EREM 79/3

Journal of Environmental Research, Engineering and Management
Vol. 79 / No. 3 / 2023
pp. 95–107
DOI 10.5755/j01.erem.79.3.33628

Landslide Movement of Bendungan District Trenggalek Using an Artificial Neural Network

Received 2023/03 | Accepted after revisions 2023/08

https://doi.org/10.5755/j01.erem.79.3.33628

Landslide Movement of Bendungan District Trenggalek Using an Artificial Neural Network

Didik Taryana[1]*, Rudi Hartono[1], Dicky Arinta[1], Agus Purnomo[2], Ike Sari Astuti[1]

[1] Department of Geography, Faculty of Social Sciences, State University of Malang, Indonesia

[2] Department of Social Sciences, Faculty of Social Sciences, State University of Malang, Indonesia

***Corresponding author:** Didik.taryana.fis@um.ac.id

Landslide is one of the disasters that often occurs in Indonesia in the East Java Province, especially in Bendungan District, Trenggalek Regency. Analysis of landslide susceptibility in Bendungan District is needed to spatially locate the landslide occurrences. The purpose of this study was to predict landslide events using an artificial neural network. Rainfall, topography, physical soil properties, and land-use were used as the explanatory variables. An analytic hierarchy process approach was applied to determine the weight of the variables. The model satisfactorily classified the landslide hazards with an area under curve of 0.96. The northwest area of the Bendungan District was found to be a region at high risk with rainfall and soil texture as the most influential parts in triggering the landslides.

Keywords: neural network analysis, landslide movement, analysis hierarchy process.

Introduction

Landslide signifies a physical process where soil movement occurs and can threaten communities and their livelihood. Landslide is known as a globally hydroclimatic hazard. Landslides, when occurring massively, can lead to significant physical and economic losses (Bista, 2022). One obstacle in mitigating the negative impacts of landslides is the fact that landslides can be hardly predicted. Due to this danger, the ability to precisely predict and measure the risk level of landslide occurrences both temporally and spatially is very important not only for land or watershed managers but also for people living in the areas of close proximity (Abdulwahid and Pradhan, 2017; Flentje et al., 2007). The needs of accurate and reliable landslide risk information are even stronger where the areas susceptible to landslides are inhabited by people with low resilience capacity.

Landslides are physical processes that are largely controlled by a variety of factors. For instance, numerous studies identify the key role of topography, climate, geology, soil, landform, land surface cover, and anthropogenic factors such as human activities and land use types (Tarolli and Sofia, 2016; Wang et al., 2019). All these factors interact and affect the degree of risks or susceptibility to landslides. Characterizing landslide behavior requires a thorough understanding of the dynamics of landslides and the analysis of key impact factors (Yerro et al., 2019). Relying this requirement to the traditional collection of field data can be tedious, challenging, and expensive. Therefore, there should be an alternative to provide a reliable information on landslide risks assessment (Dou et al., 2015; Fan et al., 2019a).

Advancement in computation and geospatial technologies has been proven supportive to the efforts for landslide modeling (Ekeanyanwu et al., 2022). There have been varying machine learning (ML) algorithms used in predicting landslide risks such as artificial neural network (ANN), logistics regression, random forest classification and regression, and support vector machine algorithms (Alqadhi et al., 2021; Nhu et al., 2020). Among these, the ANN appears to be the most popular approach gaining wider application. The use of the artificial intelligence (AI) through the implementation of ANN in modeling landslides is an example of the application of such advancement. Integration of ANN models and geospatial technologies has been widely used in estimating landslide occurrences with reasonable success (Abiodun et al., 2019; Nhu et al., 2020). Numerous studies exploit the GIS or remote sensing data combined with field measurement to monitor the dynamics of landslide governing factors and model them for determining landslide risks and susceptibility (Bvindi, 2019; Munthali, 2020). The ANN is a type of algorithm that mimics the process of the human brain in making decisions by the presence of neuron systems. In brief, the neural network configuration transforms the inputs through a series of layers and generates output layers (Zou and Ergan, 2023). From a landslide perspective, the input layers represent the landslide governing factors, and the output layers signify the predicted landslide occurrences. At this point, there is no agreed understanding about specific landslide factors that can be inputted into an ANN configuration. This suggests that there is always room for the ANN implementation concerning the uniqueness of the landscape.

Landslide is one of the disasters that often occurs in Indonesia. The area of East Java Province has a high potential for landslides is Trenggalek Regency (Riadi and Windiastuti, 2019). The region of Trenggalek Regency where landslides occur is a disaster area with a medium to high level of vulnerability (Susilo et al., 2021). The Trenggalek Regency is notable for a steep topography of more than 40% covering an area of ± 28 378.11 ha and the area of lowlands with a slope between 0–15% is ± 42 291.38 ha (Bappeda Trenggalek Regency, 2016). Bendungan District is an area under the slopes of Mount Wilis with an undulating hilly topography and steep slopes (Isnaini et al., 2022). In 2016, as many as 31 landslides occurred in Bendungan District Trenggalek (Utama et al., 2021). The landslides caused damage to buildings, agricultural lands and affected access to roads between the villages thus disrupting the network and accessibility of the affected settlements located nearby (Fabio et al., 2022; Wilopo et al., 2022). Efforts are needed to reduce the risk of landslides in Bendungan District in order to reduce the negative effects from the associated losses. One of such efforts aimed at reducing losses caused by landslides can be done by conducting a landslide vulnerability analysis which will provide information on the vulnerability of landslides so as to minimize landslide disasters (Das et al., 2022; Vasileiou et al., 2022). Vulnerability mapping efforts are represented by potential hazards through landslides (Das et al., 2022; Vasileiou et al., 2022). This study attempts to model landslide risks in Bendungan District and classify the region based on their corresponding risk degree. More specifically, this study aims at identifying the key factors controlling landslide occurrence, determining their relative importance, and applying them to map landslide susceptibility in the study area.

Methods

Study area

Landslide hazard mapping research was performed in Bendungan District, Trenggalek Regency, using the analytic hierarchy process, spatial multi-criteria evaluation, and artificial neuron network methods. The geographic coordinates of the study area are 111°41'25.56"E to 111°47'19.03"E and 7°53' 8.70"LS to 7°58'41.11"LS. Respectively, the research location is in the north of the Trenggalek Regency, west of Tulungagung Regency, east of Ponorogo Regency and the foot of Mount Kiman-Wilis, East Java Province. The research area studies are presented in *Fig. 1*.

Based on landslide events obtained from the Pusdalops BPBD East Java from 2016 to 2022, there are 31 recorded landslide events that occurred in the Bendungan District and its surroundings. However, out of the 31 events, only about 20 reports could be plotted for the exact location, since the information on the coordinates of the incident was not clearly stated. In addition, field observations found 8 points of avalanches that can be documented, so historical data of a total of 28 landslide events are used in calculating landslide hazards.

