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Bayesian Spatial Modeling of Landslide Events Using Integrated Nested Laplace Approximation (INLA): A Study Case on Natural Conditions and Community Actions in East Java, Indonesia

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Abstract

Bayesian Spatial Modeling Using Integrated Nested Laplace Approximation (INLA) is an advanced statistical technique that can be used to model and analyze occurrences in geographic areas. Landslides are one of natural disasters that occur due to natural and human factors and pose a serious threat to East Java Province which has complex natural conditions. The disaster brings various losses, including economic, infrastructural, human life, and environmental. This study investigates the factors contributing to landslides across 29 districts and 9 cities in East Java, Indonesia, using spatial regression modeling by Integrated Nested Laplace Approximation (INLA). The factors include the number of seaside villages, the number of slope topography villages, and the area of temporarily uncultivated gardens and fields in 2021. The modeling results show that the number of seaside villages, the number of slope topography villages, and the area of fields that are temporarily uncultivated have a significant influence on the occurrence of landslides so that efforts to mitigate and prevent such disasters can be focused on the contributing factors. We conclude that the model might be able to identify potential landslide risk areas through mapping.

Keywords: bayesian spatial modeling; integrated nested laplace approximation (INLA); landslide; natural disasters; spatial statistics

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INTRODUCTION

East Java province, with its natural beauty encompassing mountains and sloping areas, has become a primary target for human settlement and evolving activities. Rapid population growth and changes in land use that are not in line with sustainable environmental management have increased the risk of landslides in this region (Putri et al., 2017). The significant economic growth and rapid urbanization have led to increased human activities, such as infrastructure development, agriculture, and mining, without adequate planning. This situation has had a serious impact on slope stability and environmental balance, increasing the potential for landslides.

The diverse topography in East Java, from high mountains to lowlands on the seaside, provides a unique dynamic to landslide risks. High rainfall, often extreme, can trigger soil movements in vulnerable areas (Rokhman et al., 2018). The importance of understanding natural and human-induced factors that trigger landslides drives the need for comprehensive regional mapping analysis. This mapping serves as a crucial basis for identifying high-risk zones, subsequently guiding effective mitigation and disaster response efforts (Rosyid et al., 2020).

Landslide disasters often cause infrastructure damage, material losses, and even loss of life. Data from the National Disaster Management Agency (BNPB) in 2023 showed a high number of landslide incidents in Indonesia, with East Java ranking second-highest. Landslides are a frequent natural disaster in Indonesia, including in East Java. BNPB data for 2023 showed 1,021 landslide incidents in Indonesia, resulting in 32 fatalities, 27 injuries, and 1 missing person. Out of these, 182 incidents occurred in East Java, resulting in 10 fatalities, 12 injuries, and 1 missing person (National Disaster Management Agency (BNPB), 2023).

Understanding the triggering factors of landslides in East Java is crucial for designing effective preventive and mitigation measures. These factors can be categorized into two: natural factors and human activities (Suhardiman, 2022). The numerous villages located on seaside geographies and those with mountainous slope topography in each district in East Java are some natural factors that can trigger landslides. On the other hand, activities such as land clearing for farming and expansion due to the increasing population growth are examples of human-induced factors contributing to the vulnerability of an area to landslides.

Mapping landslide occurrences based on these two main categories of causes is an urgent need (Mulyasari, 2021). By mapping the distribution patterns of occurrences and analyzing dominant factors in each area, prevention and mitigation efforts can be carried out more systematically and efficiently. This research aims to map landslide occurrences in East Java based on these two categories of causal factors, providing a basis for the formulation of comprehensive and sustainable landslide disaster management strategies in this province.

Through this research utilizing the Besag-York-Mollié (BYM) method with R-INLA, where the BYM method is a Poisson lognormal model that incorporates an ICAR component for spatial autocorrelation and an ordinary random effects component for non-spatial heterogeneity. In this report, we present the implementation of the BYM model (Riebler et al., 2016), and the output generated by this model is the relative risk (RR) of landslides in each district in East Java. It is expected that this study will yield a clearer understanding of the distribution patterns and dominant factors triggering landslides in East Java. The outcomes of this research can subsequently be utilized by policymakers, academia, and the wider community to formulate targeted preventive and mitigation strategies, thereby minimizing the detrimental impacts of landslides in the future.

