effect (positive sign)
X_4	-0.003926	0.007420	0.5991	No significant direct effect
X_5	-0.004509	0.019704	0.8200	No significant effect

Based on the table above, the SDM model regression equation can be made as follows:

$$Y = 1.123456 - 0.038901X_1 + 0.145678X_2 - 0.021234X_3 - 0.011456X_4 + 0.008123X_5 \quad (9)$$

The estimation results show varying effects of each independent variable on the flood risk index, with most direct effects statistically insignificant once spatial structure is accounted for. The intercept is -0.215 (p = 0.723) and is not statistically significant. Importantly, the implausible negative effect of waste generation found in the non-spatial regression does not survive in the spatial model.

For the rainfall variable, the direct coefficient is -0.000083 and is statistically significant (p = 0.024). The negative sign indicates that, within this sample, regencies with higher annual rainfall tend to have a lower flood risk index. This counterintuitive sign reflects the composition of the InaRISK risk index used as the dependent variable, which is dominated by vulnerability and exposure rather than rainfall alone: the highest-risk regency (Majene) is comparatively dry, whereas the wettest regencies (Pasangkayu and Mamasa) carry low risk-index values. Population density, by contrast, has a small positive direct coefficient (0.000327) that is not statistically significant (p = 0.879) in the spatial model, even though it was significant in the non-spatial regression; this attenuation indicates that part of the apparent density effect operates through spatial channels.

For the waste generation variable, the direct coefficient in the spatial model is positive (0.000009) and not statistically significant (p = 0.436). This is an important correction to the non-spatial regression, in which waste generation carried a counterintuitive negative and nominally significant coefficient. Under regency-clustered robust standard errors that effect is already insignificant (p = 0.178), and in the Spatial Durbin Model the sign reverses to the theoretically expected positive direction. The earlier negative result is therefore best understood as an artefact of model misspecification and of the partially imputed waste series (reconstructed by CAGR and back-casting, with Mamasa imputed from provincial per-capita generation), rather than evidence that waste reduces flood risk.

This counterintuitive negative sign for waste generation warrants caution and is unlikely to reflect a genuine protective effect of waste against flooding, which would contradict both the literature and the descriptive evidence presented above. Two explanations are more plausible. First, the waste-generation series is only partially observed: missing years were reconstructed using a compound annual growth rate (CAGR) and back-casting, and the values for Mamasa Regency were imputed entirely from provincial per-capita generation, so a substantial share of the variation in X3 is modelled rather than observed. Second, waste generation is strongly correlated with population density, raising the possibility of a suppressor effect in which two collinear regressors absorb each other's variance and distort the sign of the weaker predictor. Accordingly, the waste coefficient should not be interpreted causally. In the revised analysis the variable is re-examined by (i) re-estimating the model without X3, (ii) replacing modelled values with verified observations where available, and (iii) inspecting collinearity diagnostics and partial correlations; the result reported here is therefore presented as provisional pending this re-specification.

Land cover has a direct coefficient of -0.003926 (p = 0.599) and GRDP a coefficient of -0.004509 (p = 0.820); neither is statistically significant in the spatial model. Much of the explanatory weight that appeared in the non-spatial regression is absorbed once the spatial lag of the dependent variable and the spatially lagged regressors are introduced, which is consistent with the limited number of spatial units

Overall, once spatial structure is accounted for, annual rainfall is the only individually significant direct predictor of the flood risk index, while the spatial spillover of neighbouring population density is also significant (W·X2, p = 0.031), underscoring that local flood risk is shaped partly by conditions in adjacent regencies. Population density, waste generation, land cover and GRDP have no statistically significant direct effects in the spatial model, and given the small number of spatial units these coefficients are interpreted as indicative rather than confirmatory. Therefore, **the SDM model confirms that flood risk in West Sulawesi is a complex spatial phenomenon with significant spillover effects. The most effective interventions are population density control and regional coordination of land management**.