According to local residents, apart from the occurrence of moderate-to-severe landslides, micro or small-scale avalanches are often found on the shoulder of the roads, as well as terraced fields and rice fields that collapse after the high-intensity rains (Zimmern, 2020). The point of occurrence of landslides is presented in the distribution of landslide points (*Fig. 2*). The research findings of small avalanches are scattered in almost all areas of Bendungan District, where moderate to severe landslide levels are found at several observation points. According to local residents and Babinsa, landslides always occur after heavy rains and are considered normal by local residents. During the early 2020–2022, there have been no landslide events that caused casualties. The maximum loss is only in the form of materials such as occasional damage to the walls of the house that is pushed by landslide materials (Acosta et al., 2021; Guo et al., 2020).

ANN model for landslide development

Landslide hazard mapping research was conducted in Bendungan District, Trenggalek Regency, with the ANN method using survey research methods which include observations, recording, and measurements in the field and secondary data (Dalir et al., 2022). The study was also designed using a quantitative approach with the aim of calculating the parameters causing landslides as ac-

Fig. 1. *Bendungan District administration map*

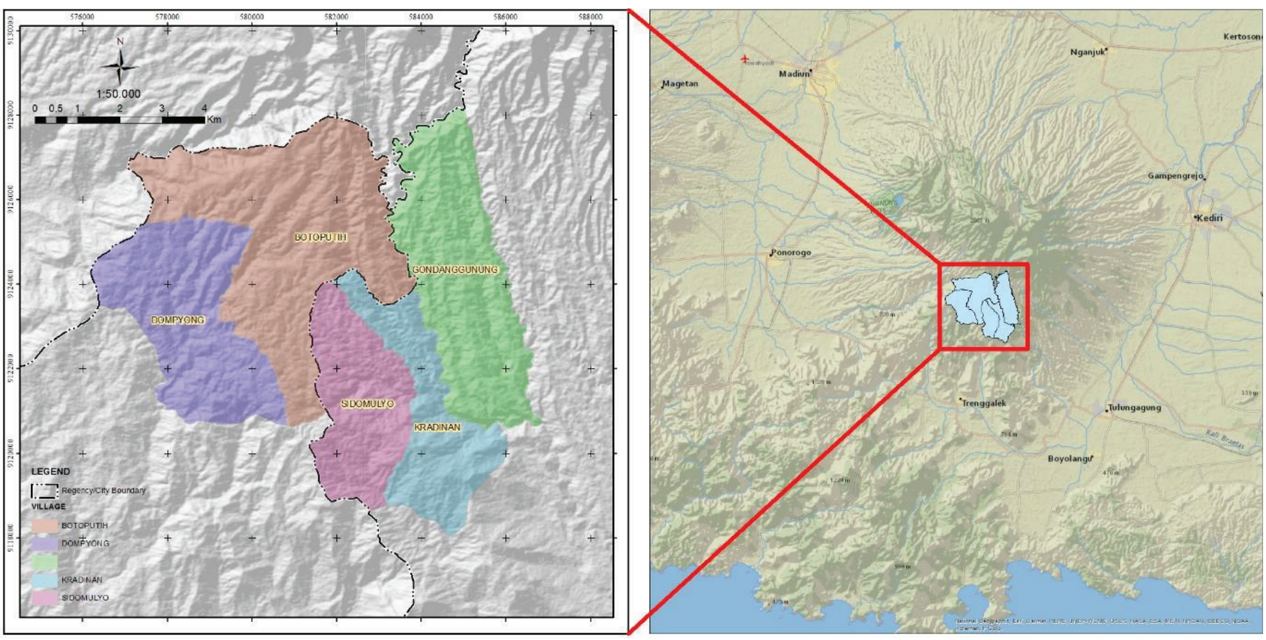
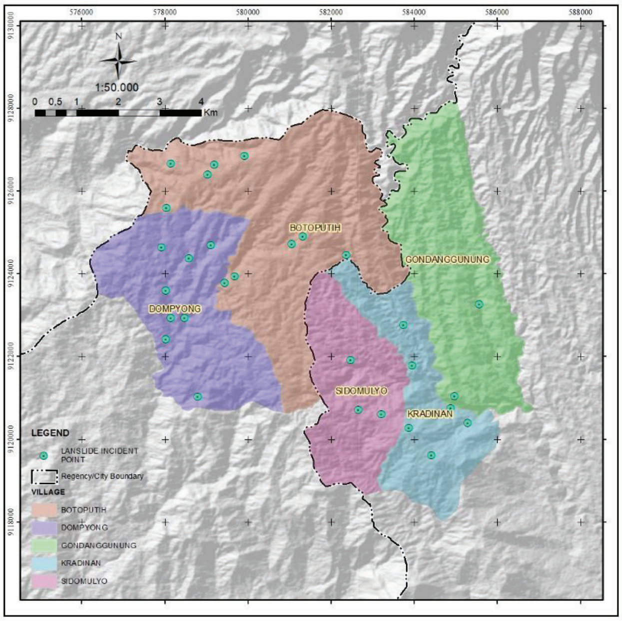


Fig. 2. *Map of landslide distribution in Bendungan District*



curately as possible (Daviran et al., 2022; Fu et al., 2022). Fieldwork and surveys were carried out to collect landslide hazard parameters, namely soil texture class and soil extensibility or COLE Index and landslide occurrence (Dou et al., 2015; Obda et al., 2022). The parameters were sampled based on the landform variability in the study area. All data used in the study were summarized in *Table 1*. Data collection techniques in this study included interviews, observations, and documentation. The in-depth interviews were also conducted with village and sub-district officials. Personnel of the Babinsa officers and the Kab. Trenggalek were asked to obtain information according to expert judgment about the role of the parameters used in landslide hazard vulnerability. The use of ANN algorithms in making ANN nodes is based on numeric data. These numbers will later be calculated using certain formulas gradually in the program where the user cannot intervene in the ongoing calculations; therefore, the GIS data which were previously in the form of spatial data are converted into the numerical data so that it can be processed further (Al Barsh et al., 2020). The mean square error (MSE) value as the test value for the accuracy of the model was used for data training, the lower or close to zero MSE value means that the model is getting better, and the MSE value 0 indicates that there is no error (Prayudani et al., 2019).

The output value obtained is then transformed into the original matrix form and then converted back into the form of raster spatial data so that the results can be interpreted and presented into a landslide hazard map using the ANN method (Hammad et al., 2020; Shahri et al., 2019). The original data attributes must be re-entered such as the type of coordinates used, the coordinates of the upper and lower corners and the side corners and the amount of spatial resolution. This process is in accordance with the concept of integration and utilization of GIS proposed by Ju et al. (2022) that land characteristics data can be stored in various layers, the data collected for each spatial unit can be analyzed and calculated so that the value of a space related to land suitability is obtained (Wu and Lane, 2017; Yildirim et al., 2018). The ANN is an analysis used to determine the weights that have been assessed by experts/expert judgment regarding the landslide disasters (Danumah, 2017; Osiakwan et al., 2022). Assessment to the performance of classification was carried out using a combination by considering iterations and the resulting errors. The model with the smallest errors was selected. For validation, an inventory map of landslide events in 2014–2019 in the form of raster data was used, omissions and model commissions were compared to pixel units using a confusion matrix to get the overall accuracy value. The generated landslide classes were used to develop the hazard class index through the use of natural breaks classification (Cao et al., 2016; Sema et al., 2017).

