Fundamental Kerentanan Tanah Longsor

Metode Pemetaan Kerentanan Tanah Longsor

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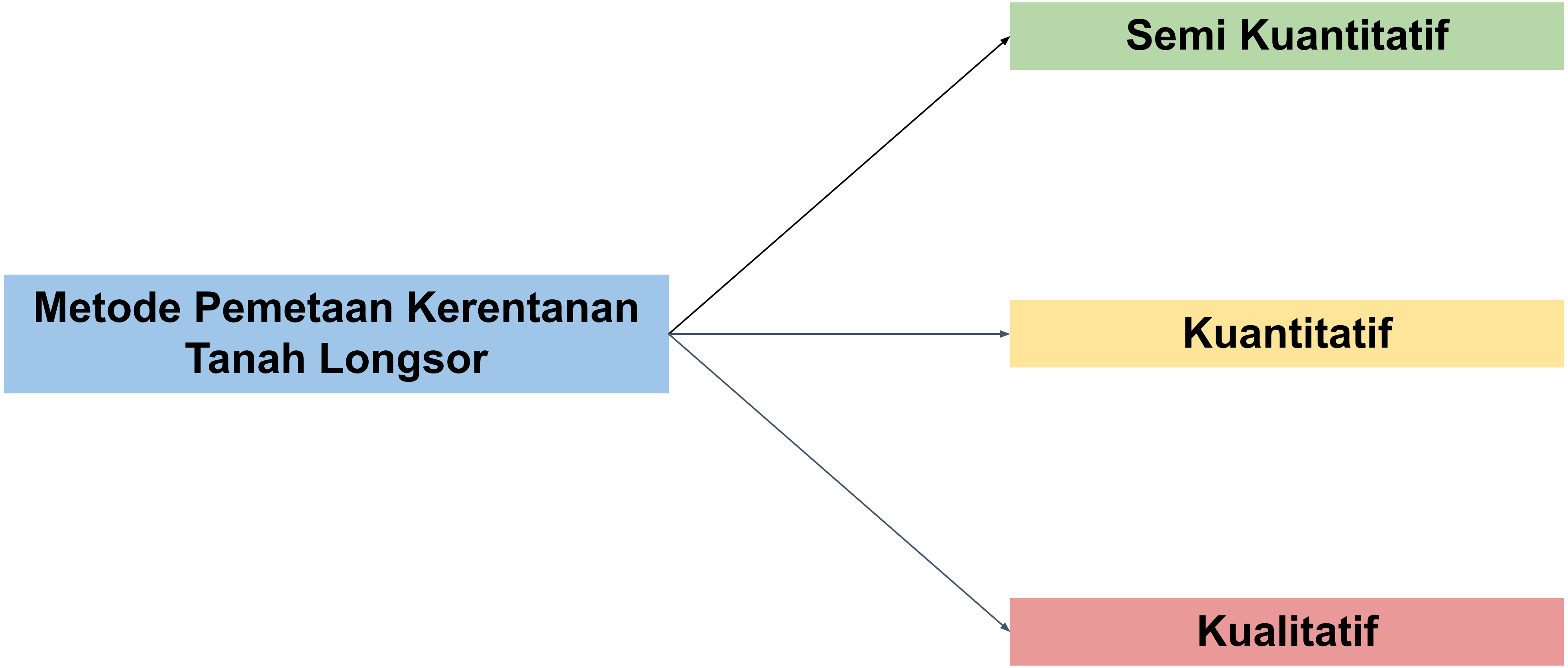
Metode Pemetaan Kerentanan Tanah Longsor



Metode Pemetaan Kerentanan Tanah Longsor

Semi Kuantitatif

- ***Analytical Hierarchy Process* (AHP)**
  Menentukan bobot dengan matriks perbandingan berpasangan (*pairwise comparison*) dari setiap faktor pemicu longsor.

- ***Weighted Overlay* (WO) / *Weight of Evidence* (WOE)**
  Menentukan bobot pada setiap parameter berdasarkan pengaruhnya terhadap longsor (didasarkan pada literatur dan perhitungan ahli).

