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Identification of landslide susceptible zones in Idukki district (Southern Western Ghats) employing the REPTree model and geospatial techniques

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Abstract

Landslides, being the most frequent natural catastrophe in the Western Ghats of India, need immediate attention and further research to minimize their impacts. This research aimed at identifying landslide susceptible zones in Idukki district, situated in the Southern Western Ghats, one of the most impacted districts. For the analysis, a machine learning ensemble model called REPTree (Reduced Error Pruning Tree) has been employed, and the map has been created using geospatial techniques. The conditioning factors selected for the analysis include slope, distance from the road, soil texture, curvature, lineament density, aspect, topographic position index (TPI), lithology, land use/land cover (LULC), stream power index (SPI), elevation, and rainfall. According to this modeling, 13.30% of the district is very highly susceptible; 17.00% is highly susceptible to sliding. The validation of the created map employing the ROC curve techniques proved that the map has good predictive capacity. This ascertained the efficacy of the REPTree model in identifying susceptible zones, which therefore can be successfully applied in other regions of similar geomorphological and climatic settings.

1. Introduction

Landslides are common in the Western Ghats region of Kerala (Akshaya et al. 2021), especially due to severe rainfall. In addition to this, land use practices and development activities increase the frequency of landslides (Abraham et al. 2021; Ajin et al. 2022b; Thomas et al. 2021). The recent landslides with significant death tolls are: the Koottickal disaster with a total death of 10 people (Ajin et al. 2022a), the Kokkayar disaster with 7 deaths (Ajin et al. 2022a), the Pettimudi disaster with 70 deaths (Achu et al. 2021), the Kavalappara disaster with 59 deaths (Ajin et al. 2022a), and the Puthumala disaster with 17 deaths (Ajin et al. 2022a).

The 2018 monsoon devastated the state of Kerala due to the flooding and landslides, which caused severe loss of property and numerous lives. According to Hao et al. (2020), a total of 4728 landslides have been reported in Kerala in the year 2018, with a total of 48 causalities (Ajin et al. 2022a). Most of the landslides have been recorded in the Idukki district. A total of 2219 landslides have been reported in Idukki district during the 2018 monsoon season (Hao et al. 2020). Hence, there needs to be a validated susceptibility map that helps planners and policymakers take steps to reduce the effects of landslides in this district and that can be used as a model for other areas with similar geological and environmental conditions.

The objectives of this analysis are to identify the area susceptible to landslides by applying the REPTree model and geospatial techniques, and to assess the predictive accuracy of the created susceptibility map. Twelve

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landslide conditioning factors such as slope, distance from the road, soil texture, curvature, lineament density, aspect, topographic position index (TPI), lithology, land use/land cover (LULC), stream power index (SPI), elevation, and rainfall have been employed for this modeling.

2. Materials and methods

2.1. Study Area

The Idukki district is comprised of rugged mountains and forests, with fourteen mountain peaks exceeding 2000 metres (Jones et al. 2021). This undulating topography and land use modifications as a part of development and recreational activities weaken the stability of the district, resulting in frequent landslides (Jones et al. 2021). The major rivers flowing through this district are Periyar, Muthirappuzhayar, Thodupuzhayar, and Thalayar, and the district spans an area of around 4358 km^2 (Thomas et al. 2021). The location of the Idukki district is depicted in Figure 1.