D. Flood Risk Mapping

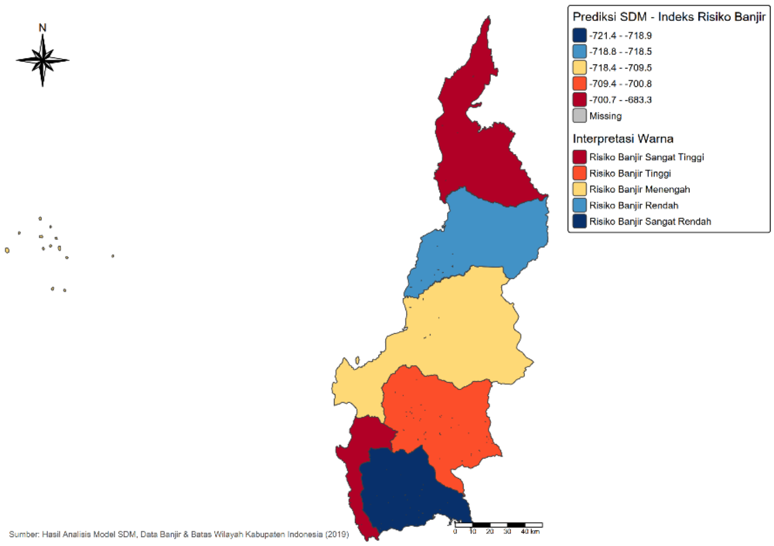

Figure 8 Spatial Durbin Model (SDM) Prediction Map of Flood Risk Index per District in West Sulawesi Province

Based on the normalised flood risk index, the distribution of flood risk in West Sulawesi shows a clear spatial gradient. Majene is in the very high flood risk category and is the dominant hotspot, with by far the highest index value; this is consistent with its high vulnerability and exposure despite comparatively moderate rainfall. Pasangkayu, Mamuju and Central Mamuju form an intermediate, medium-risk group, while Polewali Mandar is in the low-risk category. Mamasa, with its mountainous topography, records the lowest risk index and is the flood coldspot. Flood mitigation should therefore be prioritised in Majene and the central coastal regencies through improved drainage, coastal spatial planning and watershed vegetation, while recognising that localised flash-flood hazards can still occur in mountainous areas such as Mamasa.

Implications for Risk-Based Disaster Insurance

Although the spatial models above estimate physical flood risk rather than insurance quantities directly, the normalized flood risk index (Y, bounded between 0 and 1) provides a natural basis for translating the risk map into a risk-based premium structure. Following standard actuarial practice, the annual pure (technical) premium for a representative insured unit can be expressed as the product of the expected claim frequency and the expected loss severity, P_pure = E[N] x E[L], while the gross premium adds loadings for expenses, uncertainty, and capital, P_gross = P_pure x (1 + theta). In a risk-based scheme the frequency component is made an increasing function of the local flood risk index, so that the premium rate carried by each regency scales with its mapped risk.

Operationally, the index is discretized into the hotspot-coldspot zones identified by the LISA analysis, and each zone is assigned a risk relativity (rating factor) relative to a provincial base rate. For illustration, applying relativities of, for example, 1.5 to very-high-risk zones, 1.0 to medium-risk zones, and 0.6 to very-low-risk zones to a common base rate would place Majene and Pasangkayu (hotspots) in the highest premium band, Mamuju and Central Mamuju in the middle band, and Polewali Mandar (coldspot) in the lowest. These relativities are illustrative and must be calibrated against historical claims or modelled loss data before operational use; the contribution of this study is the spatial risk surface on which such calibration can be built.

Two design principles follow. First, affordability: because premiums in a risk-based scheme rise with risk, the premium burden in hotspot regencies should be evaluated relative to local economic capacity (GRDP and household income), and cross-subsidies or public premium support may be required where risk-based premiums exceed an affordability threshold. Second, risk pooling: pooling exposure across the six regencies, combining high-risk coastal districts with lower-risk inland ones, diversifies the portfolio and stabilizes the pooled loss, which is the mechanism that makes a provincial flood-insurance scheme viable. The hotspot-coldspot pattern therefore informs not only where mitigation should be prioritized, but also how premiums, cross-subsidies, and pooling boundaries could be structured. These priorities are reinforced by the recorded flood losses over the past decade: Mamuju (about Rp 38.4 billion) and Polewali Mandar (about Rp 36.0 billion) sustained the largest cumulative damages, followed by Majene (about Rp 19.4 billion), while Mamasa recorded the lowest (about Rp 4.0 billion). These loss figures are reported here only to motivate the insurance argument and to indicate where exposure is concentrated; they are not used as variables in the statistical analysis.