Kualitatif

- **Inventaris Longsor (*Landslide Inventory*)**
  - Mengumpulkan data kejadian longsor dari citra satelit dan survei lapangan.
  - Memetakan distribusi longsor berdasarkan data historis.

- **Heuristik**
  - Menentukan daerah rawan longsor berdasarkan interpretasi ahli terhadap faktor geomorfologi dan geologi.
  - Tidak menggunakan perhitungan kuantitatif, hanya berdasarkan pengalaman dan pengetahuan lapangan.

Kuantitatif

- **Metode Statistik**
  - ***Frequency Ratio* (FR)** : Menghitung rasio antara proporsi kejadian longsor dalam suatu kelas faktor dengan proporsi total area kelas faktor.
  - ***Index of Entropy* (IOE)** : Mengukur kontribusi setiap faktor menggunakan *entropy information theory* untuk menilai ketidakpastian dalam hubungan antara faktor pemicu dan kejadian longsor.
  - ***Certainty Factor* (CF)** : Mengukur tingkat kepastian hubungan antara faktor pemicu dan kejadian longsor.
  - ***Logistic Regression* (LR)** : Menggunakan model regresi untuk mengidentifikasi hubungan antara variabel independen (faktor pemicu) dan variabel dependen (kejadian longsor) yang dapat digunakan untuk memprediksi kemungkinan longsor di suatu lokasi.

- ***Machine Learning***
  - ***Artificial Neural Networks* (ANN)** : Menggunakan model jaringan saraf tiruan untuk mengidentifikasi pola hubungan antara faktor pemicu dan kejadian longsor dengan output prediksi zona rawan longsor.
  - ***Random Forest* (RF)** : Menggunakan banyak pohon keputusan (*decision tree*) untuk memprediksi kemungkinan kejadian longsor.
  - ***Support Vector Machine* (SVM)** : Menganalisis pola distribusi data menggunakan fungsi kernel untuk menangani hubungan non-linear antara faktor pemicu dan kejadian longsor.

Penggunaan FR dan AHP untuk Pemetaan Kerentanan Longsor [1]

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ELSEVIER

Landslide susceptibility mapping using frequency ratio and analytical hierarchy process method in Awabel Woreda, Ethiopia

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ABSTRACT

A landslide is a serious geo-environmental problem that results in the death of life and the devastation of infrastructure, properties, and agricultural lands. This research aimed to identify landslide susceptibility zones in selected Kebels of Awabel Woreda, central Ethiopia. Frequency ratio (FR) and analytical hierarchy process (AHP) methods were used. 175 landslide inventory data collected from Google Earth and field data were collected for testing and training data sets. Using the analytical hierarchy process, all the thematic layers (stream distance, slope, aspect, rainfall, lineament density, elevation, lithology, soil, land use/land cover, and curvature) were reclassified and weighted based on their relative contribution to landslide occurrence with the help of experts' knowledge. The results show that 11.85% and 20.52 % of the study fall under the very high and high susceptible zones, respectively, while the low susceptible zones cover 26.3% and 14.74% of the area. The landslide susceptibility zone identified by the frequency ratio model shows that (6.09%) and (16.9%) of the area covered very high and high susceptible zones, respectively, while 30.4% and 23.4% of the area covered low and very susceptible zones, respectively. The predicted landslide-susceptible areas were validated using existing landslide points with the help of the ROC tool in ArcGIS. Area under the curve (AUC) results were 84.5% for the AHP model and 73% for the frequency ratio model. The find of this study will provide an input for decision makers and land use planners in the future.

Artikel Review : Penggunaan AI, ML, dan *Deep Learning* (DL) untuk Kerentanan Longsor [2]

remote sensing

MDPI

Review

Application of Artificial Intelligence and Remote Sensing for Landslide Detection and Prediction: Systematic Review

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Abstract: This paper systematically reviews remote sensing technology and learning algorithms in exploring landslides. The work is categorized into four key components: (1) literature search characteristics, (2) geographical distribution and research publication trends, (3) progress of remote sensing and learning algorithms, and (4) application of remote sensing techniques and learning models for landslide susceptibility mapping, detections, prediction, inventory and deformation monitoring, assessment, and extraction and management. The literature selections were based on keyword searches using title/abstract and keywords from Web of Science and Scopus. A total of 186 research articles published between 2011 and 2024 were critically reviewed to provide answers to research questions related to the recent advances in the use of remote sensing technologies combined with artificial intelligence (AI), machine learning (ML), and deep learning (DL) algorithms. The review revealed that these methods have high efficiency in landslide detection, prediction, monitoring, and hazard mapping. A few current issues were also identified and discussed.