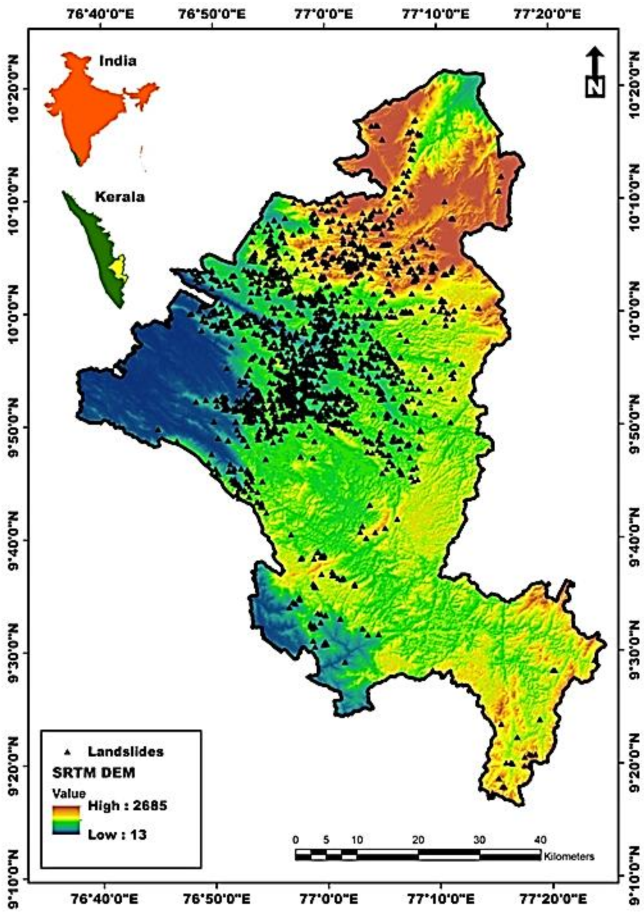

Figure 1. Location of the study area with landslide incidences

2.2. Creation of landslide inventory

A training dataset (80%) and a validation dataset (20%) were created (Muhammad et al. 2021) from the landslide incidence data obtained from the study of Hao et al. (2020). In the training dataset, there are 1775 slides, and in the validation dataset, there are 444 slides.

2.3. Derivation of conditioning factors

Using the ArcGIS 10.4 spatial analyst tools, the parameters like slope, aspect, and elevation were extracted from the SRTM DEM. Using raster calculator and spatial analyst tools, the curvature, SPI, and TPI were generated from the DEM. The lithology and lineaments were derived from the map produced by the Geological Survey of India, whilst the soil types were derived from the map published by the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP). The lineament density was computed using ArcGIS's line density tool. Using the ERDAS Imagine 9.3 software, the LULC types were identified from the Landsat 8 OLI images. The topographic map and Google Earth were used to extract the road networks, and the Euclidean distance tool in ArcGIS was used to generate the distance from the road layer. The rainfall was extracted from the World Climate Report portal, which is available at https://www.worldclim.org/. The REPTree model weights were determined using the R 4.2.1 software. The landslide susceptibility of the study area has been categorized into five zones by applying the Natural Breaks method (Senan et al. 2022).

2.4. REPTree model

The REPTree is an ensemble model that leverages information gain or variance to build a decision tree using reduce-error pruning and back overfitting, and C4.5 will use an embedded technique to fill in the missing values (Nhu et al. 2020; Vishwakarma et al. 2022). Equation 1 and the entropy (E) function were applied to estimate the IGR values (Bui et al. 2020).

$$IGR(x,S) = \frac{E(S) - \sum_{i=1}^{n} \frac{E(S_i)|S_i|}{|S|}}{-\sum_{i=1}^{n} \frac{|S_i|}{|S|} log_2 \frac{|S_i|}{|S|}} \tag{1}$$

Where S = training dataset, S_i = subset (i = 1, 2, 3, …. n), E = entropy function

2.5. Validation of the created map

For binary classification problems, predictive accuracy has been extensively measured using the area under the ROC curve (AUC) technique (Wu et al. 2007). The validation is considered excellent for AUC scores between 0.9 and 1.0, good for scores between 0.8 and 0.9, and fair for AUC scores between 0.7 and 0.8 (El Khouli et al. 2009). IBM SPSS Statistics 23.0 was employed for creating the ROC curve and computing the AUC scores.

3. Results

From the analysis, it is confirmed that the central part of the district is very-highly susceptible to landslides. In the created map, susceptibility is represented by five different zones (Figure 2). The validation of the created map confirmed good accuracy with an AUC score of 0.801 (80.1%). The ROC curve is depicted in Figure 3. The percentage of area of each zone is mentioned in Table 1.

