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Determining Rainfall Thresholds of Landslide Events for Sumatra Islands

CORRESPONDENCE

Email : Perdinan@apps.ipb.ac.id
Phone : (0251) 8623850

Perdinan[1*], Ayu Arista Andarini Putri [1], Bambang Dwi Dasanto[1], Yon Sugiarto[1], Raynaldi Rachmat[1]

[1]Department of Geophysics and Meteorology, Faculty of Mathematics and Natural Sciences, IPB University, Jl. Meranti Wing 19 Level 4 FMIPA Building, IPB Dramaga Campus, Babakan, Dramaga Sub-district, Bogor Regency, 16680

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Abstract

Extreme weather can trigger a number of meteorological disasters such as landslides. This disaster may cause serious losses on livelihoods and hamper the growth of economy or development targets. This research focuses on determining a threshold triggering landslide events. Rainfall is considered as one of the common factor contributing to the landslide occurrence. The rainfall intensity as the trigger for landslides can be determined using a series of statistical methods. The threshold determination is performed using statistical techniques composed of Cumulative Rainfall Threshold (CT) and sorting analysis, dummy regression, cluster analysis, and change detection method. The methods are applied to determine the thresholds for landslides occurring in Sumatra Islands for the period of 2010-2017 retrieved from the website Data Informasi Bencana Indonesia managed by Badan Nasional Penanggulangan Bencana (DIBI BNPB). We evaluated daily rainfall data for the period of 2010-2017 compiled for 10 climate stations operated by Bureau Meteorology, Climatology, and Geophysics named in Bahasa Indonesia Badan Meteorologi, Klimatologi, dan Geofisika that are accessible for the Sumatra Island. The analyses suggest that the rainfall thresholds that should be monitored for detecting the potential occurrences of landslides in the study area are 15 mm per day, 30 mm per day, dan 65 mm per day. These values can be seen as warnings at different levels with the largest value, i.e., 65 mm, indicated higher confidence for the landslide event to occur. In other words, these values represent different levels of alert for the landslide occurrence that provide inputs for designing strategies of disaster prevention to mitigate the adverse impacts of landslide disaster.

KEYWORDS : extreme rainfall, landslides, trigger, thresholds, Sumatera Island, disaster prevention

INTRODUCTION

Landslides refer to the mass movement of soil or rock down a slope[1]. Landslides can occur in various environments, whether on steep or gentle slopes, from mountainous regions to coastal cliffs and even underwater. Gravity is the main driving factor behind landslides, but there are several factors that can affect slope stability and create conditions for landslides to occur. These factors can include earthquakes, human activities such as land clearing for development, and heavy rainfall.

Rainfall is one of the triggering factors for landslides [2], [3], [4]. Constant rainfall can increase soil saturation, resulting in reduced soil suction pressure. This weakens the soil structure and increases vulnerability to landslides[5]. High-intensity rainfall can then cause landslides. Additionally, high-intensity rainfall can cause landslides in soils with low water saturation by increasing pressure in the soil pores [6].

Approximately 90% of landslide events worldwide are estimated to be triggered by high-intensity rainfall [7]. Furthermore, the number of landslide occurrences has increased in recent years [8]. This can be attributed to anticipated climate change, which is expected to increase the frequency and intensity of rainfall [9].

The island of Sumatra has a morphology consisting of mountains and hills. Additionally, Sumatra is in a tropical climate region that receives high amounts and intensities of rainfall. Landslide incidents also occur in almost all areas of Sumatra. Research on the relationship between landslide occurrences and rainfall in Sumatra is important to evaluate the threshold value of rainfall that can trigger landslides. This information can be used for early warning systems to alert the occurrence of landslides caused by extreme rainfall [10].

METHODS

Tools and Data

The data used in this research includes landslide occurrence from the years 2010-2017 in Sumatra Island, obtained from the DIBI BNPB website. This data includes information about the location and date of the landslides. The second dataset used in this research is the daily rainfall data from 10 BMKG weather stations in Sumatra Island. The locations of the BMKG weather stations that serve as data sources in this research can be seen in Figure 1.