METHOD

Data and Study Area

The secondary data in this study were obtained from the Badan Pusat Statistik (BPS), more precisely in the East Java Province in Figures report in 2022. There are 5 variables used in this study, consisting of 4 independent variables (X) and 1 dependent variable (Y), where this research observation was carried out in the City District of East Java Province in 2021. The independent variables include the number of villages with mountain topography, the number of villages with sea geography, the number of fields, and the number of gardens in the City District of East Java. Meanwhile, the dependent variable is the number of landslides in East Java regencies. Figure 1 shows the number of landslide accident in East Java in 2021. Throughout 2021, the largest number of landslides occurred in areas on the edge of the Java Sea. Meanwhile, the area with a fairly low incidence occurred in the northern part of East Java.

The independent variables used in this research are: 1. Number of Slope Topography Villages, which defined as the number of villages located on the slopes or peaks of mountains, 2. Number of Seaside Villages, which defined as the number of villages located by the sea or directly adjacent to the sea, 3. Field, which defined as non-rice field agricultural land (dry land) that is usually planted with annual crops and used only for a season or two seasons, then will be abandoned when it is no longer fertile (mobile), and 4. Gardens, which defined as non-rice field agricultural land (dry land) planted with seasonal or annual crops and separated from the yard around the house and its use does not move (BPS, 2022).

