Volume 5 Issue 2 (2025) Pages 165-176 P-ISSN:2798-2696 E-ISSN:2798-0057

JOSTECH

Journal of Science and Technology

Website: https://ejournal.uinib.ac.id/jurnal/index.php/jostech Email: jostech@uinib.ac.id

Development of a Fuzzy Logic Model for Landslide Vulnerability Classification in Majalengka Regency

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Received 07 February 2025, Accepted 17 September 2025, Published 30 September 2025

Abstrak

Pada penelitian ini, dikembangkan metode logika fuzzy untuk klasifikasi tingkat kerentanan tanah longsor di Kabupaten Majalengka. Variabel input dari penelitian ini adalah ketinggian, kemiringan lahan, jenis tanah, kepadatan penduduk, dan curah hujan. Data masukan untuk lima variabel pertama diperoleh dari BPS Majalengka, sedangkan data curah hujan diperoleh dari MERRA-2. Tingkat kerentanan longsor sebagai variabel output diklasifikasikan dengan menggunakan MATLAB. Kami menerapkan model logika fuzzy Mamdani untuk menganalisis tingkat kerentanan longsor pada periode 2020-2021. Berdasarkan hasil penelitian, ditemukan bahwa terdapat beberapa kecamatan yang bahkan berpotensi mengalami longsor, yaitu Kecamatan Argapura, Banjaran, Lemahsugih, Bantarujeg, Maja, Malausma, dan Sindang. Berdasarkan hasil penelitian, dapat disimpulkan bahwa hasil yang diperoleh dari model kami sesuai dengan kejadian longsor yang sebenarnya. Hasil dari penelitian ini diharapkan dapat membantu pemerintah daerah dalam memetakan daerah-daerah yang rentan longsor sebagai strategi mitigasi longsor di masa mendatang.

Kata Kunci: Logika Fuzzy, Klasifikasi, Tanah Longsor, Majalengka, MATLAB

Abstract

This paper presents a fuzzy logic model developed to classify landslide vulnerability levels in Majalengka Regency. The model utilizes five input variables: altitude, land slope, soil type, population density, and rainfall. The input data for the first four variables were obtained from BPS Majalengka, while rainfall data were sourced from MERRA-2. MATLAB was employed to classify the landslide vulnerability levels, and the model was applied to analyze the vulnerability levels in Majalengka Regency for the period 2020-2021. The results indicate that seven sub-districts are potentially vulnerable to landslides, namely Argapura, Banjaran, Lemahsugih, Bantarujeg, Maja, Malausma, and Sindang. In conclusion, the model's results are consistent with actual landslide occurrences. This study's findings can be utilized by local governments to map landslide-vulnerable areas and inform landslide mitigation strategies for the future.

Keywords: Fuzzy logic, Classification, Landslide, Majalengka, MATLAB.

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INTRODUCTION

Indonesia is located at the intersection of four tectonic plates: the Eurasian, Australian, Indian, and Pacific plates. This geographical positioning results in a significant potential for natural disasters in Indonesia. Landslides are one of the natural disasters that pose a high potential hazard, particularly because they frequently occur in residential areas. According to [1] and [2], a landslide is a process of disturbance in the balance of forces that causes the movement of soil and rock masses down a slope due to gravitational forces when the driving forces exceed the resisting forces. Generally, landslides can be triggered by geological factors such as altitude, slope, and soil type [3], [4], [5] as well as rainfall [6], [7], [8]. Additionally, population density can directly influence the soil's resilience and increase the risk of landslides.

The occurrence of landslides in West Java has been increasing over the past few years [9]. This condition is also supported by a trend that is exacerbated by rising rainfall intensity due to climate change. Landslides not only cause significant material damage, impacting the local economy but can also cause damage to the morphology of the environment and cause a decrease in surrounding plant vegetation. As a mitigation strategy, various studies have been conducted to minimize the impact of landslides, one of which is by mapping and classifying landslide-vulnerable areas. One of the common methods to map and classify landslide-vulnerable areas is the GIS (Geographic Information System) method. GIS is a powerful tool for analyzing spatial data, allowing for efficient monitoring and identification of areas susceptible to landslides. The use of GIS to map landslide-vulnerable areas has been conducted by previous studies, including [10], [11], [12], and [13]. However, GIS has limitations due to its deterministic nature, which struggles to accommodate data uncertainty and environmental variability.