Table 1. Definitions of variables and their measurements

Data Type	Sources	Periods
Landslide occurrences in Sumatra Island	DIBI BNPB (Indonesian Disaster Information Center)	2010-2017
Daily rainfall in Sumatra Island	BMKG (Indonesian Meteorology, Climatology, and Geophysical Agency)	2010-2017

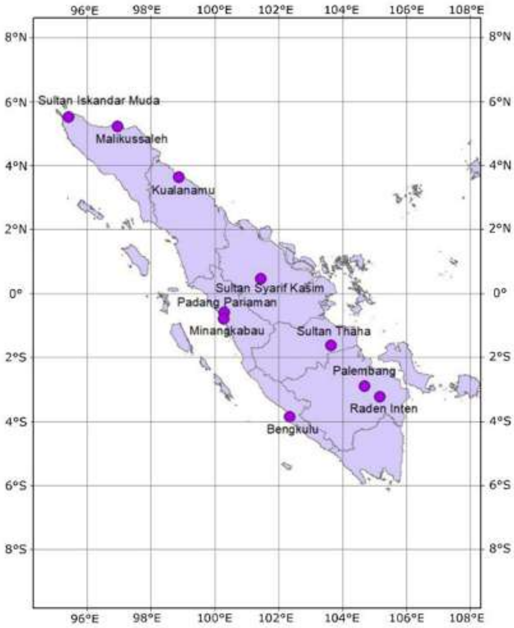

Figure 2. Map of the location of the BMKG stations used as data sources

Research Procedure

The research is conducted in several stages. The first stage involves compiling landslide occurrence data and rainfall data related to those landslide events. The next step is to create a scatter plot graph with multiple data points and visually estimate the threshold value. The third step is to determine the threshold value through sorting and plot analysis. Once the threshold value is obtained, it is validated using techniques such as dummy regression, cluster analysis, and change point detection methods.

Data Compilation, Scatter Plot, and Visual Threshold Estimation

The determination of the rainfall threshold that triggers landslides is done using the Cumulative Rainfall Threshold (CT) method [11]. The concept of this method is to compare the amount of rainfall in the last 3 days (72 hours) with the rainfall in the previous 15 days before the landslide event. The determination of the threshold value for rainfall that triggers landslides is done by creating a scatter plot with the x-axis representing the cumulative rainfall value of the previous 15 days before the 72-hour event (P15) and the y-axis representing the cumulative rainfall value during the 72 hours (P3). Visual estimation of the threshold value is then performed based on the scatter plot.

Threshold Value Determination through Sorting Analysis

Sorting analysis is done by creating scatter plots between each three-day and fifteen-day rainfall data against the data number. Three threshold values are taken when there are breakpoints in the scatter plot results.

Analysis Validation: Dummy Regression

A dummy variable is a variable used to create categories for qualitative data, and qualitative data is in the form of nominal scale. The purpose of using multiple regression with dummy variables is to predict the value of a dependent variable based on one or more independent variables, where one or more of the independent variables used are dummy variables [12]. In this study, rainfall values below the estimated threshold are categorized as 1, and vice versa as 0, and regression analysis is performed using the Minitab application.

Analysis Validation: Cluster Analysis

Clustering is the process of grouping objects into clusters based on their similarities. Cluster analysis is a multivariable method for grouping n objects into m clusters (m≤n) based on their characteristics (Johnson & Wichern, 2014). The goal of clustering is to find natural clusters from a set of observation units (Johnson & Wichern, 2014) The method used in this study is the non-hierarchical K-means clustering method. This is done because the desired number of clusters is already determined, namely two clusters: one when rainfall is below the threshold and one when rainfall is above the threshold. This analysis is performed using the Minitab application.

Analysis Validation: Change Point Detection Method

The changepoint function in R Studio provides many methods for analyzing change points in univariate time series. One of these functions is bcp. The bcp function is designed to perform Bayesian single change point analysis of univariate time series. It returns the posterior probability of change points occurring at each time index in the series. In this study, a probability of change points above 0.7 is used to determine the threshold (probabilities above 0.7 are considered as the threshold).