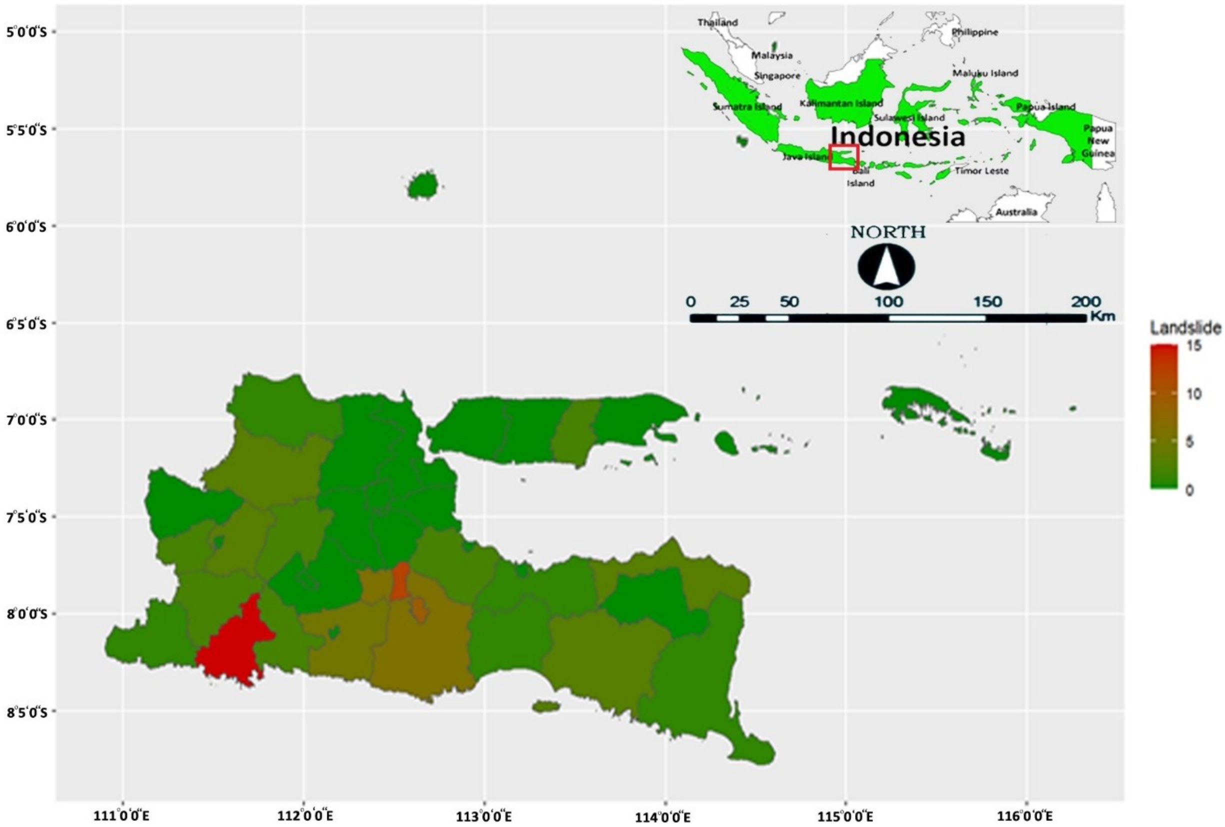

Figure 1. Mapping Landslide Incidents for each District/City East Java in 2021. As for the longitude and latitude coordinate data of the East Java Province City/District, it was obtained from the GADM Maps and Data web https://gadm.org/.

Spatial Statistics

Spatial statistics can be defined as the statistical description of spatial data, patterns, or spatial processes used to measure similarity or patterns in the geographic distribution of an event (Sankey, 2017; Scott, 2015). Spatial statistics allows for a quantitative description along with statistical significance indications within observed data regarding a pattern or process operating in space, such as distance, time, and area (Saputra, 2018). This quantitative and statistical description enables the exploration and modeling of spatial patterns and processes and their relationship with other spatial phenomena. Spatial statistics differ from traditional statistics as they integrate space and spatial relationships into their analyses.

Typically, the observed counts Y_i in area i are represented by a Poisson distribution with a mean of $E_i\theta_i$. Where, E_i represents the expected counts and θ_i represents the relative risk in area i. The logarithm of the relative risk θ_i is calculated as the sum of an intercept that captures the overall disease risk level, along with random effects that account for additional variability beyond what is expected from a Poisson distribution.

The general model for spatial data is expressed as follows (1)(2):

$$Y_i \sim P_o(E_i\theta_i), i = 1, \dots, n \qquad (1)$$

$$\log(\theta_i) = \alpha + u_i + v_i \qquad (2)$$

Here, α represents the overall risk in the region of study, u_i is a random effect specific to area i to model spatial dependence between the relative risks, and vi is an unstructured exchangeable component that models uncorrelated noise, $v_i \sim \mathrm{N}(0, \sigma_v^2)$. It is also common to include covariates to quantify risk factors and other random effects to deal with other sources of variability. For example, $\log(\theta_i)$ can be expressed as (3):

$$\log(\theta_i) = \boldsymbol{d}_i \beta + u_i + v_i \qquad (3)$$

where $\boldsymbol{d}_i = (1, d_{i1}, \ldots, d_{ip})$ is the vector of the intercept and p covariates corresponding to area I, and $\beta = (\beta_0, \beta_1, \ldots, \beta_p)'$ is the coefficient vector. In this setting, for a one-unit increase in covariate $d_j, j = 1, \ldots, p$, the relative risk increases by a factor of $\exp(\beta_p)$, holding all other covariates constant. With spatial method, it will be obtained how influential the independent variables are on the dependent variable by modeling the spatial regression equation (4):

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \qquad (4)$$

Where,

Y_i	= Observation value of the i-th location response variable
$\beta_0(u_i, v_i)$	= The intercept coefficient of the i-th location
$\beta_k(u_i, v_i)$	= Coefficient of the k-th variable at the i-th location
(u_i, v_i)	= Coordinate point (longitude, latitude) of the i-th position
ε_i	= Error of the i-th location

Bayesian Model

Bayesian modeling is a statistical approach based on Bayes' theorem, where probabilities are influenced by beliefs about the likelihood of a specific outcome (Riffenburgh, 2012). Available knowledge about parameters in this statistical model is updated with information from observed data (Schoot, 2021). Background knowledge is stated as a prior distribution and combined with observed data in the likelihood function to determine the posterior distribution. The posterior can also be used to make predictions about future events. This method is an efficient way to make real-time predictions by combining existing datasets with new observations, allowing the incorporation of prior knowledge into the model. This approach is particularly useful in combining uncertainty, handling missing data, and making informed decisions.

