Geospatial Analysis of Landslide Susceptibility Through Machine Learning In Relation to Environmental Indicators Across Global Regions

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ABSTRACT

Landslides cause over a billion dollars per year in damages and the situation is only exacerbated by climate change. Landslide forecasting, as a result, is key for detecting these disasters. Traditional landslide prediction models often rely on localized data and extensive computational resources, limiting their applicability on a global scale and therefore have an accuracy rate of around 30%. Addressing this gap, our research leverages a dataset which uses an enhanced version of NASA's Global Landslide Catalog. The dataset spans from 2010-2020, containing 10,100 landslide events with meteorological and geological factors preceding the event. After identifying key drivers of landslides and the minimum slope requirements for different lithologies, a Random Forest model was created using python to predict landslides based on their severity index. An 81% accuracy rate was found when trained and tested, proving to be much more effective when compared to traditional models. The model can now be used to provide a novel, data-driven perspective on landslide prediction allowing for a quicker evacuation of areas prone to landslides and providing enough time for countermeasures to be employed.

INTRODUCTION

Landslides continue to stand as one of the most prevalent natural disasters, harming both human life and infrastructure across the world. Globally, 500,000 individuals are affected and nearly a billion dollars per year are spent trying to fix the damage caused by said disasters. And with global warming on the rise, several factors that induce landslides have become amplified which has led to an increase in the number of global landslides. From 2030-2066, a 40% increase in the number of landslides and a 60% increase in subsequent years has been predicted based on current statistics.

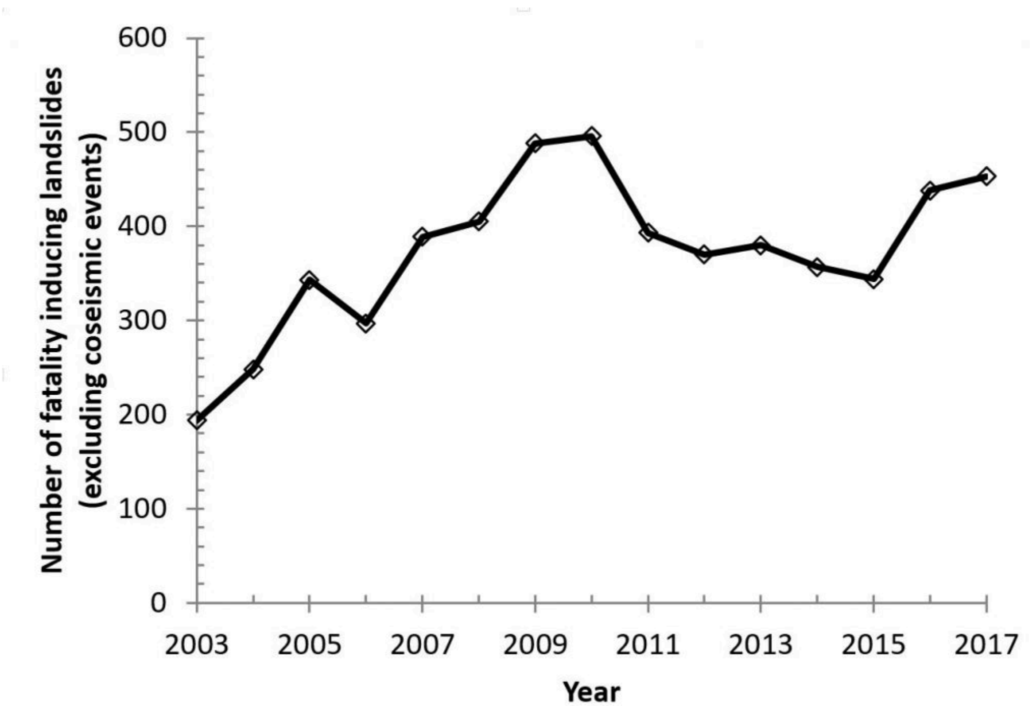

Figure 1: graph showing a gradual increase in fatality inducing landslides over the past two decades; highlights the potential for more growth over the next few decades

Landslides come in a variety of different forms. Debris avalanches, earthflows, falls, and translational landslides all stem from their own unique causes but each is just as dangerous as the other.

Recent advancements in machine learning have opened the door to avenues for enhancing our understanding of landslide susceptibility. By leveraging large datasets and identifying patterns within, these algorithms offer the potential to significantly improve the efficiency of predictive models. However, despite the promising nature of this technology, there is limited research applying to machine learning and landslide prediction in the context of utilizing global climatic factors.