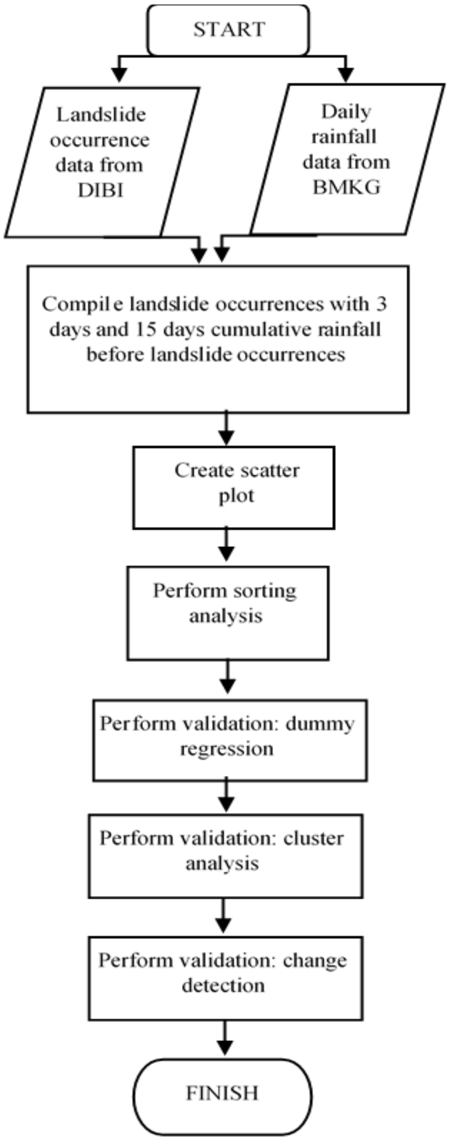

Figure 1. Research procedure flowchart

Results and Discussion

Scatter Plots

The plots below are scatter plots created from the values of 3P, which represents the rainfall events three days before the landslide (y-axis), and 15P, which represents the rainfall events 15 days before the landslide (x-axis) for each landslide event.

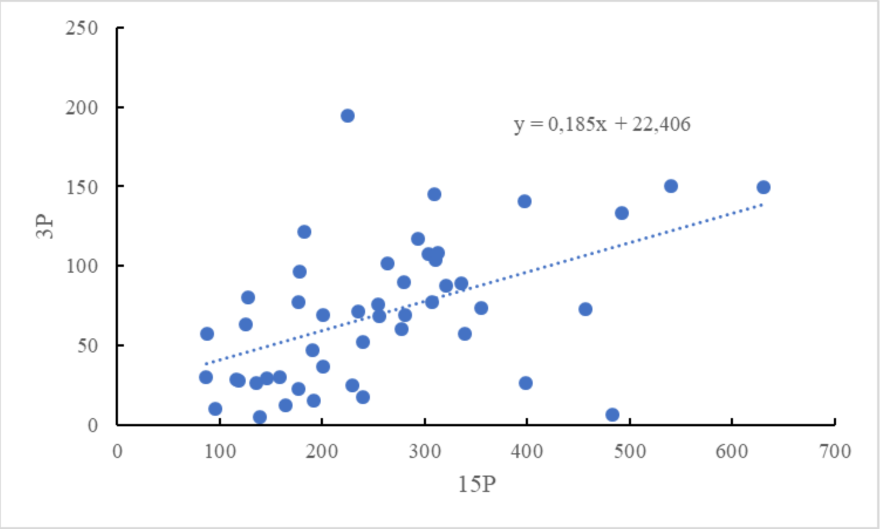

Figure 3. Scatter plot of estimated threshold for 15-day rainfall of 75 mm

No breakpoints are visible in the plot with an estimated threshold of 75 mm for the 15-day rainfall. There is an upward trend pattern, indicating that as the value of rainfall in the 15 days before the landslide increases, the rainfall three days before the landslide also increases. The trend equation shown by this plot is y=0.185x+22.406.

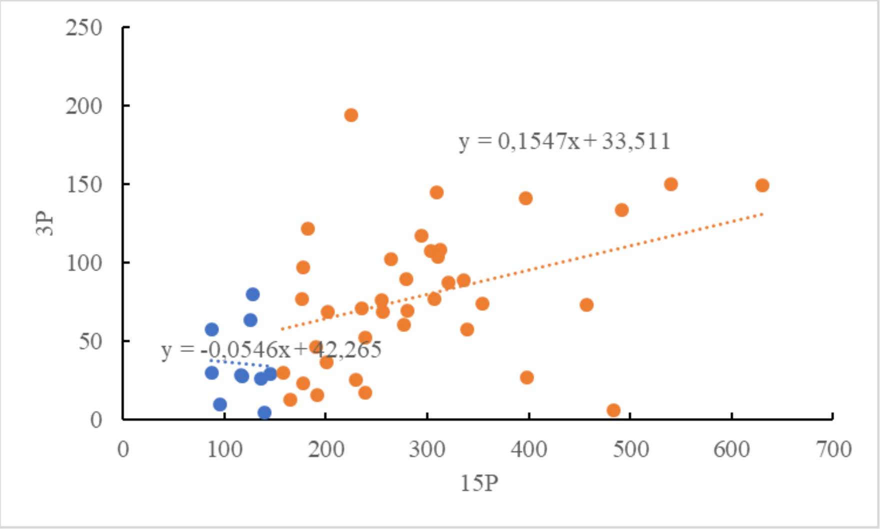

Figure 4. Scatter plot of estimated threshold for 15-day rainfall of 150 mm

In the plot with an estimated threshold of 150 mm for the 15-day rainfall, there are two data patterns observed at the breakpoint formed by the threshold. For the 15-day rainfall below 150 mm, a downward trend pattern is formed with the equation y=-0.0546x+42.265. For the rainfall above 150 mm, an upward trend pattern is formed with the equation y=0.1547x+33.5