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Penggunaan CF dan *Deep Neural Network* (DNN) [3]

Landslide susceptibility assessment using the certainty factor and deep neural network

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Areas with vulnerable ecological environments often breed many geological disasters, especially landslides, which pose a severe threat to the safety of people's lives and property in these areas. To aid in landslide prevention and mitigation, an approach combining the coefficient of determination method (CF) and a deep neural network (DNN) were proposed in this study for landslide susceptibility evaluation. The deep neural network can excavate the deep features of samples and improve the accuracy of the susceptibility model. In addition, the logistic regression model (LRM) and support vector machine (SVM) were selected to create landslide susceptibility maps for comparison, which also involved the coefficient of determination method (CF). Based on landslide remote sensing interpretation and field investigations, a spatial database of mudstone landslides in the Xining area was established. Eight different conditional factors, including the elevation, slope, slope aspect, undulation, curvature, watershed, distance from a fault, and distance from a road, in the study area were selected as the evaluation factors to evaluate the susceptibility. The results revealed that four factors (i.e., the ground elevation, curvature, distance from a fault, and distance from a road) had relatively significant influences on the landslide susceptibility in the study area. Finally, the confusion matrix was used to evaluate the accuracy of the results obtained using the three methods, and the optimal result was selected to evaluate the landslide susceptibility in the study area. It was found that the combined CF-DNN method was more suitable for evaluating the landslide susceptibility in this area. Landslide susceptibility zoning was conducted to divide the study area into four sensitivity levels: low (32.65%), medium (35.12%), high (22.44%), and extremely high (9.79%) susceptibility. The high-risk areas were primarily distributed in the high-elevation areas along the eastern edge of the Huangshui Basin.

Pendekatan statistik *Generative Additive Model* (GAM) dan ANN [4]

Mapping Susceptibility With Open-Source Tools: A New Plugin for QGIS

Giacomo Titti[1,2], Alessandro Sarretta[2], Luigi Lombardo[3], Stefano Crema[2], Alessandro Pasuto[2] and Lisa Borgatti[1,2]*

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In this study, a new tool for quantitative, data-driven susceptibility zoning (SZ) is presented. The SZ plugin has been implemented as a QGIS plugin to maximize its operational use within the geoscientific community. QGIS is in fact a commonly used open-source geographic information system. We have scripted the plugin in Python, and developed it as a collection of functions that allow one to pre-process the input data, calculate the susceptibility, and then estimate the quality of the classification results. The susceptibility zoning can be carried out *via* a number of classifiers including weight of evidence, frequency ratio, logistic regression, random forest, support vector machine, and decision tree. The plugin allows one to use any kind of mapping units, to fit the model, to test it *via* a k-fold cross-validation, and to visualize the relative receiving operating characteristic (ROC) curves. Moreover, a new classification method of the susceptibility index (SI) has been implemented in the SZ plugin. A typical workflow of the SZ plugin is described, and its application for landslide susceptibility zoning in Northeast India is reported. The data of the predisposing factors used are open, and the analysis has been carried out using a logistic regression and weight of evidence models. The corresponding area under the curve of the relative ROC curves reflects an optimal model prediction capacity. The user-friendly graphical interface of the plugin has allowed us to perform the analysis efficiently in few steps.

Sumber

[1] Gulbet E dan Getahun B. 2024. Landslide susceptibility mapping using frequency ratio and analytical hierarchy process method in Awabel Woreda, Ethiopia. *Quaternary Science Advances*. 16(1): 1-17. doi.org/10.1016/j.qsa.2024.100246.

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[3] Ma W, Dong J, Wei Z, Peng L, Wu Q, Wang X, Dong Y, Wu Y. 2023. Landslide susceptibility assessment using the certainty factor and deep neural network. *Frontiers in Earth Science*. 10(1): 1-14. doi.org/10.3389/feart.2022.1091560.

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