Landslides are typically classified by their size (small, medium, or large) or the volume of material displaced. Unfortunately, there is hardly any comprehensive data for the volume of material displaced which leads to the utilization of monitoring by size. A majority of landslides are of the larger size, but only a few escalate to catastrophic proportions. Statistically, a majority of landslides are mild in terms of the damage they cause, but the few that do become catastrophic or large lead to significant economic loss and human casualties, highlighting the need for predictive models to forecast the likelihood of a landslide and gauge its potential impact.

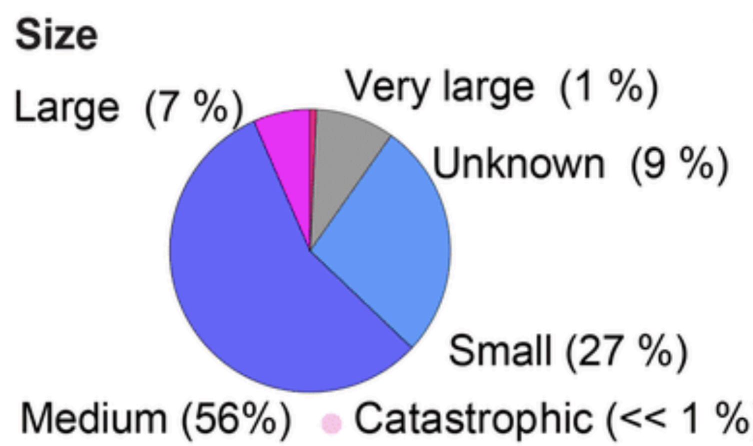

Figure 2: Pie chart depicting the size distribution of landslides ranging from small to catastrophic; unknown is attributed to those who size wasn't accurately classified

Historically, landslide susceptibility models have relied on a combination of field observations, geological surveys, and sedimentary models as seen with creation of the NASA Global Landslide Catalog. An altered version of this dataset was found that contains a list of all landslides from 2010-2020 along with key environmental variables leading up to the landslide.

The purpose of this research is to use machine learning in conjunction with the data from the extended version of the NASA Global Landslide Catalog. The integration of climate change projections allows new insights into disaster risk management, aiding in the development of a more effective early warning system (EWS). Through this study, we aim to not only advance the understanding of landslide dynamics but also provide practical solutions to help safeguard communities and reduce the impact of these disasters.

METHOD

Materials

A landslide dataset encompassing global landslide events was acquired from an altered version of the Global Landslide Catalog from NASA's Cooperative Open Online Landslide Repository (COOLR). This altered version contains meteorological data from the World Meteorological Organization (WMO) and geological data from the United States Geological Survey (USGS). The dataset encompasses a wide array of variables, such as:

- Geographical Data: Latitude and longitude coordinates, continent, and specific regions within Asia (West Asia and East Asia).

- Environmental Factors: Daily measurements over a period leading up to landslide events, temperature (°C), humidity (%), wind speed (m/s), and the Accumulated Rainfall Index (ARI).
- Geological Characteristics: Slope (degrees) and lithology, categorizing the rock and soil types prevalent at each site.

The data spans from 2010 to 2020, containing characteristics from 10,100 landslides, representing the 10s of billions of dollars of damage caused by these disasters as shown in Figure 3.