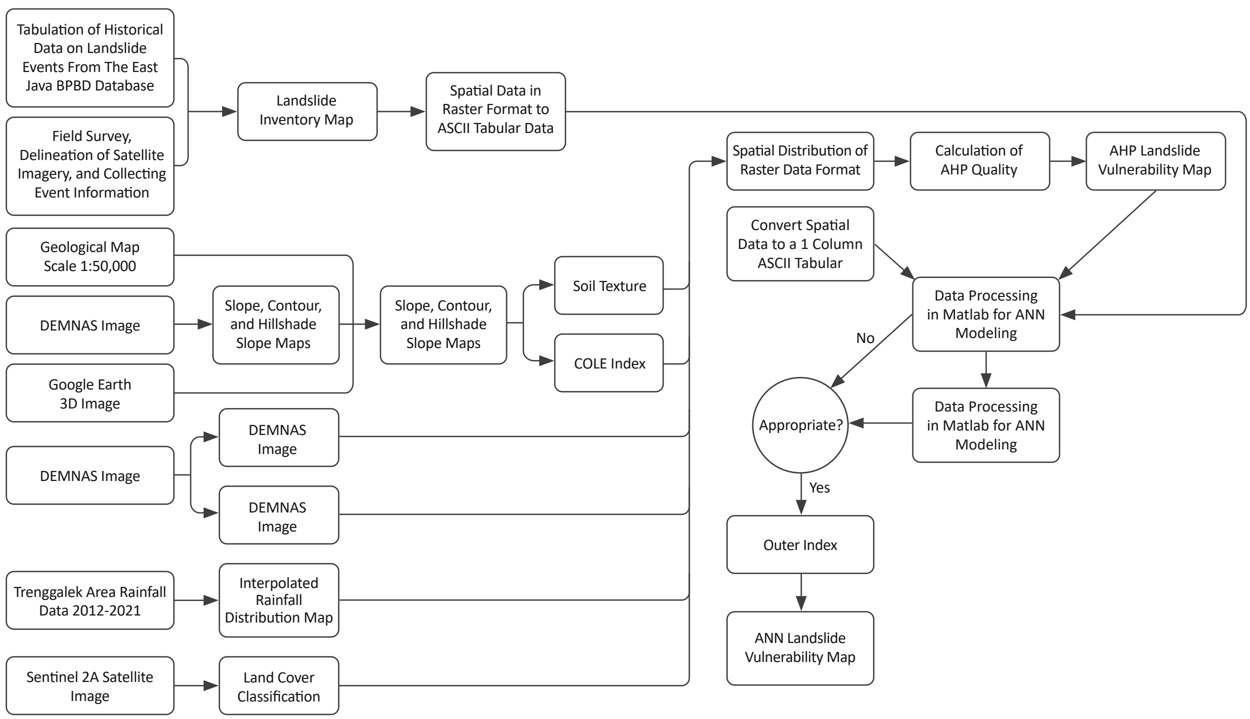
Observations in this study were carried out to collect data in order to verify the parameters of the landslide hazard related to soil characteristics such as occurrences and locations of former landslide events, and data collection of soil samples. Field observations were carried out by target sampling in each unit of the analysis in the form of a landform unit with the assumption that each landform has the same land characteristics. The documentation was carried out by obtaining information from pictures, writings, diagrams and other data sources from relevant institutions and agencies that support disaster research and land geology disasters. This study collected several data, including the following *Table 1*.

Data analysis in this study consisted of several stages, namely the pre-field and post-field stages. The pre-field data analysis activities consisted of analyzing the consistency value of expert judgment on the landslide hazard parameters using the AHP method. Post-field data analysis is field data processing, and artificial neural network classification.

Table 1. *List of data types, scale, and sources used in the study area*

No	Variable	Scale	Source	Reasoning
1	Map of the Earth of Indonesia Trenggalek	1 : 25.000	https://tanahair.indonesia.go.id/portal-web	Making a base map for determining the landslide point
2	Geological Map of Babadan Sheet, East Java	1 : 50.000	https://geoportal.esdm.go.id/	Knowing the type of source rock in the Bendungan District
3	Digital Elevation Model data comp iled from various topographic satellite images of DEMNAS-BIG	Spatial Resolution 8.1 m	Geospatial Information Agency, online recording year 2009	Knowing the slope as one of the factors that influence landslides
4	Rainfall data for 16 stations around Kab. Trenggalek – Tulungagung in 2012–2021	Rainfall per year	Department of Public Works for Irrigation	Knowing the distribution of rainfall as one of the factors that influence the movement of landslides
5	Inventory map of landslide events from Google earth time series images and field observations.		1) www.https://earthengine.google.com, 2) Researcher	Basis in the determination of landslides

Fig. 3. *The workflow approach employed in this study*



Modeling landslide movement direction

In addition to mapping the distribution of landslide susceptibility, it is also necessary to predict the direction of landslide movement. This is because the distribution of potential landslide events is not enough to increase public awareness (Petrucci, 2022). If the landslide hazard distribution map has a low or medium level, the community will tend to underestimate the potential for disasters, even though their settlement locations may be affected due to the direction of the avalanche flow (Fan et al., 2019b; Kjekstad and Highland, 2009). Various types of landslide hazard calculation models may claim that the output product is accurate, but this distribution map is static. The hazard classification from very low to very high only shows the hazard class value at the location represented by the pixel, but is not able to provide a dynamic picture related to the avalanche activity (Skilodimou et al., 2019). With modeling of the direction of landslide movement, it is proposed that map users such as communities can better prepare themselves and increase their capabilities for future disaster events (Singh, 2022). Making a map of the direction of this landslide movement is based on using the flow direction approach in the hydrological cycle process. Namely, by using the assumption of fluid flow from a high place to a lower place, by utilizing DEM data, it is possible to intercept the topographic contour information that can map flow distribution network.

Results and Discussion

Results

Characteristics of landslide affecting factors

Slope

In this study, several physical factors, namely slope classes, soil texture, and soil COLE values, were evaluated. The slope of the mountain has an effect on landslides, namely the slope that has a steeper degree will increase the possibility of landslides (Diara et al., 2022; Zou et al., 2021). Landslides will not occur without a trigger or driving factor. A steep slope will not necessarily experience a landslide, but a slope with a steep angle of curvature and supported by a high rainfall factor will trigger landslides. Landslide is one type of soil or rock mass movement that generally occurs on less stable or unstable slopes (Chiarelli et al., 2022; Hill et al., 2022). Based on the results of the Digital Elevation Model (DEM) data processing, the DEMNAS-BIG image of Bendungan District has 5 classes of slope classes based on the classification, namely flat (0–8%), sloping (8–15%), moderately steep (15–30%), steep (30–45%), and very steep (> 45%). In Bendungan District, landslides occur on very steep, steep, and rather steep slopes. The following is the classification of slopes in Bendungan District as presented in *Table 2*.