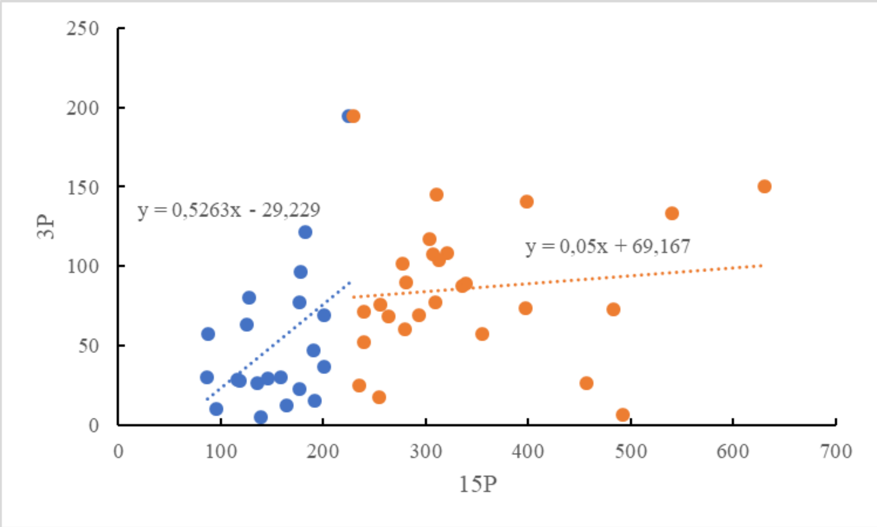

Figure 5. Scatter plot of estimated threshold for 15-day rainfall of 225 mm

In the plot with an estimated threshold of 225 mm for the 15-day rainfall, there are two data patterns observed at the breakpoint formed by the threshold. For the 15-day rainfall below 225 mm, an upward trend pattern is formed with the equation y=0.5264x-29.229. For the rainfall above 225 mm, an upward trend pattern is formed with the equation y=0.05x+69.167.

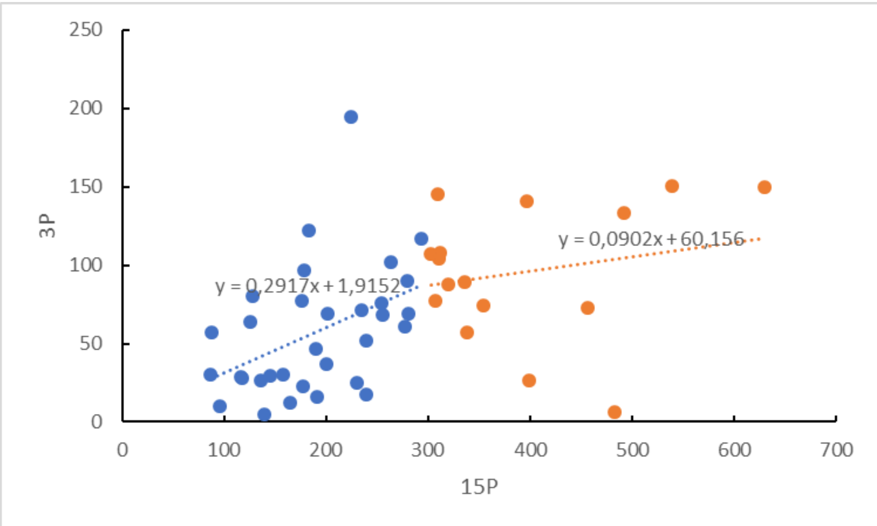

Figure 6. Scatter plot of estimated threshold for 15-day rainfall of 300 mm

In the plot with an estimated threshold of 300 mm for the 15-day rainfall, there are two data patterns observed at the breakpoint formed by the threshold. For the 15-day rainfall below 300 mm, an upward trend pattern is formed with the equation y=0.2917x-1.9152. For the rainfall above 300 mm, an upward trend pattern is formed with the equation y=0.0902x+60.156.

