YEG-Article-6-10/2024

Landslide Factor Optimization for Landslide Susceptibility Modeling

Azemeraw Wubalem

Department of Geology, College of Natural and Computational Science, University of Gondar, Ethiopia

Department of Earth Science, University of Turin, Turin, Italy

azmeraw.wubalem@uog.edu.et

alubelw@gmail.com

1. Introduction

Landslide incidents have become destructive natural hazards in many parts of the world, particularly in mountainous regions, including Ethiopia. They may destroy engineering structures, cause loss of property, degradation of the environment, and fatalities. The events frequently occur due to complex geological, geomorphological, climate change, and unplanned land practice conditions. Thus, understanding the severity of landslides and their processes is crucial for identifying the most critical conditions and triggering factors that help to predict landslide-prone and non-landslide-prone regions. This knowledge is essential for predicting, assessing, and mitigating the impacts and losses associated with landslide incidents (Wubalem, 2021). Landslide prediction model quality is influenced by mapping techniques, input datasets, and landslide sizes. Landslide size, in particular, affects the influence of factors derived from the digital elevation model (DEM) such as slope, aspect, curvature, and elevation. Larger landslide sizes are better suited to coarser or lower DEM resolution, while the smaller landslide sizes might be effectively captured under finer or higher DEM resolution (Wubalem, 2022). Therefore, landslide factor selection and landslide size analysis are key steps in landslide susceptibility modeling. Although landslide prediction modeling is conducted worldwide (Ado et al., 2022; Fang et al., 2021; Getachew and Meten, 2021). Studies related to factor optimization, particularly using the area under the receiver operating characteristic, are limited.

This case study aims to investigate the effectiveness of the area under the receiver operating characteristics curve (AUC – a visual representation of model performance) in identifying the most relevant landslide factors for susceptibility modeling (Figure 1). This case study employed fieldwork, image analysis, GIS, and bivariate statistical methods to predict the spatial landslide susceptibility probability based on past landslide events. This finding provides insights into how landslide factors affect the quality of the prediction model and their effectiveness in engineering design and landslide mitigation strategies.

2. Materials and Methods

A dataset comprising 12 landslide factors and 712 landslides was compiled from literature, detailed fieldwork, and Google Earth Imagery analysis. These landslides were divided into training (70%) and validation (30%) datasets (Figure 1a). The relationship between past landslides and factors was analyzed using the frequency ratio (FR) method and ArcGIS 10.3.1 (ESRI, 2014). Then, the degree of landslide factors was evaluated using the area under the receiver operating characteristic curve (AUC) by an overlaid method in the GIS environment. Landslide pixels for each landslide factor were extracted. Then, the most effective landslide factors were determined. The landslide susceptibility maps were generated from the sum of weighted parameters before and after optimization under a raster calculator in a GIS environment.

3. Results and Discussion

Landslide factors optimization or selection is crucial in landslide susceptibility prediction modeling. In this study, an AUC cutoff threshold of 0.5 was used. A higher threshold (e.g. 0.6 and above) could identify only highly predictive factors but might exclude those with a moderate impact on landslide occurrence. Thus, a 0.5 cutoff can include factors that moderately contribute to landslide occurrence.

The result indicates that factor optimization using the AUC method identified six factors with AUC values > 0.5; the remaining factors had AUC values < 0.5. The weighted factors were combined to create landslide susceptibility indexes (LSIs), categorized into five susceptibility zones of very low, low, moderate, high, and very high (Figure 1b) using the natural break classification method, which is appropriate for safe engineering practice, risk assessment and land-use planning (Zhang et al., 2022). The susceptibility zones range from relatively safe regions in areas of flat land and strong lithology to high susceptibility zones in areas of steep slopes, weak lithology, and low vegetation cover. ROC (Receiver Operating Characteristic) curves determined AUC values, with the FR model achieving a 66.41% prediction before removing factors that scored <0.5. After factor optimization (landslide factor selection), the FR model demonstrated a success rate of 78.1% and a predictive rate of 73.5%, indicating improved performance (Figure 1c and d). This underscores the influence of landslide factors on mapping accuracy and highlights the importance of optimization. The optimized FR model holds promise for researchers and decision-makers engaged in regional land use planning and landslide risk.

4. Conclusion

The area under the ROC curve (AUC) was used to determine the most effective landslide factors (those whose values were greater than 0.5). The result indicates that only six factors had AUC values greater than 0.5. The landslide susceptibility models were produced before and after factor optimization, and their quality was evaluated using AUC. The result indicates that the quality of the model is improved after factor optimization. The result emphasizes that landslide factor optimization is a critical step in landslide susceptibility modeling for high-quality models. The frequency of landslide occurrence needs attention, and it is crucial to conduct detailed geological engineering investigations before the construction of any engineering structures. Appropriate consideration of the ground and slope monitoring is a recommended strategy for safe and stable engineering structures.