Table 2. *Slope classification in Bendungan District*

Slope level (%)	Class	Pixel	Area (Ha)	Percentage (%)
0–8%	Flat	43 912	439.12	4.55
8–15%	Sloping	112 265	1122.65	11.63
15–25%	Slightly steep	384 563	3845.63	39.84
25–45%	Steep	291 051	2910.51	30.15
> 45%	Very Steep	133 479	1334.79	13.83
TOTAL		9652.7		

Soil texture

Soil texture determines the water regimes in the soil in the form of penetration, infiltration speed, and the ability to retain water. Soil texture also affects the physical and chemical reactions in the soil, because soil particle size can be a determining factor for soil surface area. Soil with a more dominant clay fraction will have more surface area than soil with a dominant sand and dust fraction (Palayukan et al., 2022; Vlasov et al., 2022). Soil texture affects the level of soil permeability and also the level of vulnerability to landslides in the study area. For instance, soil with a dominating sand and dust content has a greater potential for landslides than soil with a clay texture. Soil with a predominantly clay texture has more capacity to hold water.

Table 3. *Characteristics of soil texture in Bendungan District*

No	Landform	Fraction Content (%)			Texture Class*
		Clay	Silt	Sand	
1	Fault lines (v3)	12	32	56	Sandy loam
2	Foot volcano slightly eroded (v6/2)	37	38	25	Clay loam
3	Foot volcano erosion moderately (v6/3)	38	38	24	Clay loam
4	The upper slope of the volcano is heavily eroded (v5.1/4)	41	39	20	Clay
5	The upper slope of the volcano is moderately eroded (v5.3/3)	42	31	27	Clay
6	Central slope of the volcano eroded in the West (v4/4-B)	39	44	17	Silty clay loam
7	The middle slope of the volcano eroded to the East (v4/4-T)	42	41	17	Silty clay

COLE index/soil wrinkle value

Soil can undergo swelling and experience wrinkles. The nature of this condition is expressed as soil COLE value. This value is identified as the basis in the analysis of soil physical properties which focuses on changes in soil volume in wet or dry conditions. The wrinkle swelling value / COLE value will directly affect the level of vulnerability to landslides. The values of COLE from the collected samples were then classified into classes that show the degree of soil wrinkle development. *Table 4* shows the magnitude of the COLE value and its classification for each sample used.

The analysis of the physical properties of soil through the soil texture classification and the COLE value of swelling and wrinkle was carried out to obtain more in-depth information related to the characteristics of the soil in the study area. In depth information analysis aims to describe the characteristics of the soil and is associated with the results of field observations during the process of making a landslide inventory map. Based on the results of the identification of texture and wrinkle-swelling / COLE values, there is an alignment or relationship between these two parameters of physical properties of the soil (Sari et al., 2022). The materials were dominated by silt and clay fractions, while the sand fraction has a small percentage value, indicating that the soil condition has a moderate wrinkle development value. The moderate wrinkle value / COLE value in the silty clay loam texture class was due to the almost balanced clay fraction between the clay and dust.

Table 4. *Characteristics of soil texture in Bendungan District*

No	Landform	Cole Index Value	Cole Index Classification
1	Fault lines (v3)	0.016	Low
2	Foot volcano slightly eroded (v6/2)	0.044	Medium
3	Foot volcano erosion moderately (v6/3)	0.027	Low
4	The upper slope of the volcano is heavily eroded (v5.1/4)	0.00	Medium
5	The upper slope of the volcano is moderately eroded (v5.3/3)	0.037	Medium
6	Central slope of the volcano eroded in the West (v4/4-B)	0.036	Medium
7	The middle slope of the volcano eroded to the East (v4/4-T)	0.054	Medium

Rainfall

Rain is one of the crucial factors that cause landslides. Rain is a driving force that enters the soil or rock cracks so that the soil becomes saturated. The steeper the slope, the faster the slippage speed, the looser the soil, the faster the soil will pass water and seep into the soil. The thicker the soil solum, the larger the volume of soil that will slip. Determination of rainfall in Bendungan District was intended to classify the rainfall values after it was interpolated from rain stations scattered around the study area from 17 rain gauges. The rain data used is the average annual rainfall for a period of 10 years, namely 2012–2021.

Table 5. *Rainfall in Bendungan District*

Rainfall Class (mm)	Value	Area (Ha)	Percentage
2000–2500	2	655.48	92%
> 2500	3	8997.21	8%
	Total	9652.7	100.00

In areas that have high rainfall with steep slopes prone to landslides, in addition, increased rainfall causes increased pore water pressure., water content in soil increases and clay development occurs and makes soil layer saturated with water (Bizimana and Sönmez, 2015; Portelinha and Zornberg, 2017). Landslides in Indonesia were preceded by high intensity.

Topographic position index (TPI)

The TPI modeling application was used to identify morphological characteristics in the research area. The TPI derived from the DEM was used to model landscape features into morphological classes. Based on the results of the TPI modeling, morphological classes are divided into ridges, valleys, rivers, slopes, and hilltops. The TPI classification can determine which locations have the potential for landslides, such as the slopes that experience soil slippage, the valleys where deposition occurs, and the hillsides that experience erosion (REF).

Fig. 4. *Topographic position index (TPI) in Bendungan district, Trenggalek*

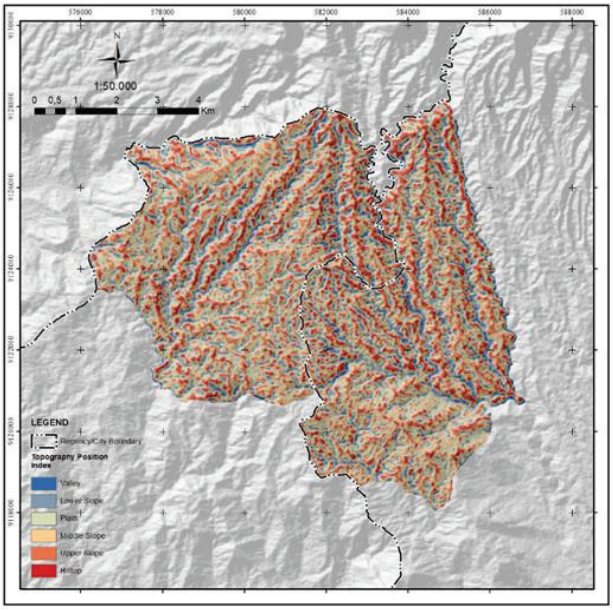
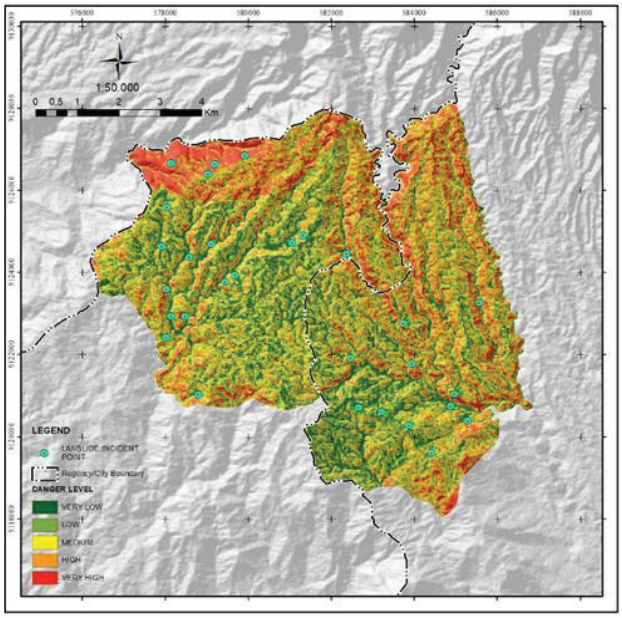


Fig. 5. *The landslide susceptibility map resulting from ANN-based modeling*



In many cases, the phenomenon of landslides occurs on the slopes and slopes that experience overturning.