Limitations

Several limitations qualify these findings. First, the spatial analysis rests on only six regencies; even when pooled into a 60-observation panel, six spatial units give the Moran's I test very low power (its expected value under the null is already -0.20) and leave few degrees of freedom for the spatial parameters, so the Moran's I and Spatial Durbin Model results are exploratory rather than confirmatory. Disaggregation to the sub-district (kecamatan) level, where the InaRISK risk index and the socio-economic predictors are also available, is the most important next step for credible spatial inference. Second, because the flood risk index varies mostly between regencies and little within them over time, inference relies on regency-clustered robust standard errors, under which only population density is marginally significant. Third, the residuals display heteroscedasticity (Breusch-Pagan p = 0.028), addressed through heteroscedasticity-robust standard errors, while residual normality is not rejected (Jarque-Bera p = 0.154). Fourth, the waste-generation series is partially imputed (CAGR, back-casting, and full imputation for Mamasa), so its effect should be treated as unreliable. Finally, the insurance premium framework is conceptual and assumption-driven, with illustrative relativities that require calibration against actual claims or modelled-loss data; recorded flood losses are used only to motivate the insurance argument and are not analysis variables

V. CONCLUSIONS AND SUGGESTIONS

This research analyzes the potential of disaster insurance by mapping flood disaster risks using a regression model with the Moran Index. The flood risk index (Y) is analyzed against the influence of five independent variables: Rainfall ($\boldsymbol{X_1}$), Population density ($\boldsymbol{X_2}$), Waste generation ($\boldsymbol{X_3}$), Land cover index ($\boldsymbol{X_4}$), and GDP ($\boldsymbol{X_5}$). The analysis shows that flood risk in West Sulawesi follows a spatial gradient: Majene is the dominant high-risk hotspot, Mamasa the low-risk coldspot, and Pasangkayu, Mamuju, Central Mamuju and Polewali Mandar fall in between. A pooled-panel regression (60 regency-year observations) explains about 44.5% of the variation in the normalised risk index; once spatial structure is modelled, annual rainfall is the only significant direct predictor and the spillover of neighbouring population density is significant, while the counterintuitive negative effect of waste generation found in the non-spatial model disappears. Because the analysis rests on only six regencies, the Moran's I and spatial-model results are exploratory, and disaggregation to the sub-district level is recommended to obtain statistically robust spatial inference. Flood mitigation should be prioritised in Majene and the central coastal regencies through improved drainage, coastal spatial planning and watershed management. In future research, it is recommended to conduct a more detailed analysis at the sub-district level so that a more detailed spatial model can be obtained.

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REFERENCES

[1] B. N. P. B. BNBP and Pemprov Sulbar, "Kajian Risiko Bencana Nasional Provinsi Sulawesi Barat 2022-2026," 2021.

[2] G. R. Rabsanjani, A. A. Akbar, and H. Herawati, "Valuasi Dampak Banjir Di Kabupaten Landak , Kalimantan Barat," vol. 20, no. 1, pp. 65–75, 2022, doi: 10.14710/jil.20.1.65-75.

[3] M. S. S. Kuba, N. A. Rumata, and C. A. Amal, "Dampak Perubahan Lahan Terhadap Bencana Banjir di Kecamatan Rappocini Kota Makassar," vol. 1, no. 2, pp. 99–106, 2024.

[4] B. N. P. B. BNBP, "Data Bencana Indonesia," 2025. https://gis.bnpb.go.id/arcgis/apps/sites/?fromEdit=true#/public (accessed Jun. 04, 2025).

[5] W. H. Dodi Adi Nugroho, "KAJIAN FAKTOR PENYEBAB BANJIR DALAM PERSPEKTIF WILAYAH SUNGAI : PEMBELAJARAN DARI SUB SISTEM DRAINASE SUNGAI BERINGIN STUDY OF THE CAUSE OF FLOOD IN THE PERSPECTIVE OF WATERSHED AREA : LESSONS," vol. 17, no. 2, pp. 119–136, 2021, doi: 10.14710/pwk.v17i2.33912.

[6] H. Setiawan *et al.*, "ANALISIS PENYEBAB BANJIR DI KOTA SAMARINDA," vol. 20, no. April, pp. 39–43, 2020.

[7] I. Purwastuti, "Kecemasan Masyarakat Terhadap Bencana Banjir Bandang Di Desa Batuganda Kecamatan Lasusua Kabupaten Kolaka Utara," *J. Mimb. Kesejaht. Sos. Ed. 2*, pp. 1–10, 2019, [Online]. Available: http://journal.uin-alauddin.ac.id/index.php/jmks/article/view/8006

[8] R. Alimin, "FAKTOR-FAKTOR PENYEBAB BANJIR DI MAMUJU :," in *ResearchGates*, 2024, no. August.