To overcome the problem, another method is developed in the classification of landslide vulnerability level using machine learning [14], [15], [16], and [17]. While this method is capable of producing models that are more adaptive to the complexity of the data, its drawbacks are the need for a large amount of training data as well as the risk of overfitting, which may reduce the generalizability of the model to different environmental conditions. Apart from the above problems, another method in classifying landslide vulnerability level has also been carried out using fuzzy logic. Alternatively, fuzzy logic, particularly the Mamdani-type fuzzy logic, offers a sophisticated approach to handling uncertainty and ambiguity in environmental data. Fuzzy logic does not require rigid categorical boundaries like deterministic methods but rather allows for more realistic modeling through membership functions. Therefore, Mamdani fuzzy logic is an optimal method for landslide vulnerability classification, as it is able to accommodate uncertainty, increase model flexibility, and produce predictions that are closer to actual conditions in the field.

In this study, we propose a new model to classify landslide vulnerability levels in Majalengka Regency, West Java, using the fuzzy logic method. Majalengka Regency is particularly prone to landslides due to its hilly and mountainous topography, as well as high population density in these areas, which puts additional pressure on the ecosystem. Building on previous research [18], [19], [20], [21], and [22], our model incorporates a broader set of input variables, including elevation, slope, soil type, population density, and rainfall, with the aim of producing more comprehensive results. We validate our model by comparing the results with actual landslide events that occurred between 2020 and 2021, using data from the Majalengka Regional Disaster Management Agency (BPPD Majalengka). The findings of this study are expected to provide a foundation for future research on landslide vulnerability and serve as a valuable resource for local governments and communities in identifying landslide-prone areas and developing effective disaster mitigation strategies.

RESEARCH METHOD

This study focuses on Majalengka Regency, which comprises 26 sub-districts, including Argapura, Banjaran, Bantarujeg, Cigasong, Cikijing, Cingambul, Dawuan, Jatitujuh, Jatiwangi, Kadipaten, Kasokandel, Kertajati, Lemahsugih, Leuwimunding, Ligung, Maja, Majalengka, Malausma, Palasah, Panyingkiran, Rajagaluh, Sindang, Sindangwangi, Sukahaji, Sumberjaya, and Talaga. The input variables used in this study are altitude, land slope, soil type, population density, and rainfall, while the output variable is the landslide vulnerability level. Data on altitude, land slope, soil type, and population density were obtained from [23], and rainfall data were sourced from the Modern-Era Retrospective analysis for Research and Applications Version 2 (MERRA-2) [24]. MERRA-2 was chosen due to the limited data completeness of the Meteorology, Climatology, and Geophysics Agency (BMKG) in the study area, which could impact the accuracy of the analysis. We used MATLAB to classify landslide vulnerability levels based on the Mamdani fuzzy logic method, which involves fuzzification of input variables, rule evaluation using IF–THEN rules, and defuzzification to obtain a crisp output representing the landslide vulnerability level. This study is limited to analyzing landslide occurrence during the period of 2020-2021 due to the limited availability of officially released data from the Regional Disaster Management Agency (BPBD). Using officially published data ensures the validity and accuracy of the analysis results. Although this study focuses on a specific period, the methodological steps outlined can be applied to address landslide vulnerability classification in future years.

The algorithm for data processing and analysis can be outlined as follows:

1. Defining input and output variables and their corresponding fuzzy sets.
   The fuzzy sets for the input and output variables are defined as follows:
   a. Altitude = {low, slightly high, high}
   b. Land slope = {slope, undulating hills, steep hills}

c. Soil type = {not sensitive, slightly sensitive, moderately sensitive, sensitive, very sensitive}
d. Population density = {low, medium, high}
e. Rainfall = {dry, normal, wet}
f. Landslide vulnerability = {vulnerable, slightly vulnerable, not vulnerable}.

2. Determining the scoring of the input and output variable.
The scoring system for each input and output variable is presented in the following tables:

Table 1. Altitude variable score

Altitude	Criteria	Label	Score
< 308 masl	low	R	33
308-770 masl	slightly high	AT	66
>770 masl	high	T	99

Table 2. Land slope variable score

Land slope	Criteria	Label	Score
<15%	slope	L	33
15-40%	undulating hills	BB	66
>40%	steep hills	PT	99

Table 3. Soil type variable score

Soil type	Criteria	Label	Score
Aluvial, Glei, Noncal	not sensitive	TP	20
Latosol	slightly sensitive	SP	40
Brown forest, Mediteran	moderately sensitive	AP	60
Andosol, Grumosol, Podsol	sensitive	P	80
Regosol, Litosol, Organosol	very sensitive	SAP	100