Integrated Nested Laplace Approximation (INLA)

Integrated Nested Laplace Approximation (INLA) is a Bayesian inference method used to estimate parameters in hierarchical statistical models (Hue et al., 2009; Rubio, 2021). This method allows for the use of more complex and flexible models than traditional Bayesian inference methods, with faster computation times and more accurate results (Martino, 2019; Berild, 2022; Merzhäuser, 2023). INLA is employed in various fields, including epidemiology, ecology, and social sciences, to analyze complex data and estimate parameters in hierarchical models.

Besag-York-Mollié (BYM)

Besag-York-Mollié (BYM) statistics is a hierarchical statistical model used in spatial analysis to analyze the distribution of spatial data (Quick, 2021; Besag et al., 1991; Moraga, 2020). This model incorporates unstructured and spatially structured random effects in the analysis of data, especially diseases (Gerber, 2013). The BYM model is one of the most popular Bayesian models in spatial health analysis, as it allows the combination of sequential and spatial random effects in disease data analysis (Morris et al., 2019). This model has been used in various studies to analyze the spatial distribution of disease data, such as cancer, providing predictions for decision-making and health management. Despite several available alternative models, the BYM model remains a popular choice due to its ease of use and interpretation of results. In this model, the spatial random effect u_i is assigned a

Conditional Autoregressive (CAR) distribution which smooth the data according to a certain neighborhood structure that specifies that two areas are neighbors if they share a common boundary. Specifically

$$u_i|\boldsymbol{u}_{-i} \sim N(\bar{u}_{\delta_i}, \frac{\sigma_u^2}{n_{\delta_i}}) \quad (5)$$

where $\bar{u}_{\delta_i} = n_{\delta_i}^{-1} \sum j \in \delta_i \; u_j, \delta_i, and\; n_{\delta_i}$ represent, respectively, the set of neighbors and the number of neighbors of area *i*. The unstructured component v_i is modeled as independent and identically distributed normal variables with zero mean and variance σ_v^2. BYM has been updated by developing its parameter called BYM2 which makes parameters interpretable and facilitates the assignment of meaningful Penalized Complexity (PC) priors (Simpson et al., 2017). The BYM2 model uses a scaled spatially structured component **u*** and an unstructured component **v***

$$\boldsymbol{b} = \frac{1}{\sqrt{\tau_b}}(\sqrt{1-\varphi}\boldsymbol{v}*, \sqrt{\varphi}\boldsymbol{u}*) \quad (6)$$

Full details, The BYM2 is as (7):

$$\log(\theta_i) = \alpha + x_i^T\delta + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\varphi}\boldsymbol{v}*, \sqrt{\varphi}\boldsymbol{u}*\right) + \log(E_i) \quad (7)$$

Here, the precision parameter $\tau_b > 0$ controls the marginal variance contribution of the weighted sum of **u*** and **v***. The mixing parameter $0 \leq \varphi \leq 1$ measures the proportion of the marginal variance explained by the structured effect **u***. Thus, the BYM2 model is equal to an only spatial model when φ =1, and an only unstructured spatial noise when φ =0 (Riebler et al., 2016).

RESULTS AND DISCUSSION

The level of landslide vulnerability in various regencies and cities of East Java Province is influenced by several factors, including the number of villages located by the sea, the number of villages with sloping topography, and the area of gardens and fields that are temporarily not cultivated. Based on the analysis results shown in **Figure 2**, it is known that there are three areas that are prone to landslides. Trenggalek City is the city with the most landslides in East Java Province in 2021. Of the five factors tested, the population factor and the area of temporarily uncultivated fields are factors that do not have a significant influence on the occurrence of landslides. Meanwhile, the other three factors have a significant relationship with the vulnerability of landslides in East Java.