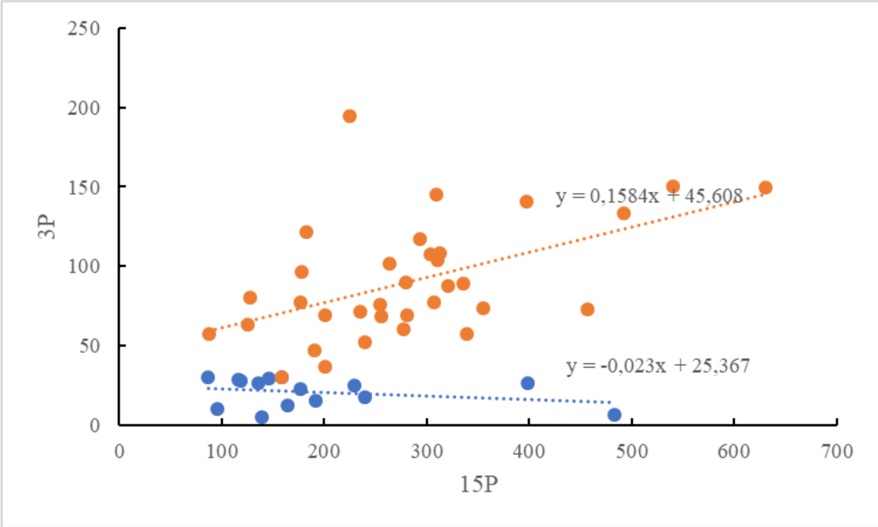

Figure 7. Scatter plot of estimated threshold for 3-day rainfall of 30 mm

In the plot with an estimated threshold of 30 mm for the 3-day rainfall, there are two data patterns observed at the breakpoint formed by the threshold. For the 3-day rainfall below 30 mm, a downward trend pattern is formed with the equation y=-0.023x+25.367. For the rainfall above 30 mm, an upward trend pattern is formed with the equation y=0.1584x+45.608.

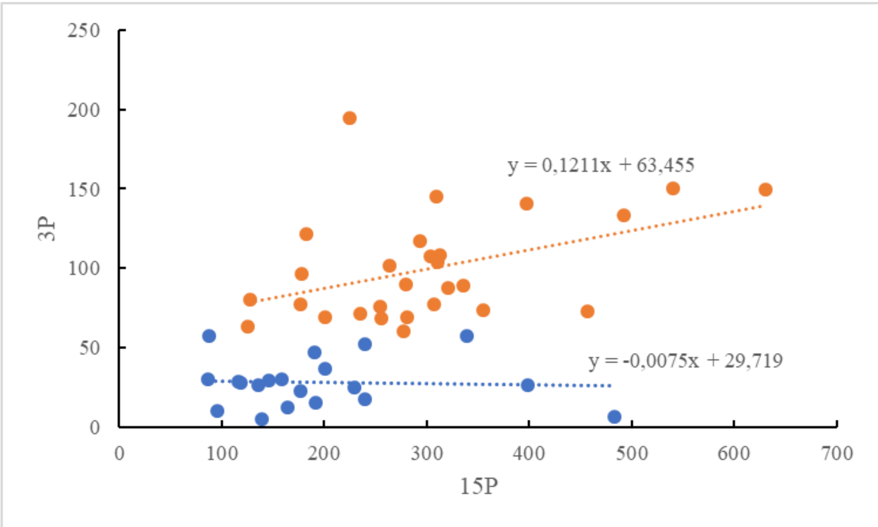

Figure 8. Scatter plot of estimated threshold for 3-day rainfall of 60 mm

In the plot with an estimated threshold of 60 mm for the 3-day rainfall, there are two data patterns observed at the breakpoint formed by the threshold. For the 3-day rainfall below 60 mm, a downward trend pattern is formed with the equation y=-0.0075x+29.719. For the rainfall above 60 mm, an upward trend pattern is formed with the equation y=0.1211x+63.455

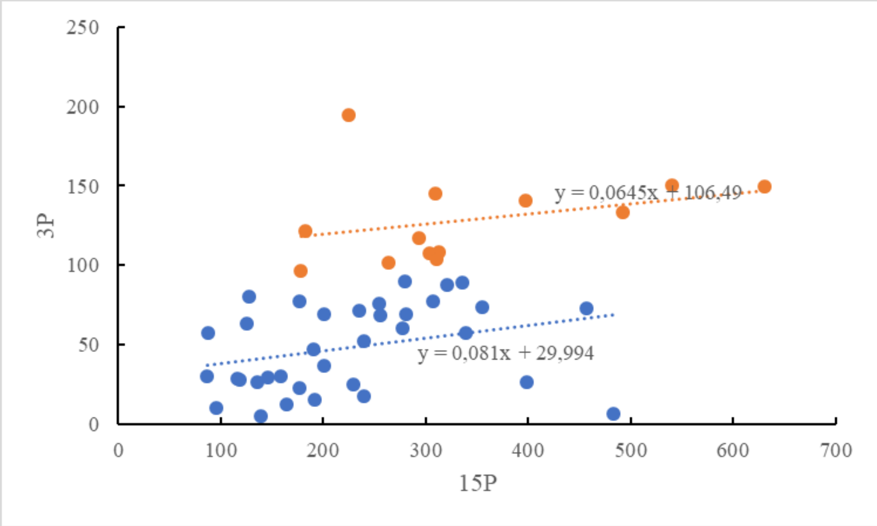

Figure 9. Scatter plot of estimated threshold for 3-day rainfall of 90 mm

In the plot with an estimated threshold of 90 mm for the 3-day rainfall, there are two data patterns observed at the breakpoint formed by the threshold. For the 3-day rainfall below 90 mm, an upward trend pattern is formed with the equation y=0.081x+29.994. For the rainfall above 90 mm, an upward trend pattern is formed with the equation y=0.0645x+106.49.