Table 4. Population density variable score

Population density (people/km^2)	Criteria	Label	Score
< 645	low	R	33
645-1620	medium	S	66
> 1620	high	T	99

Table 5. Rainfall variable score

Rainfall amount (mm/month)	Criteria	Label	Score
< 400	dry	K	33
400-800	normal	N	66
> 800	wet	B	99

Table 6. Landslide vulnerability level score

Landslide vulnerability level	Label	Score
vulnerable	V	33
slightly vulnerable	SV	66
not vulnerable	NV	99

3. Determining the membership function of each variable.
   A trapezoidal membership function is used for this purpose.
4. Establishing fuzzy rules or fuzzy rule base.
   Fuzzy rules are created using if-then statements based on the defined membership functions.
5. Calculating the Z value
   The Z value is obtained by processing the input data through the fuzzy design output, resulting in a numerical value.
6. Determining landslide vulnerability level
   The landslide vulnerability level is determined by converting the fuzzy output (Z value) into a crisp value through a defuzzification process.

RESULTS AND DISCUSSIONS

Research Data

We collected data on input variables, including elevation, slope, soil type, and population density, for each sub-district. These data were assumed to have fixed values for the period from January 2020 to December 2021, as shown in Table 7. In contrast, the rainfall variable was assumed to have a uniform value across all sub-districts, with the data presented in Table 8.

Table 7. Data of altitude, slope, soil type, and population density for each sub-district

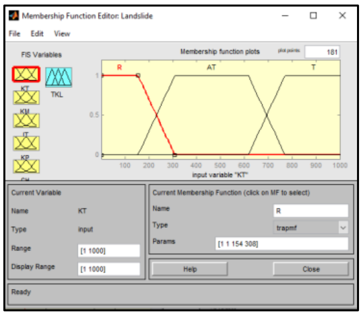
Sub-district	Altitude (masl)	Land slope (%)	Soil type	Population (people/km^2)
Argapura	857	>40%	Regosol	607
Banjaran	626	15-40%	Regosol	599
Bantarujeg	365	15-40%	Andosol	701
Cigasong	141	0-15%	Andosol	1.578
Cikijing	582	15-40%	Regosol	1.568
Cingambul	582	15-40%	Regosol	1.170
Dawuan	51	15-40%	Latasol	2.014
Jatitujuh	19	0-15%	Latasol	755
Jatiwangi	42	0-15%	Latasol	2.271
Kadipaten	51	0-15%	Latasol	2.181
Kasokandel	51	15-40%	Latasol	1.693
Kertajati	30	0-15%	Latasol	348
Lemahsugih	526	15-40%	Regosol	812
Leuwimunding	61	>40%	Latasol	1.995
Ligung	25	0-15%	Latasol	1.072
Maja	600	15-40%	Regosol	806
Majalengka	141	15-40%	Andosol	1.289
Malausma	653	15-40%	Regosol	1.077
Palasah	36	0-15%	Latasol	1.397
Panyingkiran	51	>40%	Latasol	1.436
Rajagaluh	169	15-40%	Andosol	1.378
Sindang	439	15-40%	Andosol	717
Sindangwangi	169	15-40%	Andosol	1.093
Sukahaji	125	>40%	Andosol	1.467
Sumberjaya	36	15-40%	Latasol	2.024
Talaga	626	15-40%	Regosol	1.108

Table 8. Monthly rainfall data in Majalengka Regency

Month	Rainfall data (mm)	Month	Rainfall data (mm)
January 2020	295.31	January 2021	326.95
February 2020	500.98	February 2021	442.97
March 2020	780.47	March 2021	448.24
April 2020	305.86	April 2021	164.52
May 2020	348.05	May 2021	148.3
June 2020	94.92	June 2021	160.69
July 2020	94.92	July 2021	43.34
August 2020	26.37	August 2021	71.59
September 2020	100.2	September 2021	124.84
October 2020	411.33	October 2021	194.33
November 2020	353.32	November 2021	477.06
December 2020	384.96	December 2021	343.7

Fuzzy Logic Model

The primary objective of this paper is to develop a Mamdani-type fuzzy logic model for classifying landslide vulnerability levels. To facilitate the modeling process, we define the following notations: KT (altitude), KM (land slope), JT (soil type), KP (population density), CH (rainfall), and TKL (landslide susceptibility level). Based on the fuzzy scoring values defined in Tables 1-6, fuzzy set curves are created for each input and output variable, as illustrated in Figures 1(a)-(f).