[9] Kalfin, Sukono, S. Supian, and M. Mamat, "Insurance as an Alternative for Sustainable Economic Recovery after Natural Disasters: A Systematic Literature Review," *Sustain.*, vol. 14, no. 7, pp. 1–18, 2022, doi: 10.3390/su14074349.

[10] A. H. Thieken, "Contributions of Flood Insurance to Enhance Resilience–Findings from Germany," 2018, pp. 129–144. doi: 10.1007/978-3-319-68606-6_9.

[11] J. Thistlethwaite, D. Henstra, C. Brown, and D. Scott, "Barriers to Insurance as a Flood Risk Management Tool: Evidence from a Survey of Property Owners," *Int. J. Disaster Risk Sci.*, vol. 11, no. 3, pp. 263–273, 2020, doi: 10.1007/s13753-020-00272-z.

[12] W. J. W. Botzen, H. Kunreuther, and E. Michel-Kerjan, "Protecting against disaster risks: Why insurance and prevention may be complements," *J. Risk Uncertain.*, vol. 59, no. 2, pp. 151–169, 2019, doi: 10.1007/s11166-019-09312-6.

[13] M. Tesselaar, W. J. W. Botzen, and J. C. J. H. Aerts, "Impacts of Climate Change and Remote Natural Catastrophes on EU Flood Insurance Markets." Mar. 23, 2020. doi: 10.5194/egusphere-egu2020-19644.

[14] M. Tesselaar, W. J. Wouter Botzen, T. Haer, P. Hudson, T. Tiggeloven, and J. C. J. H. Aerts, "Regional inequalities in flood insurance affordability and uptake under climate change," *Sustain.*, vol. 12, no. 20, pp. 1–30, 2020, doi: 10.3390/su12208734.

[15] N. Amornsiripanitch, S. Biswas, J. Orellana-Li, and D. Zink, "Flood Underinsurance," Federal Reserve Bank of Philadelphia, Dec. 2024. doi: 10.21799/frbp.wp.2024.23.

[16] X. You and C. Kousky, "Improving Household and Community Disaster Recovery: Evidence on the Role of Insurance," *SSRN Electron. J.*, 2023, doi: 10.2139/ssrn.4365715.

[17] W. J. Wouter and C. J. H. Jeroen, "climate and socioeconomic change," 2019.

[18] J. Jumadi *et al.*, "Utilizing Open Access Spatial Data for Flood Risk Mapping: A Case Study in the Upper Solo Watershed," *Geoplanning J. Geomatics Plan.*, vol. 11, no. 2, pp. 189–204, Dec. 2024, doi: 10.14710/geoplanning.11.2.189-204.

[19] F. Siti Dahlia, "Analisis risiko banjir terhadap fasilitas pendidikan di dki jakarta," vol. 20, pp. 185–196, 2020.

[20] M. Seprianto, M. Anggo, L. Harudu, and S. Aldiansyah, "Pemetaan Daerah Potensi Rawan Banjir Menggunakan Metode Overlay," vol. 9, no. 4, pp. 214–226, 2024.

[21] H. R. S. Saefulhakim, "Pemodelan Spasial Penentuan Instrumen Srategis Penataan Ruang Untuk Pengendalian Risiko Banjir Di Wilayah Jabodetabek," *J. Ilmu Pertan. Indones.*, vol. 16, no. 1, pp. 49–58, 2011.

[22] Kusumaning Ayu Dyah Sukowati; Eko Kusratmoko, "Model spasial banjir di Kabupaten Karawang, Jawa Barat," Universitas Indonesia, 2018. [Online]. Available: https://lib.ui.ac.id/detail?id=20475947&lokasi=lokal

[23] P. Pangi, I. Lan Bagja, L. Budiati, and D. Prasetyaning Sukmawati, "The evaluation of Spatial Planning for Flood Disasters using Sentinel-1 Satellite Imagery (Case Study: Central Java Province)," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1418, no. 1, p. 012050, Dec. 2024, doi: 10.1088/1755-1315/1418/1/012050.

[24] A. T. Kuswardhana, E. Hidayah, and R. U. A. Wahyono, "Pemetaan Geospasial Risiko Banjir di Sub-DAS Gunting, Jombang Jawa Timur," *Rekayasa Sipil*, vol. 17, no. 1, pp. 54–65, Jan. 2023, doi: 10.21776/ub.rekayasasipil.2023.017.01.8.