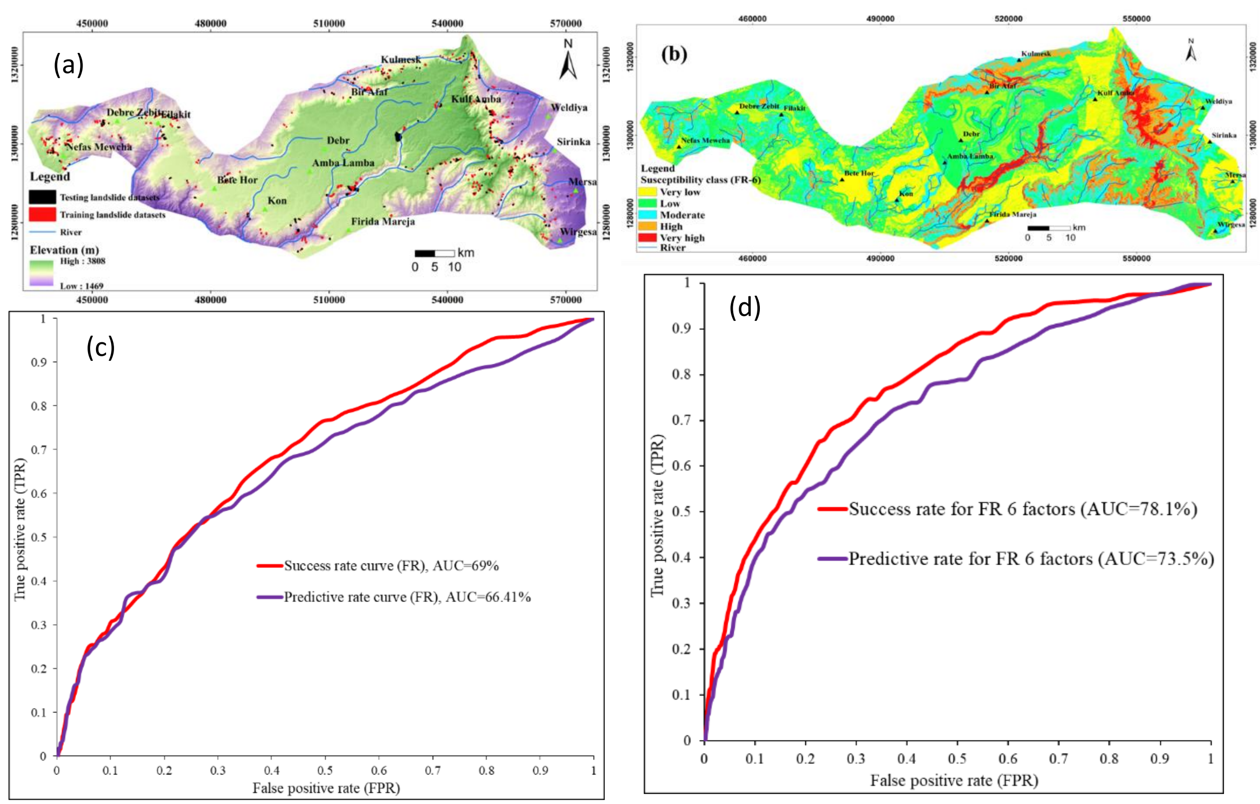

Figure 1 (a) landslide inventory (b) landslide susceptibility map (c) and (d) receiver operating characteristics curve before and after factor optimization (Wubalem et al., 2022).

Acknowledgments

There is no financial fund for this newsletter publication. I extend my deepest gratitude to my colleagues Mr. Belete Getahun, Mr. Yohannes Hailemariam, Mr. Alemu Mesele, Mr. Gashaw Tesfaw, Mr. Zerihun Dawit, and Mr. Endalkachew Goshe for their invaluable support during my work.

References

Ado, M., Amitab, K., Maji, A. K., Jasińska, E., Gono, R., Leonowicz, Z., & Jasiński, M. (2022). Landslide Susceptibility Mapping Using Machine Learning: A Literature Survey. Remote Sensing, 14(13). https://doi.org/10.3390/rs14133029

Fang, Z., Wang, Y., Peng, L., & Hong, H. (2021). A comparative study of heterogeneous ensemble-learning techniques for landslide susceptibility mapping. International Journal of Geographical Information Science, 35(2), 321–347. https://doi.org/10.1080/13658816.2020.1808897

Getachew, N., & Meten, M. (2021). Weights of evidence modeling for landslide susceptibility mapping of Kabi-Gebro locality, Gundomeskel area, Central Ethiopia. Geoenvironmental Disasters, 8(1). https://doi.org/10.1186/s40677-021-00177-z

Wubalem, A. (2021). Landslide susceptibility mapping using statistical methods in Uatzau catchment area, northwestern Ethiopia. Geoenvironmental Disasters, 8(1). https://doi.org/10.1186/s40677-020-00170-y

Wubalem, A. (2022). The impact of DEM resolution on landslide susceptibility modeling. Arabian Journal of Geosciences, 15(10). https://doi.org/10.1007/s12517-022-10241-z

Wubalem, A., Getahun, B., Hailemariam, Y., Mesele, A., Tesfaw, G., Dawit, Z., & Goshe, E. (2022). Landslide Susceptibility Modeling Using the Index of Entropy and Frequency Ratio

Method from Nefas-Mewcha to Weldiya Road Corridor, Northwestern Ethiopia. Geotechnical and Geological Engineering, 40(10), 5249–5278. https://doi.org/10.1007/s10706-022-02214-6

Zhang, J., Gao, B., Huang, H., Chen, L., Li, Y., & Yang, D. (2022). SBAS-InSAR-Based Landslide Susceptibility Mapping Along the North Lancang River, Tibetan Plateau. Frontiers in Earth Science, 10. https://doi.org/10.3389/feart.2022.901889

Author Responsibility Disclaimer

During the preparation of this work, the author did not utilize ChatGPT or any similar software to generate content and took full responsibility for the publication's content. Additionally, the author is responsible for referencing all figures, tables, and information shared in this article.