Mathematically, the influence relationship between explanatory variables that affect the occurrence of response variables can be known through spatial modeling. From the spatial modeling, the results will be obtained in the form of spatial regression and mapping. Spatial regression is used to analyze the relationship between factor variables and response variables in terms of spatial data or by considering the spatial structure of the data. Spatial regression can be used in various fields, including epidemiology, geography, and regional planning. In this study, the spatial regression model of landslide occurrence is as follows **Table 1**.

Table 1. Estimator of Fixed Effects in Spatial Regression

Fixed Effects	Mean	Standard Deviation	Credibility Interval
Intercept	-0,825	0,652	(-2.247, 0.323)
Population	-0,067	0,047	(-0.156, 0.028)
Number of Villages with Seaside Geography	-0,036	0,013	(-0.064, -0.011)
Number of Villages with Slope Topography	0,013	0,006	(0.002, 0.025)
Area of Garden that are Temporarily Not Cultivated	0,008	0,003	(0.003, 0.013)
Area of Fields that are Temporarily Not Cultivated	0,050	0,051	(-0.049, 0.152)

Source : Data of this study

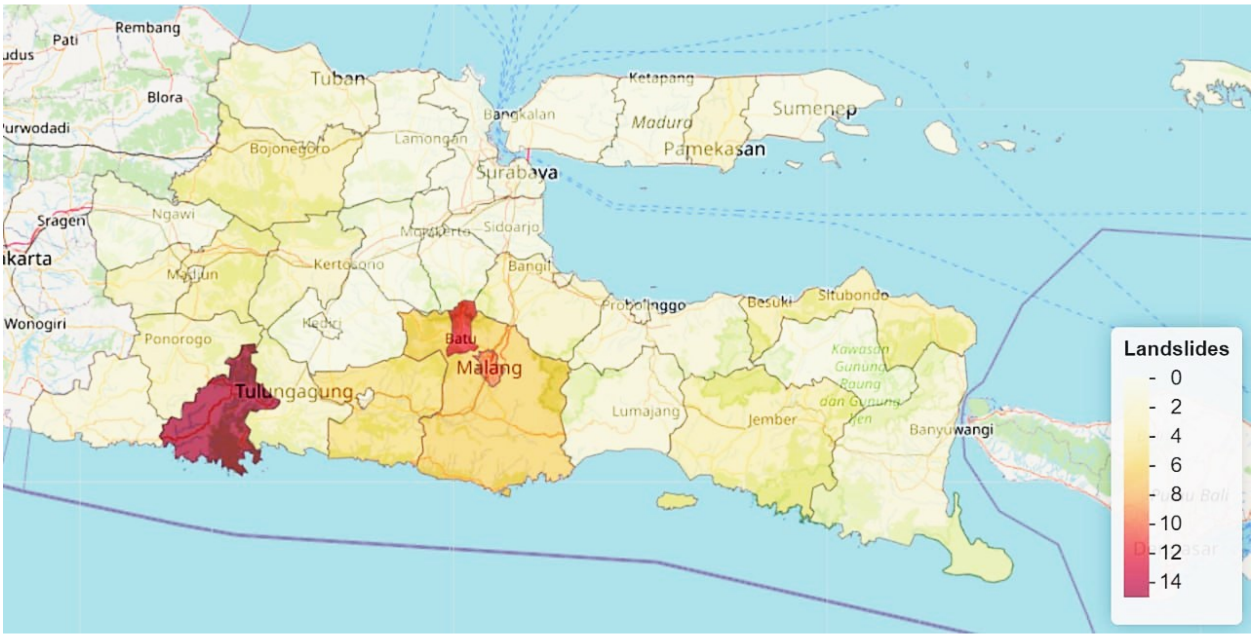

Figure 2. Landslide Map of East Java

From the results of spatial modeling of landslide occurrence in East Java Province in 2021, it can be seen the relationship between population factors, number of villages with seaside geography, number of villages with slope geography, as well as area of gardens and area of fields that are temporarily not cultivated with the occurrence of landslides by considering the geographical factors of districts and cities in East Java Province. From the credibility interval seen from the table, it is known that the number of villages with seaside geography, the number of villages with slope geography, and the area of garden that is temporarily not cultivated have a significant effect on the occurrence of landslides. A more detailed explanation can be seen in the next section.