Land cover

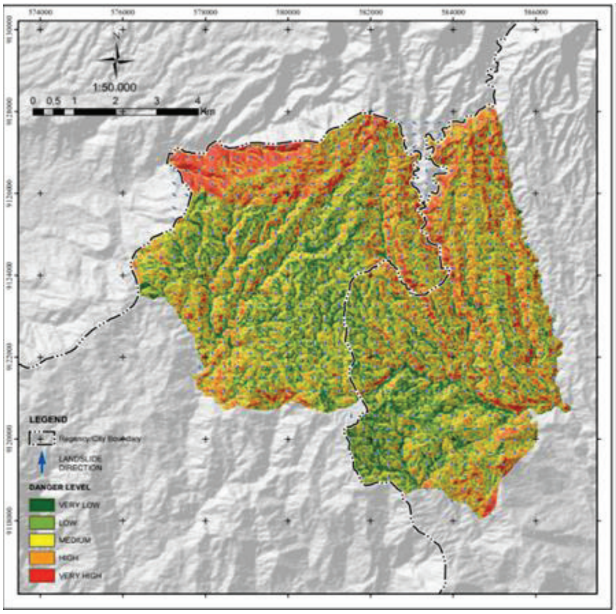
Environmental parameters were obtained through land use criteria in Bendungan District. The criteria for use are those factors that cause landslides. Land use was derived using SAGA GIS software with supervised classification from Sentinel 2A. This image was chosen because it has a fairly good resolution of 10 m and minimal cloud cover conditions so as to reduce the error rate. Five land use classes were used: sparse vegetation class, medium vegetation class, dense vegetation class, rice field vegetation class, and built up land class. Image processing was carried out using the ArcGIS 10.8 software and the results were used for subsequent modeling.

The performance of ANN

The test results of this ANN model get an MSE value of 0.17, which means that the model error is very small, and the artificial neural network calculation model can be used further without the need for adjustment and retraining of data. The regression R value shows a correlation between the training data and the target data, namely the landslide parameter data and the landslide hazard map data using the AHP method. The R value close to 1 indicates that the results of the train data have a close correlation with the target data, whereas if the R value is 0 then the training data has a random or unpatterned relationship with the target data. The results of the ANN modeling get an R value of 0.96, which means that the trained landslide parameter data with the AHP and actual landslide susceptibility data have a close or patterned relationship. The graph in the image below can be seen that the dotted line approaches the diagonal line for ideal results. The smaller the angle between the 2 lines, the closer the relationship between the 2 data points, the larger the angle between the 2 lines, the more random the relationship is between the input data and the target.

The results of the landslide susceptibility map using the ANN method show that there is an alignment of the overall value pattern for the classification of landslide hazard; in processing of the ANN calculations, parameter data is entered as originally without any weight multiplication as in the AHP method, but the output results obtained almost resemble the same pattern. This is because the training target uses tentative data from the AHP method which is delineated with the actual landslide event; the differentiating value is that the delineation of the actual landslide event gives an increase in value and reinforces pixel value of the landslide distribution in the final calculation of the ANN so that some areas previously appeared to have pixels. Describes the ability of artificial neural networks as an alternative classification that is able to accommodate

Fig. 6. *Prediction map of landslide direction of ANN method, Bendungan District, Trenggalek*



inputs that have different structures and pixel spans exemplified in land use classification by adding pixels from DEM data that have different spans and types with spectral pixel values.

Modeling of landslide movement direction

In the landslide phenomenon, the landslide process is relatively the same in one vector plane, while the debris type avalanche will also follow the valley flow pattern after the material reaches a lower point. The movement of the landslide direction is mostly influenced by the type of soil and rainfall as well as the slope so that the direction of the landslide tends to occur in the middle of the slope. The direction of landslide movement tends to lead to the northwest.

Discussion

Landslides are the result of complex factors, including various causes and triggers (Loche et al., 2022; McColl, 2022). Factors that affect landslides in this study are slope, soil texture, soil wrinkle index, rainfall, topography position index, and land cover (Miswar et al., 2022; Nugraha et al., 2022). Landslides can occur because they are triggered by one or more factors. An understanding of landslide factors is necessary for efficient hazard management. Therefore, landslide studies are very important to improve landslide prevention and risk assessment (Fu et al., 2022; Ju et al., 2022). In this study, the GIS application and the ANN approach succeeded in predicting the landslide model using spatial information as a landslide-conditioning factor. The ANN model is able to study complex relationships between input and output variables, both human and computer technology. Therefore, the ANN model is one of the best techniques used to predict landslides with good accuracy.

The ANN approach is used to generate a landslide model (Roy et al., 2022; Selamat et al., 2022). The training dataset is used to calculate the weights and to build the landslide model. Previous research found that the development of a landslide susceptibility model using the ANN method was able to produce a good predictive model. This finding is consistent with the findings of previous studies, which found that the ANN model yielded more accurate and reliable results in the development of landslide susceptibility models compared to others (Liu et al., 2022).

The integration between the GIS and the ANN is an effective tool for processing spatial data with many variables that have different parameter ranges. The ANN has the ability to accommodate the external spatial data of GIS with iteration capabilities and the advantages of pattern-based analysis (Jayasinghe et al., 2009). The function of collecting, processing, and presenting geographic information system data and the classification capability of artificial neural networks offer a complete analysis system that is widely used for landslide hazard mapping (Bagherzadeh and Gholizadeh, 2016; Jayasinghe et al., 2009).

Analysis of landslide-conditioning factors shows that rainfall and texture, the most critical landslide-conditioning factors, and rainfall-driven landslide events are among the most destructive natural disasters worldwide. Based on the results of the study, rainfall was found to be one of the important landslide-conditioning factors in Bendungan District, Trenggalek. An increase in the intensity of rainfall during the rainy season will cause an increase in the incidence of landslides. High rainfall intensity is often related to slope stability, where it affects runoff water pressure.