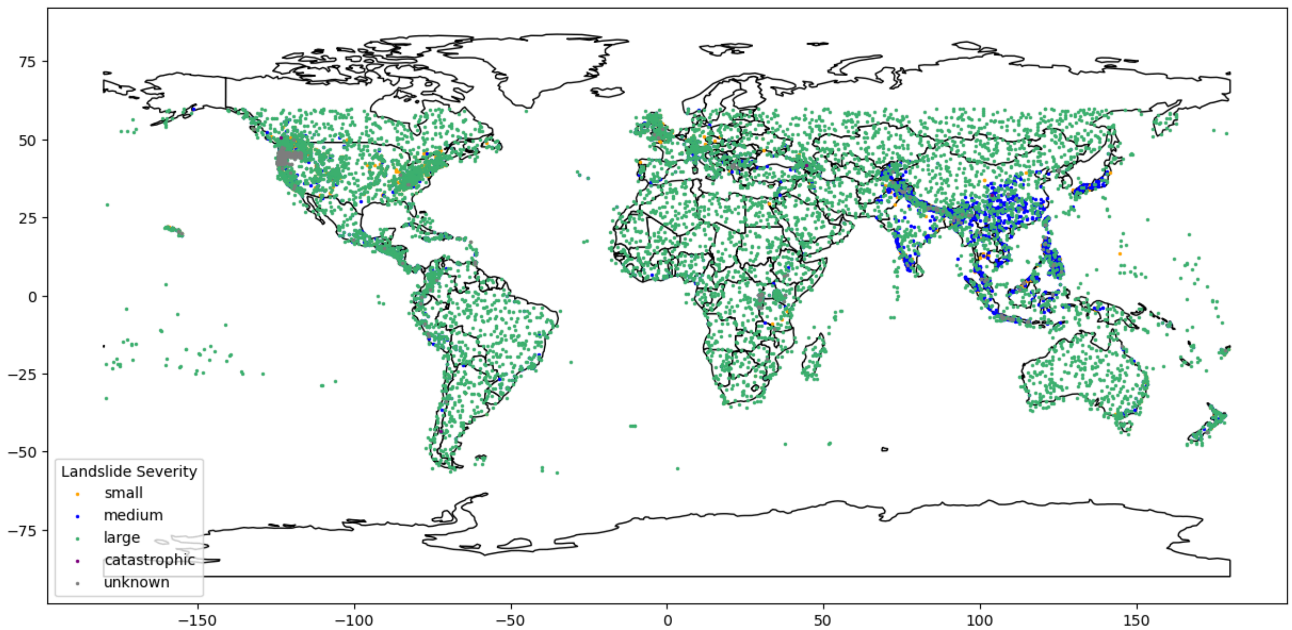

Figure 3: Map generated from python depicting the 10,000+ landslides across the globe with their corresponding severity as indicated by the key in the bottom corner. Data from Antarctica had been excluded.

Machine learning, a way to combine a computer's computational skills with a human brain thinking system, was used to systematically find relationships between 2 topographical features and 4 key environmental variables across the 24 hour period preceding the landslide.

Methodology

The methodology of this study is based on 6 phases as outlined below:

1. Data Cleaning: The initial stage of the analysis focused on preparing the dataset for machine learning applications. This entailed several key processes. First, we normalized text data, particularly within the 'continent' and 'lithology' columns, to ensure uniform capitalization across the dataset, thereby eliminating any discrepancies that could arise from case sensitivity. Next, we tackled missing values prevalent in environmental factors, opting to fill in these gaps using the median value for each column. This approach was chosen to maintain the balance of the dataset, preserving its distribution while filling in missing information. Lastly, to effectively incorporate categorical variables into the machine learning model, we employed one-hot encoding for variables such as 'lithology'. This method transformed categorical entries into a format that could be directly utilized in the analysis, enhancing the model's interpretability and accuracy.
2. Feature Selection: A subset of environmental factors was chosen based on preliminary analysis and literature review, focusing on those most relevant to landslide occurrence: precipitation, temperature, humidity, wind speed, and geological characteristics (slope and lithology).

3. Geographic Segmentation: The dataset was segmented based on the country and lithology to analyze factors in different environments.

4. Feature Importance Analysis: Post-training, the model's feature importances were extracted to identify the key environmental indicators of landslides for each geographic segment.
5. Minimum Slope Analysis: An additional analysis was conducted to determine the minimum slope required for a landslide to occur within each lithological category and severity level, providing insights into the geological predisposition to landslides.
6. Machine Learning Model: Training These two factors of feature importance and slope analysis were then used to predict landslides based on their severity and when they would occur. The RandomForestClassifier was determined to be the optimal model for this situation. To optimize the model's performance, parameter tuning was used where a grid search approach over a predefined parameter space was employed. Key parameters such as 'n_estimators', 'max_depth', 'min_samples_split', and 'min_samples_leaf' were all varied. The grid search eventually was coupled with a validation test.

RESULTS

Model Accuracy Analysis

The RandomForestClassifier demonstrated the best performance across the dataset with an 81.568% accuracy. The accuracy slightly varied across geographic regions, reflecting nuanced effects different types of lithologies had against landslide susceptibility as outlined in section 3.3. This variance underscores the importance of regional environmental context in shaping landslide dynamics.