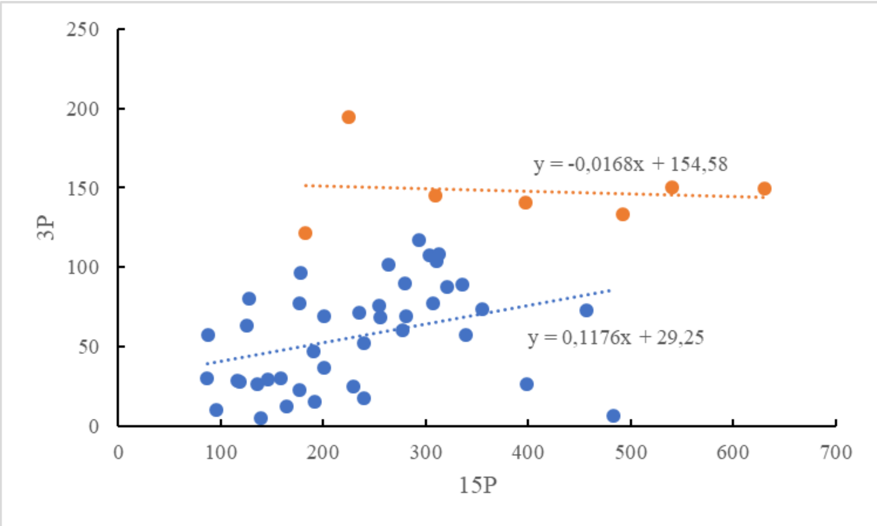

Figure 10. Scatter plot of estimated threshold for 3-day rainfall of 120 mm

In the plot with an estimated threshold of 120 mm for the 3-day rainfall, there are two data patterns observed at the breakpoint formed by the threshold. For the 3-day rainfall below 120 mm, an upward trend pattern is formed with the equation y=0.1176x+29.25. For the rainfall above 120 mm, a downward trend pattern is formed with the equation y=-0.0168x+154.58.

Sorting Analysis

The sorting analysis is performed by creating scatter plots between each data of the 3-day and 15-day rainfall against the data number. Three threshold values are taken when breakpoints occur in the scatter plot results . These three threshold values are considered as three levels of alertness for landslide disasters. The threshold values indicate the levels of rainfall at which the risk of landslide increases significantly. By identifying these thresholds, it becomes possible to establish different levels of alertness for landslide events based on the rainfall data.

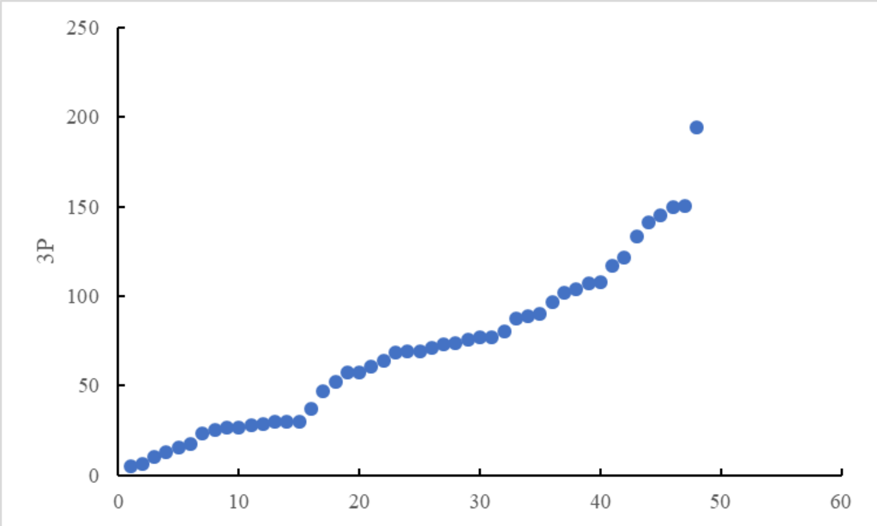

Figure 11. Scatter plot of cumulative 3-day rainfall sorting analysis

The graph above shows the sorting result of the 3-day rainfall before the landslide event. It can be observed that there are breakpoints at several points, including data number 17 with a rainfall of 46.8 mm, data number 33 with a rainfall of 87.5 mm, and data number 48 with a rainfall of 194.4 mm.

