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Multi-hazard assessment using machine learning and remote sensing in the North Central region of Vietnam

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Abstract

Natural hazards constitute a diverse category and are unevenly distributed in time and space. This hinders predictive efforts, leading to significant impacts on human life and economies. Multi-hazard prediction is vital for any natural hazard risk management plan. The main objective of this study was the development of a multi-hazard susceptibility mapping framework, by combining two natural hazards—flooding and landslides—in the North Central region of Vietnam. This was accomplished using support vector machines, random forest, and AdaBoost. The input data consisted of 4591 flood points, 1315 landslide points, and 13 conditioning factors, split into training (70%), and testing (30%) datasets. The accuracy of the models' predictions was evaluated using the statistical indices root mean square error, area under curve (AUC), mean absolute error, and coefficient of determination. All proposed models were good at predicting multi-hazard susceptibility, with AUC values over 0.95. Among them, the AUC value for the support vector machine model was 0.98 and 0.99 for landslide and flood, respectively. For the random forest model, these values were 0.98 and 0.98, and for AdaBoost, they were 0.99 and 0.99. The multi-hazard maps were built by combining the landslide and flood susceptibility maps. The results showed that approximately 60% of the study area was affected by landslides, 30% by flood, and 8% by both hazards. These results illustrate how North Central is one of the regions of Vietnam that is most severely affected by natural hazards, particularly flooding, and landslides. The proposed models adapt to evaluate multi-hazard susceptibility at different scales, although expert intervention is also required, to optimize the algorithms. Multi-hazard maps can

provide a valuable point of reference for decision makers in sustainable land-use planning and infrastructure development in regions faced with multiple hazards, and to prevent and reduce more effectively the frequency of floods and landslides and their damage to human life and property.

Keywords: *floodings; hazard assessment; hazard map; hazard prediction; human lives; machine-learning; multi-hazards; natural hazard; remote-sensing; viet nam*

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