Model Validation

In this study, a robust cross validation-technique was employed to validate the performance of the Random Forest Classifier. A specific focus was placed on the ability to predict landslide susceptibility based on the provided set of environmental indicators. A stratified K-Fold with three folds was used with each fold containing a proportionate representation of the landslide variable (binary). This approach reduces any variance, which creates a more reliable estimate of the model's true performance. This validation test used a pipeline to standardize a 0 mean across all variables and ensure the data was preprocessed before the validation.

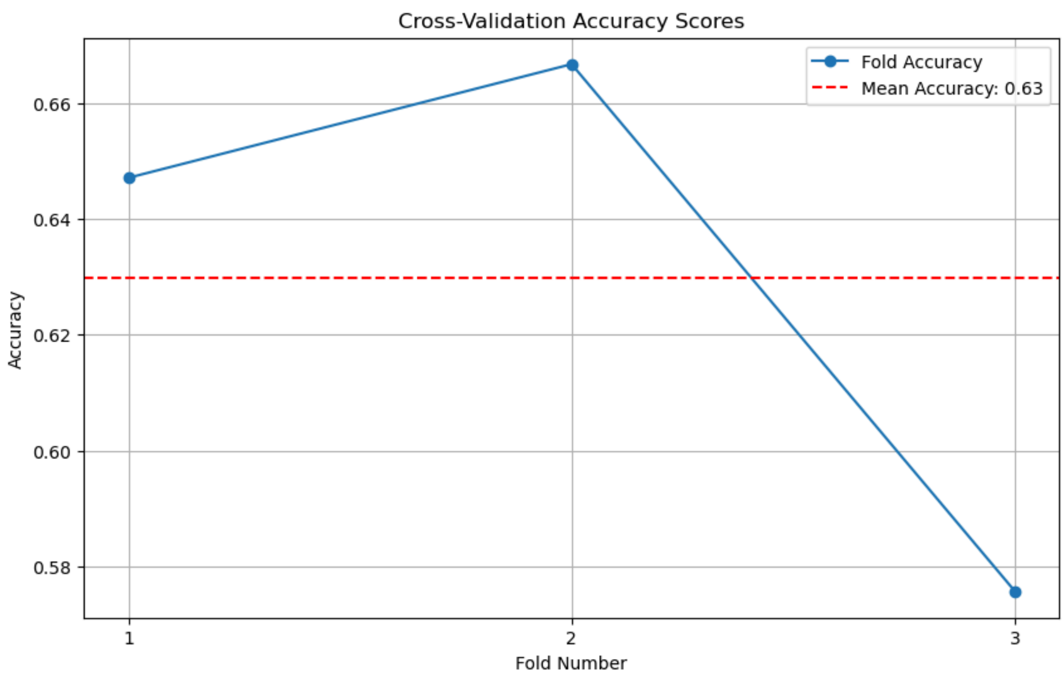

Figure 4: python generated graph that plots the fold accuracy of each of the three folds alongside the mean accuracy of all the folds as indicated by the dashed red line

Figure 4 shows the model's consistency and generalization capability across different data. Each folder's accuracy is a point on the graph while the mean accuracy line serves as a benchmark to summarize the overall efficiency in predicting landslides. The minor fluctuations show the model's stability and an above-average level of predictive accuracy in this context.

Identification of Key Indicators

Precipitation, humidity, wind, and temperature were all analyzed for their respective importance. Precipitation data from the days preceding the landslide were gathered in the ARI or Accumulated Rainfall Index in order to assess its total effect. The zeroes as seen in the features of Figure 5 indicate that it was the features the day of the landslide. As seen in Figure 5, precipitation had the greatest correlation with landslides and therefore was found to be the key driver with a nearly 52% correspondence. Temperature, humidity, and wind followed with around the same weightage ranging from 17%, 16%, and 15% respectively.

	feature	importance
3	ARI0	0.515352
0	temp0	0.172749
1	humidity0	0.164447
2	wind0	0.147452

Figure 5: Showcases and compares the importance of the four primary environmental/ meteorological factors that contribute to the erosional factors causing landslide to occur leading to the following order: precipitation, temperature, humidity, wind

The slope and lithology was also assessed in order to find the minimum slope required for a landslide to occur in varying environments.

Abbreviation	Translation	Abbreviation	Translation
ev	evaporites	sm	sedimentary
ig	igneous	ss	sandstone
mt	metaphoric	su	sulfates
nd	undifferentiated	va	volcanic ash
pa	alluvium	vb	volcanic breccia
pb	pebbles	vi	intrusive igneous
py	pyroclastic	wb	weathered bedrock

Figure 6: chart correlating lithologies to their actual definition, making it easier to read and understand Figure 7

Based on Figure 7, it is clear that grounds made of evaporites or pyroclastic material have the lowest inclination required to induce a landslide. However, these landslides tend to be on the weaker side when compared to metamorphic or sedimentary landforms.