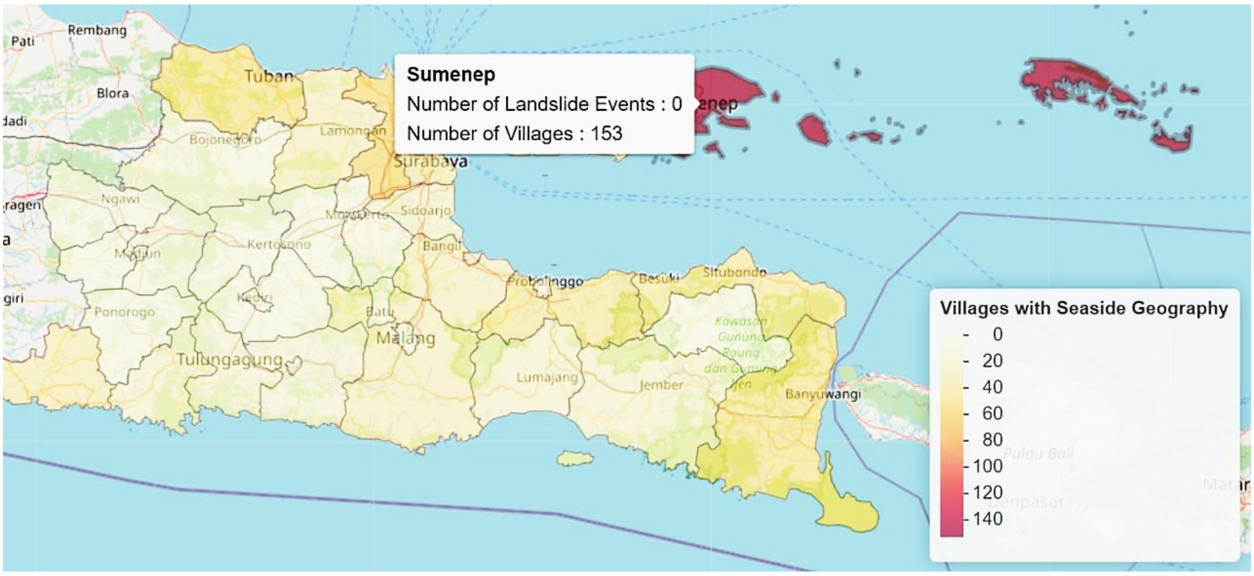

Figure 3. Map of Number of Villages with Seaside Geography in East Java Province

The first factor is the number of villages located by the sea. **Figure 3** shows that Sumenep district has the most villages with seaside geography. However, it can also be seen that no landslides occurred in the region in 2021. Based on the analysis, it has been proven that the factor of the number of villages with seaside geography has a significant influence to the proneness of landslides.
According to Renhard Haribulan et al. (2019), slope has a major influence on the occurrence of landslides. The more sloping the slope of an area, the more potential the area is for landslides. Cruden and Varnes (1996) said that landslides are categorized into two factors, namely causal and trigger

factors. Slope, rock type, and soil type are the causal factors. Meanwhile, heavy rain, seismic activities such as earthquakes and volcanic eruptions become triggering factors. According to Shahabi and Hashim (2015), steep slopes are one of the main factors for landslides in Southeast Asia which has a tropical climate, especially for areas located in mountains and valleys.

The analysis shows that regencies and cities in East Java Province have a varied number of villages with slope topography. Blitar Regency is the region with the most slope-topography villages and with five landslide events in 2021. **Figure 4** shows that most of the regencies and cities in East Java Province have slope-topography villages ranging from 50 to 150 villages. Details about the map of the number of slope-topography villages in East Java Province can be seen in **Figure 4**.