Most of the landslides in the study area occurred in hilly areas and near roads. Construction in hilly areas has a large negative impact on slope stability because it always causes engineering loads and jeopardizes the slope structure (Barrocu and Eslamian, 2022). Thus, any road construction activity that involves cutting the hillside more than 10 degrees causes discontinuities in soil and rock. The basic principle underlying this assertion is that elevation influences topographical factors, resulting in spatial diversity in various landscape processes (Shi et al., 2022). Similarly, this study found that elevation is the third most important factor influencing landslide conditions in the study area. Human activities, such as construction of buildings, roads, and agricultural activities, will change the structure and stability of slopes, causing landslides (Hosenuzzaman et al., 2022). Given the importance of this area in supporting urban activities, it must be conserved and managed carefully to ensure that local communities continue to have a high quality of life and benefit from future development. Bendungan District, Trenggalek, needs more attention to ecosystems, especially to changes in land use and human activities to prevent landslides. Therefore, recommendations for future studies in the Trenggalek area should consider the elements of land use change and find the relationship between landslide occurrence and land use change.

Conclusion

This study demonstrated the ability of an ANN-based landslide model in Bendungan sub-district, East Java, Indonesia. The model developed from varying predictors, namely the slope, soil texture, cole index, rainfall, topographic position index and land cover, can classify the susceptibility of landslide in the study area with a satisfactory result. Rainfall and soil texture appeared to be more influential in the landslide process in the study area. The approach employed in this study was useful in mapping the patterns, severity and direction of landslides.

Acknowledgements

This research was supported by State University of Malang and Trenggalek Regency. Research has no intent or conflict of interest towards any individual or group.

References

Abdulwahid, W. M., and Pradhan, B. (2017). Landslide vulnerability and risk assessment for multi-hazard scenarios using airborne laser scanning data (LiDAR). Landslides, 14, 1057-1076. https://doi.org/10.1007/s10346-016-0744-0

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Umar, A. M., Linus, O. U., Arshad, H., Kazaure, A. A., Gana, U., and Kiru, M. U. (2019). Comprehensive review of artificial neural network applications to pattern recognition. IEEE Access, 7, 158820-158846. https://doi.org/10.1109/ACCESS.2019.2945545

Acosta, J. G., Vardon, P., and Hicks, M. (2021). Study of landslides and soil-structure interaction problems using the implicit material point method. Engineering Geology, 285, 106043. https://doi.org/10.1016/j.enggeo.2021.106043

Al Barsh, Y. I., Duhair, M. K., Ismail, H. J., Abu-Nasser, B. S., and Abu-Naser, S. S. (2020). MPG Prediction Using Artificial Neural Network. International Journal of Academic Information Systems Research (IJAISR), 4(11).

Alqadhi, S., Mallick, J., Talukdar, S., Bindajam, A. A., Saha, T. K., Ahmed, M., and Khan, R. A. (2021). Combining logistic regression-based hybrid optimized machine learning algorithms with sensitivity analysis to achieve robust landslide susceptibility mapping. Geocarto International, 1-26. https://doi.org/10.1080/10106049.2021.2022009

Bagherzadeh, A., and Gholizadeh, A. (2016). Modeling land suitability evaluation for wheat production by parametric and TOPSIS approaches using GIS, northeast of Iran. Modeling Earth Systems and Environment, 2, 1-11. https://doi.org/10.1007/s40808-016-0177-8

Barrocu, G., and Eslamian, S. (2022). River Flood Erosion and Land Development and Management. In Flood Handbook (pp. 409-420). CRC Press. https://doi.org/10.1201/9780429463327-25

Bista, R. B. (2022). Does Disaster Change Income and Wealth Distribution Toward Extremity of Inequality and Poverty? Analysis of Flood and Landslides in the Vulnerable Locations of Nepal. 51(4), 467-481. https://doi.org/10.1080/07360932.2020.1715810

Bizimana, H., and Sönmez, O. (2015). Landslide occurrences in the hilly areas of Rwanda, their causes and protection measures. Disaster Science and Engineering, 1(1), 1-7.

Bvindi, A. (2019). Assessment of soil erosion hazard around the abandoned mine in formerly Mutale Municipality, Limpopo Province, South Africa.

Cao, C., Xu, P., Wang, Y., Chen, J., Zheng, L., and Niu, C. (2016). Flash flood hazard susceptibility mapping using frequency ratio and statistical index methods in coalmine subsidence areas. Sustainability, 8(9), 948. https://doi.org/10.3390/su8090948

Chiarelli, D. D., Galizzi, M., Bocchiola, D., Rosso, R., and Rulli, M. C. (2022). Modeling snowmelt influence on shallow landslides in Tartano valley, Italian Alps. Science of the Total Environment, 158772. https://doi.org/10.1016/j.scitotenv.2022.158772

Dalir, P., Naghdi, R., Gholami, V., Tavankar, F., Latterini, F., Venanzi, R., and Picchio, R. (2022). Risk assessment of runoff generation using an artificial neural network and field plots in road and forest land areas. Natural Hazards, 1-19. https://doi.org/10.1007/s11069-022-05352-5

Danumah, J. H. (2017). Assessing urban flood risks under changing climate and land use in Abidjan District, South Côte d'Ivoire.

Das, S., Sarkar, S., and Kanungo, D. P. (2022). A critical review on landslide susceptibility zonation: Recent trends, techniques, and practices in Indian Himalaya. Natural Hazards, 1-50. https://doi.org/10.1007/s11069-022-05554-x

Daviran, M., Shamekhi, M., Ghezelbash, R., and Maghsoudi, A. (2022). Landslide susceptibility prediction using artificial neural networks, SVMs and random forest: Hyperparameters tuning by genetic optimization algorithm. International Journal of Environmental Science and Technology, 1-18. https://doi.org/10.1007/s13762-022-04491-3

Diara, I. W., Suyarto, R., and Saifulloh, M. (2022). SPATIAL DISTRIBUTION OF LANDSLIDE SUSCEPTIBILITY IN NEW ROAD CONSTRUCTION MENGWITANI-SINGARAJA, BALI-INDONESIA: BASED ON GEOSPATIAL DATA. GEOMATE Journal, 23(96), 95-103. https://doi.org/10.21660/2022.96.3320

Dou, J., Chang, K.-T., Chen, S., Yunus, A. P., Liu, J.-K., Xia, H., and Zhu, Z. (2015). Automatic case-based reasoning approach for landslide detection: Integration of object-oriented image analysis and a genetic algorithm. Remote Sensing, 7(4), 4318-4342. https://doi.org/10.3390/rs70404318

Ekeanyanwu, C. V., Obisakin, I. F., Aduwenye, P., and Dede-Bamfo, N. (2022). Merging GIS and Machine Learning Techniques: A Paper Review. Journal of Geoscience and Environment Protection, 10(9), 61-83. https://doi.org/10.4236/gep.2022.109004

Fabio, I., Massimo, C., Cristiano, T., and Giuseppe, C. (2022). Village relocation as solution of the landslide risk, is it always the right choice? The case study of Cavallerizzo ghost village (Calabria, southern Italy). International Journal of Disaster Risk Reduction, 103267. https://doi.org/10.1016/j.ijdrr.2022.103267

Fan, X., Scaringi, G., Korup, O., West, A. J., van Westen, C. J., Tanyas, H., Hovius, N., Hales, T. C., Jibson, R. W., and Allstadt, K. E. (2019a). Earthquake-induced chains of geologic hazards: Patterns, mechanisms, and impacts. Reviews of Geophysics, 57(2), 421-503. https://doi.org/10.1029/2018RG000626

Fan, X., Scaringi, G., Korup, O., West, A. J., van Westen, C. J., Tanyas, H., Hovius, N., Hales, T. C., Jibson, R. W., and Allstadt, K. E. (2019b). Earthquake-induced chains of geologic hazards: Patterns, mechanisms, and impacts. Reviews of Geophysics, 57(2), 421-503. https://doi.org/10.1029/2018RG000626

Flentje, P. N., Miner, A., Whitt, G., and Fell, R. (2007). Guidelines for landslide susceptibility, hazard and risk zoning for land use planning.

