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Explainable artificial intelligence empowered landslide susceptibility mapping using Extreme Gradient Boosting (XGBoost)

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Abstract

Up to now, a wide variety of non-linear machine learning models with black-box nature have been intensively utilized to spatially predict landslide susceptibility in a given geographical context. However, the results obtained from these models can be difficult to interpret, making it challenging to identify the reasons for false positives and take corrective action. To address this problem, this study makes use of the XGBoost algorithm to predict landslide susceptibility in a lake basin and its surrounding areas. Additionally, the Shapley additive explanation (SHAP) approach as an explainable artificial intelligence (XAI) tool was used to increase the interpretability of the model's predictions. The accuracy of the XGBoost model was evaluated and found to have an OA of 92.44% and an AUC score of 98.73%. The SHAP analysis showed that slope was the most influential factor in predicting landslide susceptibility. Additionally, the dependence plot highlighted that the impact of slope angle on the model's output was consistent within the range of 8° to 21°. The findings of this study demonstrate the potential benefits of incorporating XAI techniques into the modeling process to increase transparency.

Introduction

Until the last decade, landslide susceptibility mapping was often carried out using traditional methods such as manual inspection, expert judgment, and statistical analysis, which are often subjective and time-consuming, and can lead to inconsistent results. However, with the advent of artificial intelligence and machine learning, predictive models can now be used to generate landslide susceptibility maps with improved accuracy and efficiency. Nonetheless, most operate in a "black box" manner, meaning that the reasoning behind their predictions is not transparent nor easily interpretable [1]. This lack of transparency poses significant concerns regarding the potential biases and errors that may be introduced during the modeling process, ultimately impacting the accuracy and validity of the results. For instance, if a predictive model used to generate a landslide susceptibility map results in a false positive, it could lead to the evacuation of residents or the halt of development activities in a certain area. Thus, it is crucial to develop transparent and interpretable models for landslide susceptibility mapping practices, such as explainable artificial intelligence (XAI) [2]. These models can provide an explanation for their predictions, making it easier to understand how they arrived at their conclusions and to identify any potential biases or flaws in the data or algorithms used.

Taking Lake Sapanca Basin and its surrounding as an example, this study aims to create a landslide susceptibility map that maintains its accuracy while incorporating XAI tools such as Shapley Additive Explanations (SHAP). This will be achieved by utilizing a gradient-based machine learning algorithm called XGBoost, which is considered a black-box model. A total of 14 landslide-related parameters were selected by taking into consideration of the overall characteristics of the study area.

Material and Method

The region of Lake Sapanca Basin and its surroundings, located in the Catalca-Kocaeli region of the eastern Marmara area of Turkey, is experiencing rapid urbanization and industrialization. The area of interest is located between longitudes 29° 59′ and 30° 23′ to the east, and latitudes 40° 36′ and 40° 53′ to the north, covering an approximate area of 945 km^2. Topographically, the north-facing section of the Samanli Mountains, which extend in the east-west direction and are situated in the south of the basin, comprises steep slopes, indicating the presence of relatively unstable landscape structures. The study employed a geospatial dataset consisting of 14 parameters related to landslides, including aspect, convergence index (CI), elevation, lithology, plan curvature, profile curvature, distance to rivers, road density, distance to roads, slope, soil type, topographic position index (TPI), topographic wetness index (TWI), and valley depth.

Extreme Gradient Boosting (XGBoost)

XGBoost is a highly optimized and distributed gradient-boosting algorithm designed to efficiently and effectively implement gradient-boosting models [3]. It uses an ensemble of decision trees, where each tree predicts the residual errors of the previous tree to arrive at the final prediction. Its flexible API allows users to customize and fine-tune the algorithm and perform complex operations, and it supports parallel processing, making it well-suited for large datasets and distributed computing environments. However, it is generally considered a black-box algorithm because its internal workings are difficult to interpret. Since XGBoost relies on the combination of many decision trees, it is challenging to determine how each feature contributes to the final prediction, making it hard to understand how the algorithm arrived at a specific prediction.

Shapley Additive Explanation (SHAP)

Shapley Additive Explanation (SHAP) is an approach to interpret the output of machine learning models developed by Lundberg and Lee [4]. It works by attributing the impact of each feature on a prediction, individually and not as a group [5]. The SHAP values give a comprehensive explanation of a model's predictions, taking into account the contribution of each feature and the interaction between features. This leads to a better understanding of how a model makes predictions. The SHAP values have a probabilistic interpretation, as they sum up to the difference between the expected and actual output for a given instance. This interpretation helps to compare the contribution of different features to a prediction and to evaluate the uncertainty in the explanation.

Results and Discussion

The XGBoost algorithm was used to generate landslide susceptibility maps for a region located in the Lake Sapanca Basin, utilizing 14 landslide-related parameters. The accuracy of the resulting map was assessed using four metrics: overall accuracy (OA), true positive rate (TPR), true negative rate (TNR), and area under curve (AUC) score. The XGBoost model produced a landslide susceptibility map with an OA of 92.44% and an AUC score of 98.73%, indicating a high level of accuracy. The XGBoost algorithm achieved TPR and TNR scores of 96.85% and 88.03%, respectively, demonstrating its strong intraclass separability power. The produced landslide susceptibility map highlighted that the high-risk areas were predominantly located in the northwestern parts of the basin and the northern slopes of the Samanli Mountains, while the areas with very low to low risks were mostly found in the interior of the area.