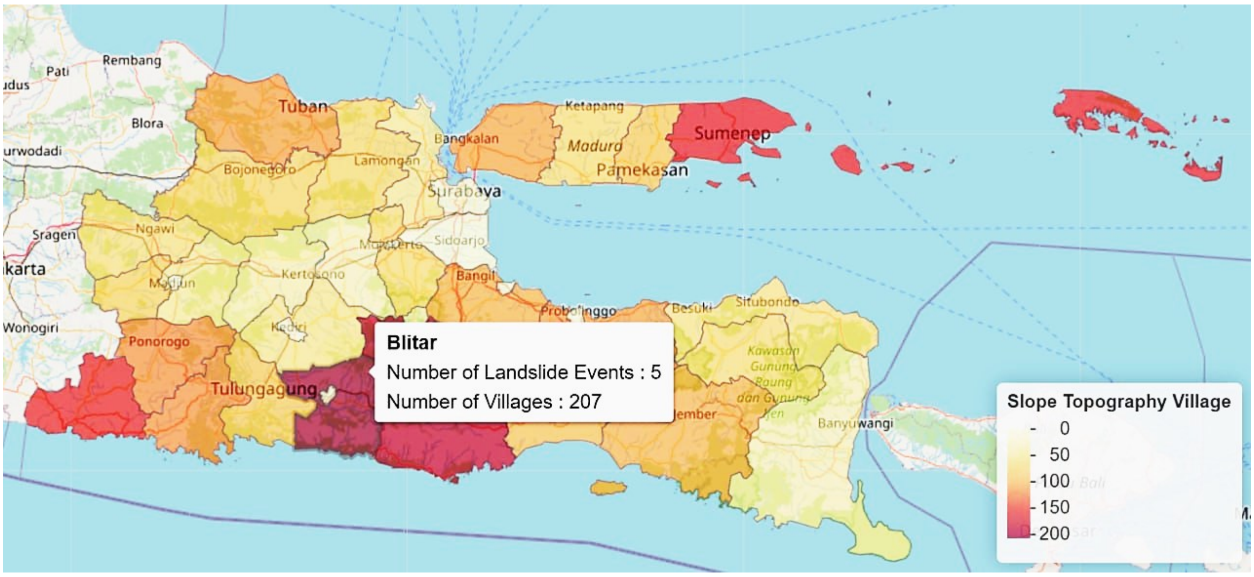

Figure 4. Map of Number of Villages with Slope Topography in East Java Province

Figure 5. Map of the Area of Garden that are Temporarily Not Cultivated in East Java Province

Figure 5 shows that almost all districts or cities in East Java Province have garden that are temporarily not in use with an area of around 200 thousand hectares. However, there is one city, Batu City, which has a plantation area that is temporarily not being cultivated with an area of around 519 thousand hectares. The area of temporarily not cultivated plantation has a significant effect on the occurrence of landslides because if the temporarily not cultivated plantation tends to be open and not managed properly, it will result in the vulnerability of landslides.

Furthermore, from the mapping results in **Figure 6**, it can be seen that Batu City is an area at risk of landslides of 31.14 times higher than other areas. This means that Batu City has a very significant risk of landslides. Then the risk of landslides in Trenggalek Regency is the second highest of all regencies and cities in East Java Province, which is 9.49 times higher.