[25] R. Liu *et al.*, "Integrating Entropy-Based Naïve Bayes and GIS for Spatial Evaluation of Flood Hazard," *Risk Anal.*, vol. 37, no. 4, pp. 756–773, Apr. 2017, doi: 10.1111/risa.12698.

[26] P. Panyadee and P. Champrasert, "Spatiotemporal Flood Hazard Map Prediction Using Machine Learning for a Flood Early Warning Case Study: Chiang Mai Province, Thailand," *Sustainability*, vol. 16, no. 11, p. 4433, May 2024, doi: 10.3390/su16114433.

[27] M. Zhran *et al.*, "Exploring a GIS-based analytic hierarchy process for spatial flood risk assessment in Egypt: a case study of the Damietta branch," *Environ. Sci. Eur.*, vol. 36, no. 1, p. 184, Oct. 2024, doi: 10.1186/s12302-024-01001-9.

[28] . G., “Conceptualization of Flooding Disaster: A Theoretical Perspective of Management,” *Disaster Adv.*, vol. 17, no. 2, pp. 40–45, Dec. 2023, doi: 10.25303/172da040045.

[29] C. O. Yuri, C. Chikal, R. Rinal, and I. Ikhwan, “Analisis Faktor Alam dan Manusia Penyebab Bencana Banjir di Daerah Aliran Sungai,” *Indo-MathEdu Intellectuals J.*, vol. 6, no. 5, pp. 8388–8401, Aug. 2025, doi: 10.54373/imeij.v6i5.3884.

[30] S. B. Tillihal and A. K. Shukla, “Flood Disaster Hazards: A State-of-the-Art Review of Causes, Impacts, and Monitoring,” 2023, pp. 77–95. doi: 10.1007/978-981-99-3660-1_5.

[31] F. Jerome Glago, “Flood Disaster Hazards; Causes, Impacts and Management: A State-of-the-Art Review,” in *Natural Hazards - Impacts, Adjustments and Resilience*, IntechOpen, 2021. doi: 10.5772/intechopen.95048.

[32] F. I. Farhan and A. C. Adi, “Forecasting Flood Vulnerability in Pontianak using Multiple Linear Regression and Geospatial Information Systems (GIS),” *Innov. Res. Informatics*, vol. 5, no. 1, Mar. 2023, doi: 10.37058/innovatics.v5i1.6567.

[33] J. T. De Castro, G. M. Salistre, Y. C. Byun, and B. D. Gerardo, “Flash flood prediction model based on multiple regression analysis for decision support system,” *Lect. Notes Eng. Comput. Sci.*, vol. 2, pp. 802–807, 2013.

[34] M. Yi, B. Wang, and H. Liu, “Flood Probability Prediction based on Regression Algorithm and Integrated Learning,” in *2025 International Conference on Intelligent Computing and Knowledge Extraction (ICICKE)*, Jun. 2025, pp. 1–7. doi: 10.1109/ICICKE65317.2025.11136465.

[35] R. W. Yanti, R. Abubakar, M. F. Fatimah, P. S. Statistika, P. S. Matematika, and U. S. Barat, “Analisis Risiko Bencana pada kasus Curah Hujan Ekstrem Provinsi Sulawesi Barat dengan Metode Moran ’ s I & Local Indicator Of Spatial Association,” vol. 5, no. 2, pp. 87–94, 2023, doi: 10.31605/jomta.v5i2.2997.

[36] R. K. Sarmah and S. Sarma, “Identification of Flood-Vulnerable Village Clusters in the Southwestern Fringe of Guwahati City Using GIS-Based Spatial Autocorrelation Technique and Real-Time SAR Imagery,” vol. 13, no. 02, pp. 169–189.

[37] J. Abedin *et al.*, “Deciphering spatial-temporal dynamics of flood exposure in the United States,” *Sustain. Cities Soc.*, vol. 108, p. 105444, Aug. 2024, doi: 10.1016/J.SCS.2024.105444.

[38] Y. Ding, H. Wang, Y. Liu, B. Chai, and C. Bin, “The spatial overlay effect of urban waterlogging risk and land use value,” *Sci. Total Environ.*, vol. 947, p. 174290, Oct. 2024, doi: 10.1016/J.SCITOTENV.2024.174290.

[39] S. A. Eslaminezhad, “GIS-Based Flood Risk Zoning Based On Data-Driven Models,” vol. 6, no. 4, pp. 75–98, 2021, doi: 10.22055/jhs.2021.36629.1163.