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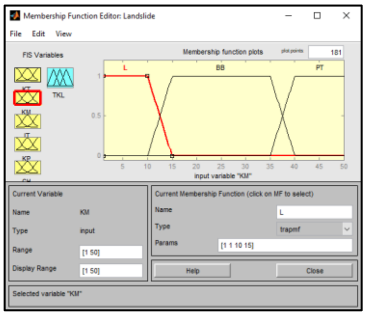

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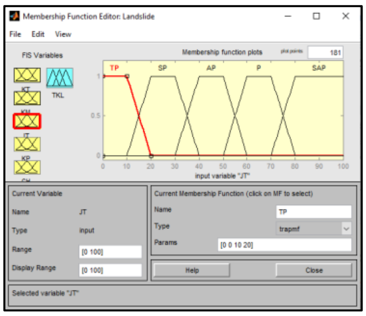

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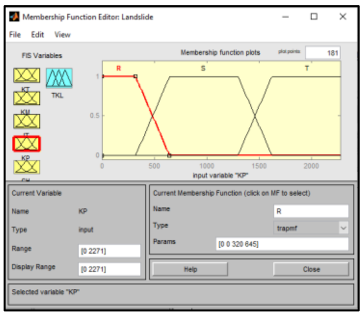

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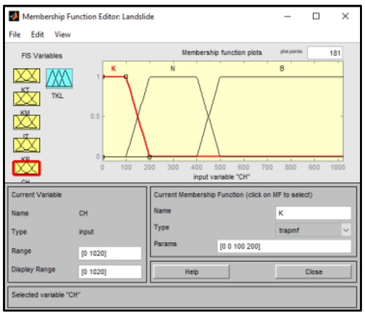

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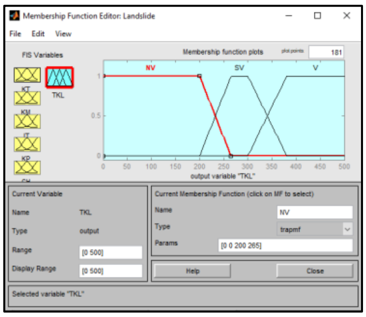

(f)

Figure 1. Fuzzy set curves for variables: (a) altitude, (b) land slope, (c) soil type, (d) population density, (e) rainfall, and (f) landslide susceptibility level.

The next step is to establish a fuzzy rule base that connects the input variables to the output variables. Based on the input variable criteria, a total of 405 fuzzy rule base combinations are generated. To illustrate, several rules are constructed as follows:

a. **Rule 1**: IF altitude is *low*, slope is *gentle*, soil type is *not sensitive*, population density is *low*, and rainfall is *dry*, THEN landslide vulnerability is *not vulnerable*.
b. **Rule 2**: IF altitude is *high*, slope is *steep*, soil type is *very sensitive*, population density is *high*, and rainfall is *wet*, THEN landslide vulnerability is *vulnerable*.
c. **Rule 3**: IF altitude is *moderate*, slope is undulating *hills*, soil type is *moderately sensitive*, population density is *medium*, and rainfall is *normal*, THEN landslide vulnerability is *slightly vulnerable*.

These examples demonstrate the logic used to construct the fuzzy rule base, which was then expanded systematically to cover all possible combinations. The complete set of rules is presented in Table 9.

Table 9. Rule bases of the model

No.	IF (Input)					THEN (Output)
	Altitude (KT)	Land Slope (KM)	Soil Type (JT)	Population Density (KP)	Rainfall (CH)	Landslide Vulnerablity (TKL)
1	R	L	TP	R	K	NV
2	R	L	TP	R	N	NV
3	R	L	TP	R	B	NV
4	R	L	TP	S	K	NV
…	…	…	…	…	…	…
402	T	PT	SAP	S	B	V
403	T	PT	SAP	T	K	V
404	T	PT	SAP	T	N	V
405	T	PT	SAP	T	B	V

Classification of landslide vulnerability level

A numerical simulation is performed with MATLAB using the research data from Tables 7 and 8, along with the fuzzy rule base in Table 9, to classify landslide vulnerability levels in Majalengka Regency for 2020-2021. The classification results for each sub-district are presented in Tables 10 and 11.