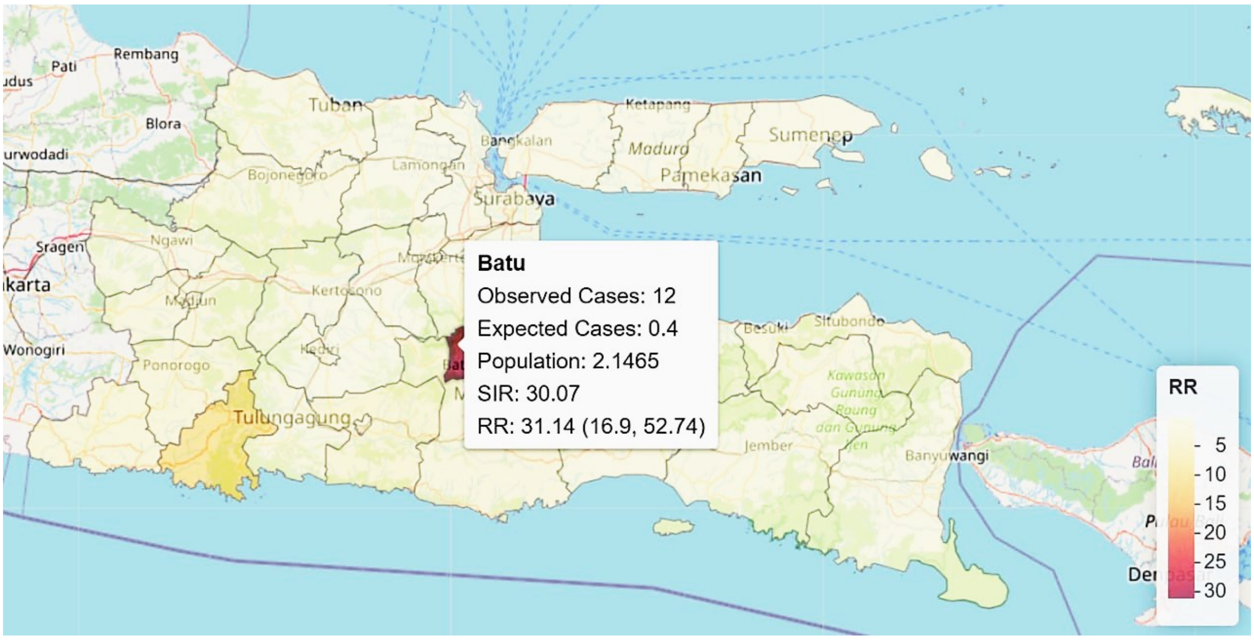

Figure 6. Relative Risk Mapping of Landslide Events in East Java Province

Through the results of spatial modeling and mapping of landslide occurrence in regencies and municipalities of East Java Province, there are several important benefits that can be taken in relation to mitigation and prevention strategies to reduce the risk and impact of landslides. Some of the key benefits include: 1. Identification of Landslide Prone Areas; Spatial modeling can provide information and map areas at high risk of landslides in East Java Province so as to help the government and the community to focus more on handling and mitigation efforts in areas that need priority handling. 2. Analysis of Landslide Causal Factors; Spatial modeling helps analyze the factors that cause landslides, such as the number of villages with seaside geography, the number of villages with slope topography, and the area of garden that are temporarily not cultivated. The analysis of such causal factors helps the government to focus mitigation efforts on factors that contribute to landslides. 3. Early Warning and Monitoring System; By knowing the factors that cause landslides, an early warning to the community on the occurrence of landslides can be given immediately so that they can take appropriate actions to avoid the danger and of course to save themselves. 4. Spatial Planning and Resource Management; The results of spatial modeling can serve as a basis for more strategic spatial planning and resource management in East Java Province. The mapping of landslide prone areas allows the temporarily uncultivated land to be properly managed and appropriate land use to reduce the risk of landslides in high risks areas. 5. Infrastructure Evaluation; Spatial modeling can assist in infrastructure evaluation and planning to improve landslide resilience. 6. Preparation of Disaster Management Plan; Spatial modeling contributes to the development of more comprehensive landslide management plans, such as short-, medium- and long-term mitigation efforts, as well as adaptation strategies to changing environmental conditions that could potentially affect the risk of future flooding.

CONCLUSION

Based on the results of spatial modeling, the mapping of landslide prone areas in East Java Province by considering the influential factors shows that areas with high vulnerability to landslides are those with the number of villages with seaside geography, the number of villages with slope topography, and the area of gardens that are temporarily not cultivated. From the results, it is known that Batu

City is the region with the highest risk of landslides compared to other regions. The results of this study are expected to assist the East Java government in future landslide mitigation efforts and in the preparation of short, medium and long terms prevention strategies. In addition, it can also be a reference for researchers who conduct similar research in the future by adding other parameters or testing predictor variables to analyze landslide prone areas more accurately in the future. Testing with different statistical models can also be done which may provide better modeling results.

CONFLICTS OF INTEREST

The authors declare no conflict of interest concerning the publication of this article. The authors also confirm that the data and the article are free of plagiarism.

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