Fu, R., He, J., Liu, G., Li, W., Mao, J., He, M., and Lin, Y. (2022). Fast Seismic Landslide Detection Based on Improved Mask R-CNN. Remote Sensing, 14(16), 3928. https://doi.org/10.3390/rs14163928

Guo, J., Yi, S., Yin, Y., Cui, Y., Qin, M., Li, T., and Wang, C. (2020). The effect of topography on landslide kinematics: A case study of the Jichang town landslide in Guizhou, China. Landslides, 17, 959-973. https://doi.org/10.1007/s10346-019-01339-9

Hammad, M., Van Leeuwen, B., and Mucsi, L. (2020). Integration of gis and advanced remote sensing techniques for landslide hazard assessment: A case study of northwest syria. ISPRS ANNALS OF THE PHOTOGRAMMETRY REMOTE SENSING AND SPATIAL INFORMATION SCIENCES, 6(6), 27-34. https://doi.org/10.5194/isprs-annals-VI-3-W1-2020-27-2020

Hill, J. C., Watt, J. T., and Brothers, D. S. (2022). Mass wasting along the Cascadia subduction zone: Implications for abyssal turbidite sources and the earthquake record. Earth and Planetary Science Letters, 597, 117797. https://doi.org/10.1016/j.epsl.2022.117797

Hosenuzzaman, M., Kibria, M. G., Sarkar, R., and Abedin, M. (2022). Landslide, Agricultural Vulnerability, and Community Initiatives: A Case Study in South-East Part of Bangladesh. In Impact of Climate Change, Land Use and Land Cover, and Socio-economic Dynamics on Landslides (pp. 123-145). Springer. https://doi.org/10.1007/978-981-16-7314-6_5

Isnaini, R., Pandin, M., Waloejo, C., and Sunyowati, D. (2022). Landslide and Moving Ground Disasters in Sumurup Village, Trenggalek District, East Java, Indonesia: A Case Study. 995(1), 012005. https://doi.org/10.1088/1755-1315/995/1/012005

Jayasinghe, P. S., Yoshida, M., and Machida, T. (2009). An agricultural field work management system for rural farmers in Sri Lanka. 1.

Ju, Y., Xu, Q., Jin, S., Li, W., Su, Y., Dong, X., and Guo, Q. (2022). Loess Landslide Detection Using Object Detection Algorithms in Northwest China. Remote Sensing, 14(5), 1182. https://doi.org/10.3390/rs14051182

Kjekstad, O., and Highland, L. (2009). Economic and social impacts of landslides. Landslides-Disaster Risk Reduction, 573-587. https://doi.org/10.1007/978-3-540-69970-5_30

Liu, W., Zhang, Y., Liang, Y., Sun, P., Li, Y., Su, X., Wang, A., and Meng, X. (2022). Landslide Risk Assessment Using a Combined Approach Based on InSAR and Random Forest. Remote Sensing, 14(9), 2131. https://doi.org/10.3390/rs14092131

Loche, M., Lombardo, L., Gorum, T., Tanyas, H., and Scaringi, G. (2022). Distinct susceptibility patterns of active and relict landslides reveal distinct triggers: A case in northwestern Turkey. Remote Sensing, 14(6), 1321. https://doi.org/10.3390/rs14061321

McColl, S. T. (2022). Landslide causes and triggers. In Landslide Hazards, Risks, and Disasters (pp. 13-41). Elsevier. https://doi.org/10.1016/B978-0-12-818464-6.00011-1

Miswar, D., Wahono, E. P., Sutyatna, A., Darmawan, R. Y., Zakaria, W. A., and Sugiyanta, I. G. (2022). The Landslide Spatial Modelling in Limau District, Tanggamus Regency. 236-250. https://doi.org/10.2991/assehr.k.220102.030

Munthali, M. G. (2020). Analysis of land use and land cover dynamics and its implications on natural resources in Dedza District Malawi. https://doi.org/10.1080/10106049.2020.1791978

Nhu, V.-H., Shirzadi, A., Shahabi, H., Singh, S. K., Al-Ansari, N., Clague, J. J., Jaafari, A., Chen, W., Miraki, S., and Dou, J. (2020). Shallow landslide susceptibility mapping: A comparison between logistic model tree, logistic regression, naïve bayes tree, artificial neural network, and support vector machine algorithms. International Journal of Environmental Research and Public Health, 17(8), 2749. https://doi.org/10.3390/ijerph17082749

Nugraha, S. S., Sartohadi, J., and Nurudin, M. (2022). Field-Based Biochar, Pumice, and Mycorrhizae Application on Dryland Agriculture in Reducing Soil Erosion. Applied and Environmental Soil Science, 2022. https://doi.org/10.1155/2022/1775330

Obda, I., El Kharim, Y., Bounab, A., Lahrach, A., Ahniche, M., and Mansouri, H. (2022). Multi-criteria assessment approach of slow-moving urban landslide hazard: The case of Moulay Yacoub, Morocco. Canadian Journal of Earth Sciences, 59(5), 300-317. https://doi.org/10.1139/cjes-2021-0064

Osiakwan, G. M., Gibrilla, A., Kabo-Bah, A. T., Appiah-Adjei, E. K., and Anornu, G. (2022). Delineation of groundwater potential zones in the central region of ghana using gis and fuzzy analytic hierarchy process. Modeling Earth Systems and Environment, 8(4), 5305-5326. https://doi.org/10.1007/s40808-022-01380-z

Palayukan, G., Hanudin, E., and Purwanto, B. (2022). Stable and unstable carbon fraction under different vegetable farming system on Mt. Merbabu's andisols, Central Java. 1005(1), 012014. https://doi.org/10.1088/1755-1315/1005/1/012014

Petrucci, O. (2022). Landslide fatality occurrence: A systematic review of research published between January 2010 and March 2022. Sustainability, 14(15), 9346. https://doi.org/10.3390/su14159346

Portelinha, F., and Zornberg, J. (2017). Effect of infiltration on the performance of an unsaturated geotextile-reinforced soil wall. Geotextiles and Geomembranes, 45(3), 211-226. https://doi.org/10.1016/j.geotexmem.2017.02.002