Table 10. Classification of landslide vulnerability level in Majalengka Regency in 2020

District	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Des
Argapura	V	V	V	V	V	V	V	V	V	V	V	V
Banjaran	SV	SV	V	SV	SV	V	SV	SV	SV	SV	SV	SV
Bantarujeg	SV	SV	V	SV	SV	V	SV	SV	SV	SV	SV	SV
Cigasong	NV	NV	SV	NV	NV	SV	NV	NV	NV	NV	NV	NV
Cikijing	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Cingambul	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Dawuan	NV	NV	SV	NV	NV	SV	NV	NV	NV	NV	NV	NV
Jatitujuh	NV	NV	SV	NV	NV	SV	NV	NV	NV	NV	NV	NV
Jatiwangi	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Kadipaten	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Kasokandel	NV	NV	SV	NV	NV	SV	NV	NV	NV	NV	NV	NV
Kertajati	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Lemahsugih	SV	SV	V	SV	SV	V	SV	SV	SV	SV	SV	SV
Leuwimunding	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Ligung	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Maja	SV	SV	V	SV	SV	V	SV	SV	SV	SV	SV	SV
Majalengka	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Malausma	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Palasah	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Panyingkiran	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Rajagaluh	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Sindang	SV	SV	V	SV	SV	V	SV	SV	SV	SV	SV	SV
Sindangwangi	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Sukahaji	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Sumberjaya	NV	NV	SV	NV	NV	SV	NV	NV	NV	NV	NV	NV
Talaga	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV

Table 11. Classification of landslide vulnerability level in Majalengka Regency in 2021

District	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Des
Argapura	V	V	V	V	V	V	V	V	V	V	V	V
Banjaran	SV	SV	V	SV	SV	V	SV	SV	SV	SV	SV	SV
Bantarujeg	SV	SV	V	SV	SV	SV	SV	SV	SV	SV	SV	SV
Cigasong	NV	NV	SV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Cikijing	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Cingambul	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Dawuan	NV	NV	SV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Jatitujuh	NV	NV	SV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Jatiwangi	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Kadipaten	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Kasokandel	NV	NV	SV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Kertajati	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Lemahsugih	SV	SV	V	SV	SV	SV	SV	SV	SV	SV	SV	SV
Leuwimunding	SV	SV	SV	SV	SV	SV	NV	SV	SV	SV	SV	SV
Ligung	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV

Maja	SV	SV	V	SV	SV	V	SV	SV	SV	SV	SV	SV
Majalengka	SV	SV	SV	SV	SV	SV	NV	SV	SV	SV	SV	SV
Malausma	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Palasah	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Panyingkiran	SV	SV	SV	SV	SV	SV	NV	SV	SV	SV	SV	SV
Rajagaluh	SV	SV	SV	SV	SV	SV	NV	SV	SV	SV	SV	SV
Sindang	SV	SV	V	SV	SV	V	SV	SV	SV	SV	SV	SV
Sindangwangi	SV	SV	SV	SV	SV	SV	NV	SV	SV	SV	SV	SV
Sukahaji	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
Sumberjaya	NV	NV	SV	NV	NV	NV	NV	NV	NV	NV	NV	NV
Talaga	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV

For validation, a comparison was made between the simulation results and the actual data of landslides in Majalengka Regency in 2020-2021 sourced from BPBD Majalengka [25]. The data is presented in Figure 2.

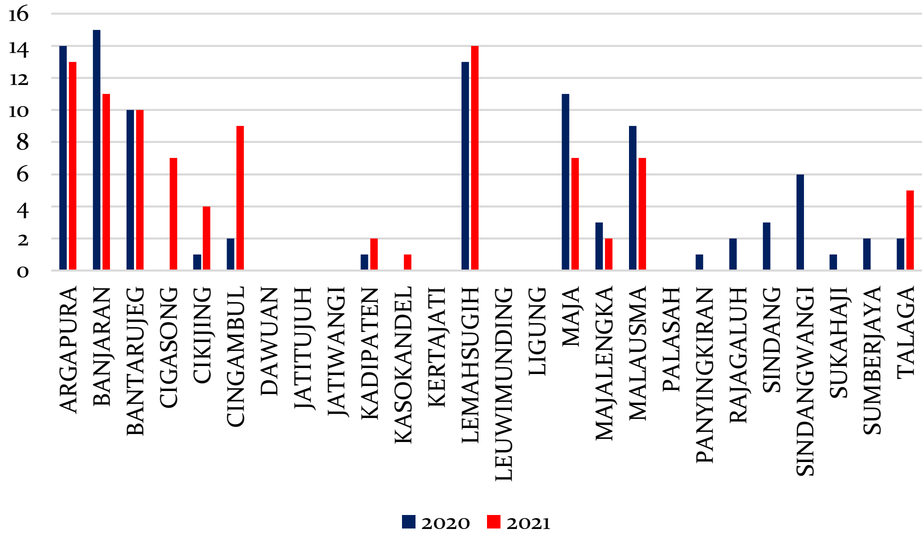

Figure 2. Actual occurrence data of landslides in Majalengka Regency in 2020-2021 [25].