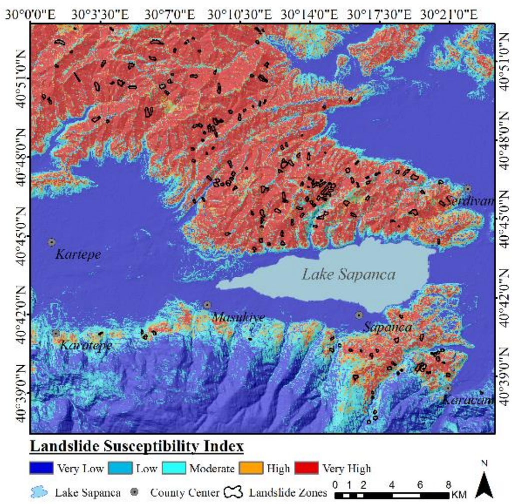
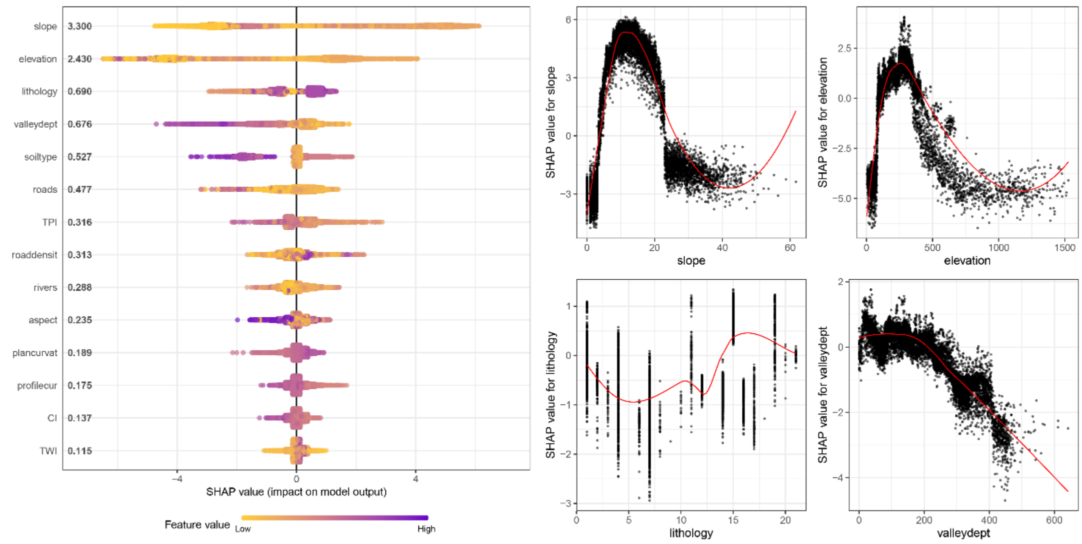


Figure 1. Landslide susceptibility map produced with XGBoost algorithm

With the application of the SHAP analysis, two different explanation results were obtained: summary plot and dependence plot. The former explains the overall impact of each feature on the model's output, while the latter shows how a single feature affects the predictions made by the model. Specifically, the dependence plot displays the relationship between a selected feature and the SHAP values for that feature across the entire dataset, allowing us to understand how changes in that feature's value impact the model's predictions. The summary plot revealed that the slope had the strongest impact on the model's output, followed by elevation and lithology, respectively. In contrast, TWI and CI had the lowest contribution to the XGBoost model's prediction. On the other hand, the dependence plot highlighted that the effect of slope angle on the model's output is consistent across the range between 8° and 21°, but not across its entire range of values.



(a) (b)

Figure 2. (a) SHAP summary plot for whole geospatial covariates and (b) dependence plots for slope, elevation, lithology, and valley depth

Conclusions

Using Lake Sapanca Basin and its surrounding regions as a case study, this study seeks to establish a landslide susceptibility map that employs an XAI tool while maintaining high levels of accuracy. To summarize, the principal conclusions of this work can be encapsulated as follows:

- The XGBoost algorithm successfully generated accurate landslide susceptibility maps for the Lake Sapanca Basin region, achieving an OA of 92.44% and an AUC score of 98.73%.
- The SHAP analysis allowed for a better understanding of the XGBoost model's output by providing two different explanation results: the summary plot and the dependence plot. The summary plot revealed that slope, elevation, and lithology were the most influential factors in predicting landslide susceptibility, while TWI and CI had the least contribution to the model's output.
- The produced landslide susceptibility map indicated that high-risk areas were predominantly located in the northwestern parts of the basin and the northern slopes of the Samanli Mountains, while very low to low-risk areas were mostly found in the interior of the area and the western parts of Lake Sapanca.

References

1. Kavzoglu, T. (2009). Increasing the accuracy of neural network classification using refined training data. *Environmental Modelling & Software*, 24(7), 850–858. doi: https://doi.org/10.1016/j.envsoft.2008.11.012
2. Kavzoglu, T., & Teke, A. (2022). Advanced hyperparameter optimization for improved spatial prediction of shallow landslides using extreme gradient boosting (XGBoost). *Bulletin of Engineering Geology and the Environment, 81(5), 201*. https://doi.org/10.1007/s10064-022-02708-w
3. Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In Proceedings of *22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, CA, USA, 13–17 August, 785–794.
4. Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, Long Beach, CA, USA, 4–9 December, 4766–4775.
5. Kavzoglu, T., & Teke, A. (2022). Predictive Performances of Ensemble Machine Learning Algorithms in Landslide Susceptibility Mapping Using Random Forest, Extreme Gradient Boosting (XGBoost) and Natural Gradient Boosting (NGBoost). *Arabian Journal for Science and Engineering*, 47, 7367–7385. https://doi.org/10.1007/s13369-022-06560-8