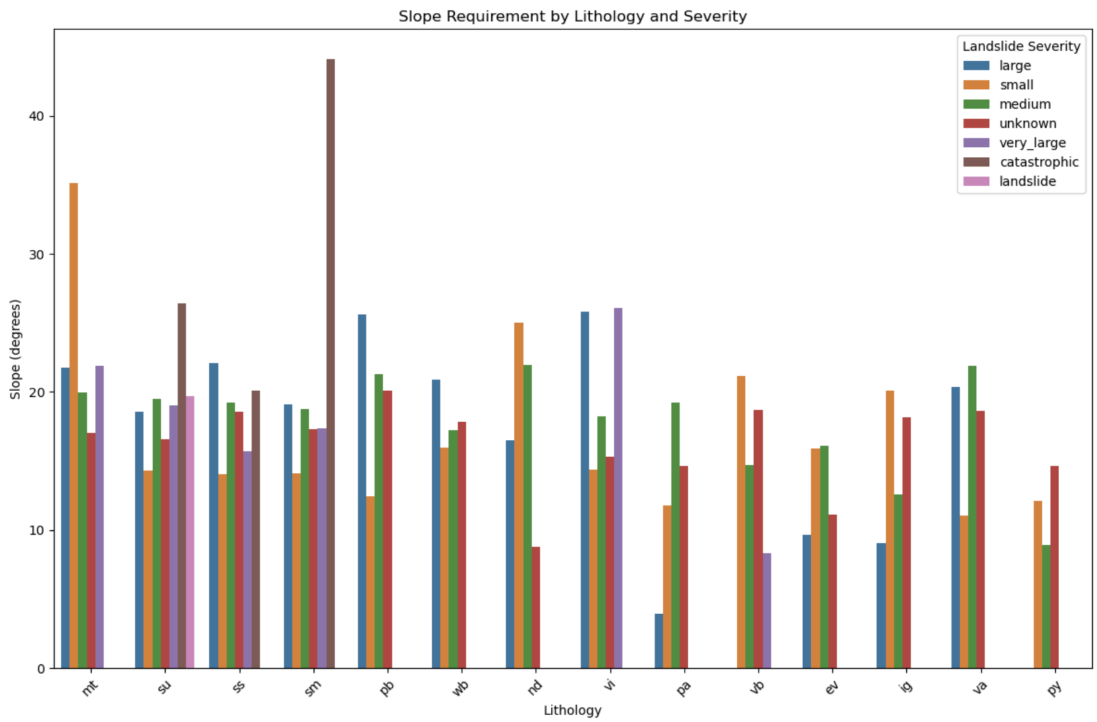

Figure 7: created in python to depict **a)** the minimum slope required to induce a landslide based on the type of rock that makes up the land and **b)** the corresponding severity caused by these slopes with these lithological properties

DISCUSSION

The overall high accuracy of the model highlights the effectiveness of machine learning techniques in understanding and predicting nonlinear natural phenomena like landslides. The observed variability in model performance across various datasets shows the influence of varied environmental factors on landslide susceptibility. It suggests that a one-size-fits-all approach may not be optimal for predictive analysis of landslides.