Prayudani, S., Hizriadi, A., Lase, Y., and Fatmi, Y. (2019). Analysis accuracy of forecasting measurement technique on random K-nearest neighbor (RKNN) using MAPE and MSE. 1361(1), 012089. https://doi.org/10.1088/1742-6596/1361/1/012089

Riadi, B., and Windiastuti, R. (2019). Spatial Analysis of Flood and Landslide Vulnerable Areas (Case Study in Trenggalek Regency). 313(1), 012007. https://doi.org/10.1088/1755-1315/313/1/012007

Roy, P., Ghosal, K., and Paul, P. K. (2022). Landslide susceptibility mapping of Kalimpong in Eastern Himalayan Region using a Rprop ANN approach. Journal of Earth System Science, 131(2), 1-23. https://doi.org/10.1007/s12040-022-01877-2

Sari, H. R., Pulungan, N. A. H., and Sartohadi, J. (2022). Variation of Surface Soil Characteristics in Landslide Deposition Areas Based on Landslide Activities and Slope Position in Bompon Sub-Watershed, Magelang. 79-85. https://doi.org/10.2991/absr.k.220305.012

Selamat, S. N., Majid, N. A., Taha, M. R., and Osman, A. (2022). Landslide Susceptibility Model Using Artificial Neural Network (ANN) Approach in Langat River Basin, Selangor, Malaysia. Land, 11(6), 833. https://doi.org/10.3390/land11060833

Sema, H. V., Guru, B., and Veerappan, R. (2017). Fuzzy gamma operator model for preparing landslide susceptibility zonation mapping in parts of Kohima Town, Nagaland, India. Modeling Earth Systems and Environment, 3, 499-514. https://doi.org/10.1007/s40808-017-0317-9

Shahri, A. A., Spross, J., Johansson, F., and Larsson, S. (2019). Landslide susceptibility hazard map in southwest Sweden using artificial neural network. Catena, 183, 104225. https://doi.org/10.1016/j.catena.2019.104225

Shi, N., Wang, C., Wang, J., Wu, N., Naudiyal, N., Zhang, L., Wang, L., Sun, J., Du, W., and Wei, Y. (2022). Biogeographic Patterns and Richness of the Meconopsis Species and Their Influence Factors across the Pan-Himalaya and Adjacent Regions. Diversity, 14(8), 661. https://doi.org/10.3390/d14080661

Singh, N. (2022). A Scalable Holistic Physical and Social Sensing Framework for Disaster Management.

Skilodimou, H. D., Bathrellos, G. D., Chousianitis, K., Youssef, A. M., and Pradhan, B. (2019). Multi-hazard assessment modeling via multi-criteria analysis and GIS: a case study. Environmental Earth Sciences, 78, 1-21. https://doi.org/10.1007/s12665-018-8003-4

Susilo, A., Sunaryo, S., Suryo, E. A., Rachmawati, T., and Sutasoma, M. (2021). Analysis of Landslide and Land Subsident Using Geophysical Method in the East Java Province, Indonesia. In Landslides. IntechOpen. https://doi.org/10.5772/intechopen.100160

Tarolli, P., and Sofia, G. (2016). Human topographic signatures and derived geomorphic processes across landscapes. Geomorphology, 255, 140-161. https://doi.org/10.1016/j.geomorph.2015.12.007

Utama, A., Hadi, M. P., and Nurjani, E. (2021). Geographic Information Systems Application to Drought Distribution Identification with Standardized Precipitation Index (SPI) Method in Trenggalek Regency. INTENSIF: Jurnal Ilmiah Penelitian Dan Penerapan Teknologi Sistem Informasi, 5(2), 266-278. https://doi.org/10.29407/intensif.v5i2.15645

Vasileiou, K., Barnett, J., and Fraser, D. S. (2022). Integrating local and scientific knowledge in disaster risk reduction: A systematic review of motivations, processes, and outcomes. International Journal of Disaster Risk Reduction, 103255. https://doi.org/10.1016/j.ijdrr.2022.103255

Vlasov, D., Kukushkina, O., Kosheleva, N., and Kasimov, N. (2022). Levels and Factors of the Accumulation of Metals and Metalloids in Roadside Soils, Road Dust, and Their PM10 Fraction in the Western Okrug of Moscow. Eurasian Soil Science, 55(5), 556-572. https://doi.org/10.1134/S1064229322050118

Wang, K., Zhang, C., Chen, H., Yue, Y., Zhang, W., Zhang, M., Qi, X., and Fu, Z. (2019). Karst landscapes of China: Patterns, ecosystem processes and services. Landscape Ecology, 34, 2743-2763. https://doi.org/10.1007/s10980-019-00912-w

Wilopo; Puspasari, P. S., Sobar; Maarif, Syamsul; Widana, I. Dewa Ketut Kerta. (2022). Socio-Geospatial Characteristic of Communities Affected by Contemporary Hydrometeorological Disaster during the Covid-19 Pandemic in Cimanggung Sub-District, Sumedang District, West Java Province. Technium Soc. Sci. J., 29, 523. https://doi.org/10.47577/tssj.v29i1.6137

Woldseth, R. V., Aage, N., Bærentzen, J. A., and Sigmund, O. (2022). On the use of artificial neural networks in topology optimisation. Structural and Multidisciplinary Optimization, 65(10), 294. https://doi.org/10.1007/s00158-022-03347-1

Wu, Q., and Lane, C. R. (2017). Delineating wetland catchments and modeling hydrologic connectivity using lidar data and aerial imagery. Hydrology and Earth System Sciences, 21(7), 3579-3595. https://doi.org/10.5194/hess-21-3579-2017

Yerro, A., Soga, K., and Bray, J. (2019). Runout evaluation of Oso landslide with the material point method. Canadian Geotechnical Journal, 56(9), 1304-1317. https://doi.org/10.1139/cgj-2017-0630

Yildirim, V., Memisoglu, T., Bediroglu, S., and Colak, H. E. (2018). Municipal solid waste landfill site selection using multi-criteria decision making and GIS: case study of Bursa province. Journal of Environmental Engineering and Landscape Management, 26(2), 107-119. https://doi.org/10.3846/16486897.2017.1364646

Zimmern, V. (2020). Why brain criticality is clinically relevant: A scoping review. Frontiers in Neural Circuits, 14, 54. https://doi.org/10.3389/fncir.2020.00054

Zou, Q., Jiang, H., Cui, P., Zhou, B., Jiang, Y., Qin, M., Liu, Y., and Li, C. (2021). A new approach to assess landslide susceptibility based on slope failure mechanisms. Catena, 204, 105388. https://doi.org/10.1016/j.catena.2021.105388

Zou, Z., and Ergan, S. (2023). Towards emotionally intelligent buildings: A Convolutional neural network based approach to classify human emotional experience in virtual built environments. Advanced Engineering Informatics, 55, 101868. https://doi.org/10.1016/j.aei.2022.101868

This article is an Open Access article distributed under the terms and conditions of the Creative Commons Attribution 4.0 (CC BY 4.0) License (http://creativecommons.org/licenses/by/4.0/).