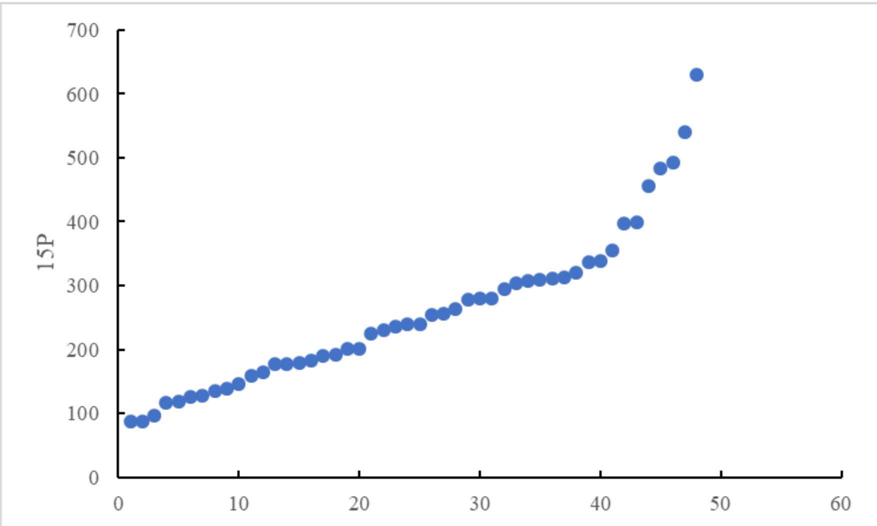

Figure 12. Scatter plot of cumulative 15-day rainfall sorting analysis

The graph above shows the sorting result of the 15-day rainfall before the landslide event. It can be observed that there are breakpoints at several points, including data number 21 with a rainfall of 225 mm, data number 42 with a rainfall of 396.5 mm, and data number 44 with a rainfall of 456 mm.

Tabel 2. Obtained Threshold Values

Level of Alertness	Daily Rainfall (mm)
Level I	15
Level II	30
Level III	65

The threshold values for the 3-day and 15-day rainfall are simplified into daily rainfall threshold values, and three levels of alertness for landslide disasters are obtained. The lowest alert level, Level I, has a daily rainfall threshold of 15 mm. Level II alertness is set at a daily rainfall threshold of 30 mm, and the highest alert level, Level III, has a daily rainfall threshold of 65 mm.

Dummy Regression

Dummy variables are used to categorize qualitative data and are in the form of nominal scale data[14] . The purpose of using multiple regression with dummy variables is to predict the value of the dependent variable based on one or more independent variables, where one or more independent variables used are dummy variables.

In this dummy case, the correlation coefficient is 25.63%, indicating a positive relationship between the 3P and 15P variables, but the correlation is not strong. The regression equation obtained is y = 18.6 + 0.1946x + 3.1D. The p-value from the dummy regression is 0.861 (greater than 0.05), indicating that the influence of the independent variables on the dependent variable is not significant.

Cluster Analysis

Cluster Analysis is a multivariate method that aims to group n observation objects into m clusters ($m < n$) based on p variables, so that each observation located in one cluster has a higher similarity in characteristics compared to observations located in other clusters [15]. In this case, two clusters are selected, one below the triggering threshold for landslide events and one above the triggering threshold. The values at the cluster boundaries in the dendrogram represent the triggering threshold for landslide events.

