ABSTRACT

Landslides are rapid events with devastating impacts on the biophysical environment, including loss of lives and property. These hazards are expected to increase due to current climate change phenomena and their related outcomes, such as extreme weather events. Accurate and timely landslide inventories and hazard assessments are vital for effective disaster management, improving preparedness and practical hazard assessment in areas with complex geography. However, in tropical regions characterised by rapid vegetation regrowth, obtaining immediate and accurate datasets after landslide events is a significant challenge. Prompt post-event inventorying is crucial for capturing changes in the landscape. The aims of this study were: (1) to develop a landslide inventory method that incorporates attention mechanisms and model interpretation techniques using convolutional neural networks and existing inventory knowledge; (2) to characterise landslide susceptibility in a landslide-prone area with a deep neural network model to better understand spatial risk patterns and the influence of key predictive factors; and (3) to assess deep neural networks and transfer learning algorithms regarding their generalisability, parameter sensitivity, reliability, and plausibility.

This research employed an experimental design incorporating machine learning and deep learning algorithms. A comparative analysis of landslide mapping was conducted using three attention-based convolutional neural network models and the standard U-Net. The landslide susceptibility mapping used a deep neural network model and transfer learning techniques. Input data included twelve landslide conditioning factors, such as geological, topographical, vegetation, and distance variables. Model performance was assessed using both quantitative and qualitative methods. Quantitative evaluation involved the area under the curve and the receiver operating characteristic (ROC) curve (AUC). At the same time, qualitative assessment included geomorphic plausibility testing, conducted with zonal statistics, and validation through field-based interviews.

The results demonstrate that attention-based models, particularly the spatial attention model, significantly improve the accuracy of landslide detection and mapping. They also suggest that edges and boundaries are the main object features on which the spatial attention model bases its identification of landslide and non-landslide objects. Additionally, both the source and target areas display similar susceptibility patterns, and the models are transferable across different domains, as evidenced by the superior performance of the transfer learning model compared to the baseline model. The AUC scores were 84%, 97%, and 83% for the source area model, the transfer learning model, and the baseline model, respectively. The most influential and interacting factors included aspect, slope, elevation, and distance to streams and roads. The model's outputs were all found to be geomorphically plausible, and field interviews have the potential to serve as a qualitative evaluation method for LSS models. Furthermore, human activities are likely to increase landslide susceptibility in the area. By implementing targeted interventions based on these relationships, authorities can help reduce the impact of landslide hazards. Additionally, landslide susceptibility models should prioritise providing explanatory knowledge over merely predictive accuracy. Transfer learning must be used cautiously to address issues related to scaling and modifiable areal unit problems that may occur.

Key Words: Landslide mapping, Landslide susceptibility, Attention U-nets, geomorphic plausibility, Deep Neural networks.

INTISARI

Longsor adalah peristiwa yang terjadi dengan cepat dengan dampak yang menghancurkan pada lingkungan biofisik, termasuk kehidupan manusia. Bahaya ini diproyeksikan akan meningkat di bawah fenomena perubahan iklim yang berlaku dan hasil terkaitnya, seperti peristiwa cuaca ekstrem. Inventarisasi dan penilaian yang akurat dan tepat waktu adalah prekursor penting untuk manajemen bencana tanah longsor, Penilaian bahaya dan manajemen risiko yang efektif di wilayah geografis yang kompleks. Namun, di wilayah tropis yang ditandai dengan pertumbuhan kembali vegetasi yang cepat, memperoleh data yang cepat dan akurat setelah kejadian longsor merupakan tantangan besar. Inventarisasi data longsor segera setelah kejadian diperlukan untuk menangkap perkembangan landscape, bahkan dalam skala yang sangat kecil. Tujuan dari penelitian ini meliputi: (1) merancang metode inventarisasi tanah longsor yang mengintegrasikan teknik berbasis perhatian dan interpretasi model menggunakan jaringan Neural Konvolusional (CNN) dan *existing knowledge*; (2) mengkarakterisasi daerah rawan tanah longsor menggunakan model *Deep Neural network* sebagai sarana untuk meningkatkan pemahaman tentang pola risiko spasial dan peran faktor prediktif utama; (3) mengevaluasi DNN dan algoritma Pembelajaran *Transfer*, generalisasinya, sensitivitas parameter, keandalan dan plausibilitasnya.

Penelitian ini menggunakan desain eksperimental, menggunakan algoritma *machine learning* dan *deep learning*. Pemetaan longsor dilakukan menggunakan jaringan Neural Konvolusional berbasis perhatian (*attention*), dengan membandingkan 3 varian model. Prediksi kerentanan longsor menggunakan model DNN dan *transfer learning*. 12 faktor pengkondisian longsor digunakan sebagai data masukan, termasuk variabel geologi, topografi, dan vegetasi. Model dievaluasi secara kuantitatif menggunakan *Area Under Curve*, *Receiver Operating Characteristics* (ROC AUC), dan secara kualitatif menggunakan kriteria plausibilitas geomorfik berdasarkan indeks medan dan wawancara.

Hasil penelitian menunjukkan bahwa model berbasis *attention*, khususnya *attention* spasial, meningkatkan akurasi deteksi longsor. Hal ini juga menunjukkan bahwa batas merupakan fitur objek dominan yang menjadi dasar model perhatian spasial dalam menentukan objek longsor. Selain itu, *source area* dan *target* menunjukkan pola kerentanan yang serupa, dan model yang digunakan dapat ditransfer lintas domain, yang ditunjukkan oleh kinerja model *transfer learning* yang lebih unggul dibandingkan dengan model dasar. Skor AUC adalah 84%, 97%, dan 83% untuk model area sumber, model pembelajaran transfer, dan model dasar, masing-masing. Faktor yang paling berpengaruh dan saling berinteraksi adalah aspek, kemiringan, elevasi, dan jarak ke sungai dan jalan. Semua *output* model memenuhi kriteria analisis plausibilitas geomorfik, dan wawancara memiliki potensi sebagai prosedur evaluasi kualitatif. Namun, aktivitas manusia cenderung memperburuk kerentanan tanah longsor di area tersebut. Dengan menerapkan intervensi terarah berdasarkan hubungan ini, otoritas dapat membantu mengurangi dampak bahaya longsor. Selain itu, model kerentanan longsor harus memprioritaskan penyediaan pengetahuan penjelasan daripada sekadar akurasi prediktif. *Transfer learning* harus digunakan dengan hati-hati untuk mengatasi masalah terkait modifikasi skala yang mungkin terjadi.

Kata Kunci: Tanah longsor, Kerentanan tanah longsor, Attention U-net, Plausibilitas geomorfik, Jaringan Syaraf Dalam.