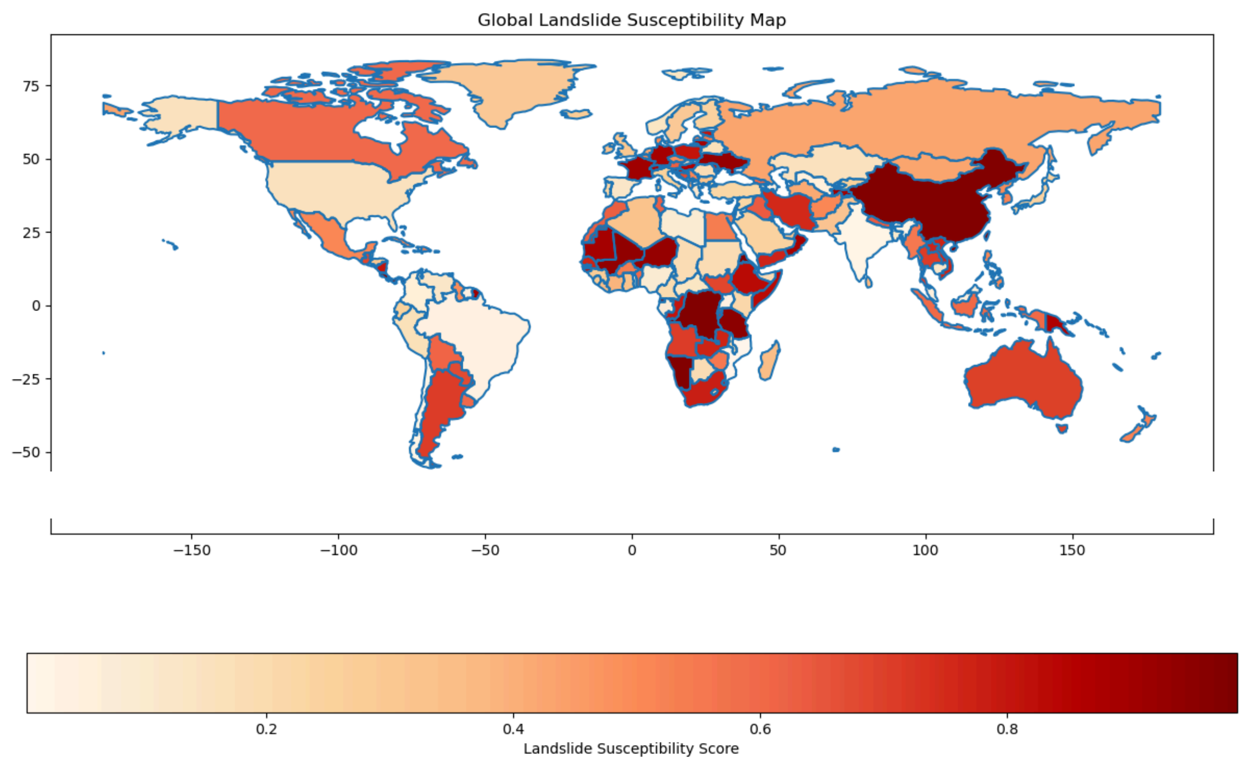

Figure 8: depicts global landslide susceptibility based on all the factors from before; shows Asia and Africa as future primary victims to landslides; The United States of America as a whole doesn't face a large amount of landslides (only on the West Coast primarily), hence the lighter color

The model's ability to identify key indicators of landslides and their respective importance in predictive modeling confirms the relevance of these factors. The relationships identified further points to potential implications of using climate change and atmospheric variables to predict future landslide patterns. Such variables allowed the creation of a susceptibility map as seen in Figure 8 where historical data, environmental factors from individual regions, etc. were all taken into account in order to create this map depicting the susceptibility to a landslide for each specific country.

The insights gained from this study open paths to future exploration. A clear need for more granular environmental data was utilized to explore the effects of human activities such as deforestation, or urban growth. This additional data could further the world of predictive modeling for not just landslides, but all types of natural disasters (droughts, wildfires, avalanches, etc.).The development of models to incorporate real-time data presents a promising opportunity to advance landslide EWS. These changes could bring about significant reductions in the economic and social losses faced during landslides and other disasters as well.

CONCLUSIONS

This study aimed to predict landslides through a machine learning approach based on an altered version of the NASA Global Landslide Catalog found online. Using this dataset that encompassed 10,100 landslides as well as the environmental variables, a RandomForestClassifier model was generated to predict landslides across the globe in relation to key landslide-inducing factors in the environment, such as precipitation, wind, temperature, and humidity while also referencing the various slopes, based on lithologies, that cause landslides. The model was then trained based on these features indicating an 81.568% accuracy.

Local governments can utilize this Random Forest model in order to prevent lots of damage. Economically a lot of money can be saved, and lives can be saved as well. By forecasting the potential of these landslides, proactive measures can be implemented to evacuate the area and thus reduce the amount of damage caused.

Future research should aim to incorporate a broader array of variables, including anthropogenic factors to further refine the capability of these models. Leveraging real-time data would be a huge step in the right direction as well.

In conclusion, the integration of machine learning in studying landslide susceptibility presents a promising avenue to actually predicting these natural disasters. The journey from data collection to model validation highlights the importance of interdisciplinary approaches in tackling the challenges posed by natural hazards in an era marked by climactic uncertainties.

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