Discussion

Based on the results depicted in Tables 10 and 11, it can be shown that Argapura is consistently classified in the vulnerable (V) category throughout 2020 and 2021, indicating a very high level of vulnerability. Vulnerable periods are experienced by Lemahsugih, Sindang, Banjaran, Maja, and Bantarujeg, especially in March and June, which coincide with the rainy season. Most sub-districts are classified as slightly vulnerable (SV) in most months, such as Cikijing, Cingambul, Panyingkiran, Rajagaluh, and Sindangwangi. Jatiwangi, Kadipaten, Kertajati, Palasah, and Ligung are consistently categorized as not vulnerable (NV) throughout the year. It is indicated that these areas have more stable geological characteristics or minimal landslide triggering factors. It is also indicated that environmental factors may still allow landslides to occur, but at a lower risk than areas that are always vulnerable.

There is no significant change in the pattern of landslide vulnerability, although some areas show a slight improvement. For example, Lemahsugih was previously categorized as vulnerable in some months of 2020, but in 2021, it is more often classified as slightly vulnerable. Sindang and Banjaran still exhibit vulnerability patterns in March and June. A slight increase in the 'not vulnerable' category is observed in some sub-districts, such as Leuwimunding and Majalengka. High rainfall in March appears to be the primary factor causing some sub-districts to shift from slightly vulnerable to vulnerable. In addition to rainfall, topography and soil type are also contributing factors to landslide vulnerability. Specifically, Argapura, Banjaran, Lemahsugih, and Maja sub-districts have regosol soil types, while Bantarujeg and Sindang sub-districts have Andosol soil types. Both regosol and Andosol soil types are prone to soil movement, with regosol being very sensitive and Andosol being sensitive, thereby increasing the potential for landslides.

Furthermore, an analysis of Figure 2 reveals that Argapura has the highest number of landslide events in both years, consistent with its vulnerable classification based on the fuzzy logic model. Similarly, Lemahsugih and Bantarujeg exhibit a high number of landslide events, aligning with their vulnerable classification in certain months. Cikijing, Cingambul, Sindangwangi, and Rajagaluh have a notable but lower number of landslide events, which corresponds to their slightly vulnerable classification. Leuwimunding's moderate number of landslide events also aligns with its slightly vulnerable category. In contrast, Jatiwangi, Kadipaten, Kertajati, Palasah, and Ligung have a very low or zero number of landslide events, consistent with their not vulnerable classification. Overall, the landslide vulnerability classification in Tables 10 and 11 shows a strong correlation with the actual number of landslide events in Figure 2. Specifically, sub-districts classified as vulnerable tend to have a high number of landslide events, while those classified as slightly or not vulnerable have fewer or no landslide events.

CONCLUSION

Based on the fuzzy logic-based classification, seven sub-districts in Majalengka Regency were identified as highly vulnerable to landslides: Argapura, Banjaran, Lemahsugih, Bantarujeg, Maja, Malausma, and Sindang. This classification is consistent with actual landslide data from BPBD Majalengka. The temporal analysis shows that landslides most frequently occur in March, coinciding with peak rainfall (780.47 mm in 2020 and 448.24 mm in 2021). High rainfall intensity is therefore a major triggering factor. Soil type also plays a significant role. Regosol soils in Argapura, Banjaran, Lemahsugih, Maja, and Malausma, as well as Andosol soils in Bantarujeg and Sindang, are highly susceptible to slope movement, thereby increasing landslide risk. Overall, the Mamdani fuzzy model accurately reflects actual landslide patterns, with vulnerable sub-districts showing high incident frequency, while slightly or not vulnerable sub-districts experienced fewer or no landslides. The findings of this study are expected to support local governments and communities in mapping landslide-prone areas and formulating effective mitigation strategies for the future.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the academic community of the Department of Geological Engineering, Universitas Padjadjaran, and the Department of Physics, Universitas Jenderal Soedirman, for their insightful discussions, valuable suggestions, and expertise on disaster mitigation, particularly landslides. We also extend our gratitude to the anonymous referees for their constructive comments and suggestions.

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