Table 1. Percentage of landslide susceptible zones

Susceptible zones	Percentage of susceptible zones
Very low	28.31
Low	18.08
Moderate	23.31
High	17.00
Very high	13.30
Total	**100**

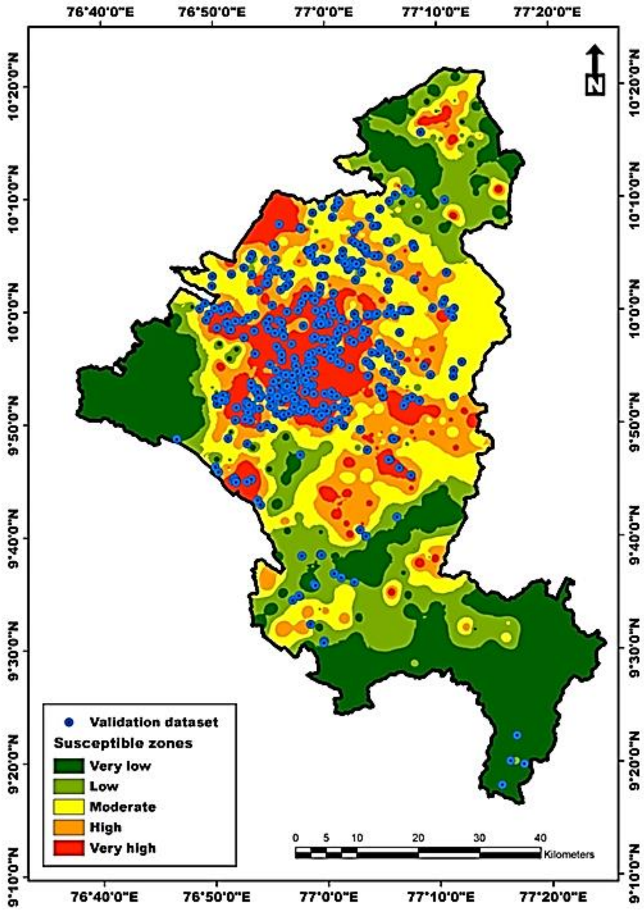

Figure 2. Landslide susceptibility map

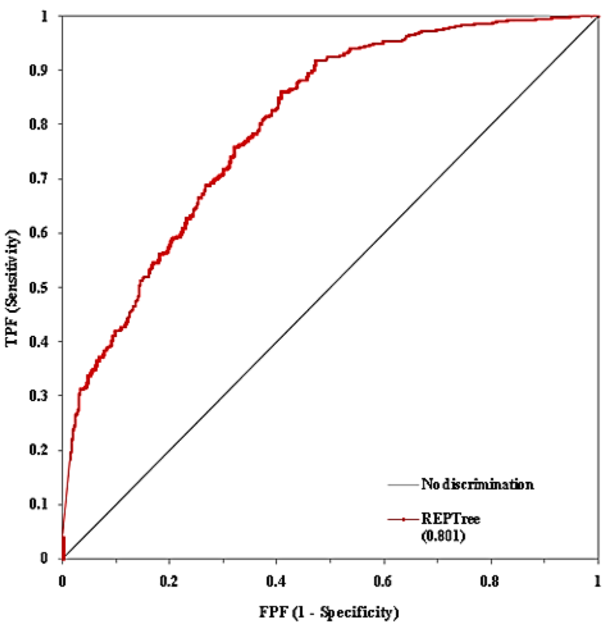

Figure 3. The ROC curves

4. Conclusion

The susceptibility map created employing the REPTree model identified 13.30% of the district as very highly landslide susceptible. A susceptible map of good predictive capacity will be of the utmost useful for decision makers in identifying suitable mitigation strategies, including zoning regulations. This map will also help identify roads and other infrastructure in critical zones so that an effective plan for evacuation can be prepared.

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