Landslide susceptibility modelling based on decision tree classification model of machine learning: A case study of Kullu-Rohtang Pass transport corridor (Himachal Pradesh), India

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Research Article

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Abstract

Landslide hazards are responsible for causing substantial destruction and losses in mountainous region. In order to lessen the damage in these vulnerable areas, the key challenge is to predict the landslide events with accuracy and precision. The principal objective of the study conducted is to assess the landslide susceptibility along the transport corridor from Kullu to Rohtang Pass in Himachal Pradesh, India. To achieve this objective, a detailed landslide inventory has been prepared based on the imagery data and frequent field visits. A total of 197 landslides were taken under consideration including 153 rock slides and 44 debris slides. Nine landslide factors were prepared initially and their relationships with each other and with the type of landslide was analysed. Later, information gain ratio measure was used to identify the triggering factors having best score for eliminating the unimportant factors. Train_test_split method was used to classify the dataset into training and testing groups. Decision tree classification model of machine learning was applied for landslide susceptibility model (LSM). The performance was evaluated using classification report and receiver operating characteristic (ROC) curve. Results obtained have proved that the decision tree classification model of machine learning performed well and have a good accuracy in forecasting landslide susceptibility in the area considered for this study.

Full Text

Due to technical limitations, full-text HTML conversion of this manuscript could not be completed. However, the manuscript can be downloaded and accessed as a PDF.

Tables

Due to technical limitations the Tables are available as a download in the Supplementary Files.

Figures

Figure 1

Demarcation of the study area. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

Landslide types: (a) Rock slide (b) Debris slide

Figure 3

Decision Tree for landslide prediction

Figure 4

(a) Landslide inventory map (b) slope (c) elevation (d) land use and land cover (LULC) (e) geology and geomorphology (f) lineament density (g) aspect (h) distance to road (i) distance to drainage (j) relative relief

Figure 5

Information gain ratio (IGR) for triggering factors

Figure 6

Information gain ratio (IGR) for triggering factors

Figure 7

(a) Original dataset visualization in 2-D (b) result visualization in 2-D

Figure 8

(a) Without eliminating any factor (b) eliminating relative relief (c) eliminating relative relief and aspect (d) eliminating relative relief, aspect and distance to drainage.

Supplementary Files

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