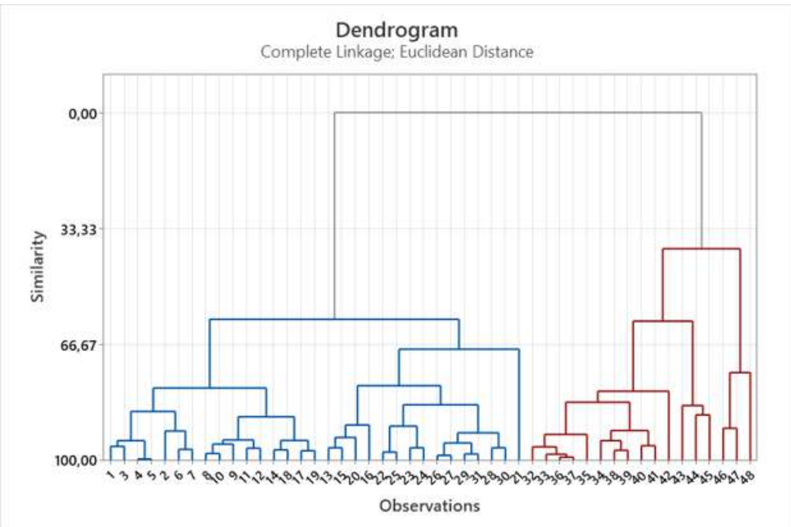

Figure 12. Scatter plot of cumulative 15-day rainfall sorting analysis

From the dendrogram above, it can be seen that the data has been grouped into two major clusters, and the data at the boundary are data number 21 and 32. Data number 21 represents a cumulative 3-day rainfall of 194.4 mm and a cumulative 15-day rainfall of 225 mm. Data number 32 represents a cumulative 117.1 mm rainfall and a cumulative 15-day rainfall of 293.8 mm. Therefore, the obtained thresholds for the 3-day rainfall are 194.4 mm and 117.1 mm (daily rainfall of 65 mm and 39 mm), while the thresholds for the 15-day rainfall are 225 mm and 293.8 mm (daily rainfall of 15 mm and 20 mm)

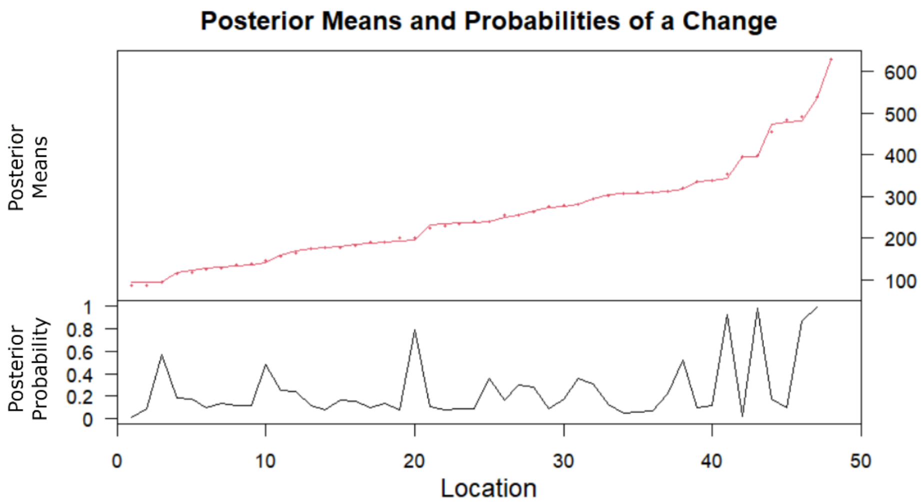

Figure 13. Result of change detection analysis

Table 2 Result of change detection analysis

Probability	Data Number	3P (mm)	15P (mm)
0.79	20	69	201.25
0.924	41	74	354.5
0.986	43	26.8	398.65
0.872	46	133.5	491.8
0.99	47	150.2	539.9

The table above shows the results of the change detection analysis using the bcp method. It identifies five positions where there is a high probability of a change point. These positions indicate values that are likely to be the threshold values triggering landslide events. The respective data numbers and their corresponding 3-day and 15-day cumulative rainfall values are as follows:

1. Data number 20: 3-day cumulative rainfall of 69 mm and 15-day cumulative rainfall of 201.25 mm.
2. Data number 41: 3-day cumulative rainfall of 74 mm and 15-day cumulative rainfall of 354.5 mm.
3. Data number 43: 3-day cumulative rainfall of 26.8 mm and 15-day cumulative rainfall of 398.65 mm.
4. Data number 46: 3-day cumulative rainfall of 135.5 mm and 15-day cumulative rainfall of 491.8 mm.
5. Data number 47: 3-day cumulative rainfall of 150.2 mm and 15-day cumulative rainfall of 539.9 mm.

These values indicate significant changes in rainfall patterns, suggesting that they could be potential threshold values triggering landslide events.

Conclusion

The analysis results indicate that the rainfall threshold that needs to be monitored to detect the potential occurrence of landslides in the study area are 15 mm per day, 30 mm per day, and 65 mm per day. These values can be considered as warnings at different levels, with the highest value of 65 mm indicating a higher confidence for landslide occurrence. In other words, these values represent various levels of alertness to landslide events, providing input for designing disaster prevention strategies to reduce the adverse impacts of landslides.

It is recommended that the result of this analysis is used to create a tiered warning system based on increasing levels of rainfall intensity. This helps emergency responders and the local community to prepare for potential landslides, with appropriate response actions for each level.

The analysis of the topography of landslide occurrence locations and the vulnerability level of the locations to landslides is not discussed in this study. The identification of rainfall thresholds specific to areas with specific vulnerability levels should be considered for further research.

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