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Geospatial Model of Landslide Potential Using Random Forest through Google Earth Engine Platform in Sukamakmur District, Bogor Regency

Model Geospasial Potensi Longsor Menggunakan Random Forest Melalui Platform Google Earth Engine di Kecamatan Sukamakmur, Kabupaten Bogor

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ABSTRACT

This research aims to map the potential landslide disaster in Sukamakmur Sub-district, Bogor Regency, using Random Forest method through Google Earth Engine platform. Sukamakmur Sub-district is an area with a high risk of landslides due to high rainfall and steep topographic conditions. The Random Forest method was chosen due to its ability to handle complex data and produce accurate predictions. In this study, the data used include slope, Topographic Wetness Index (TWI), distance from river, soil texture, rainfall, geological type, and land cover, which were processed using Google Earth Engine platform. The results showed that the Random Forest model was able to map landslide potential in Sukamakmur Sub-district with high accuracy. The model successfully identified areas with very high, high, medium, low, and very low landslide potential. The area included in the very high landslide potential category reached 1,331.39 Ha, while the high category covered 8,524.05 Ha. The most contributing factors in predicting landslides are slope and rainfall. This research contributes to disaster mitigation efforts by providing accurate landslide potential maps. The results can be used by the Regional Disaster Management Agency (BPBD) of Bogor Regency as a basis for decision-making in an effort to reduce the risk of landslides in Sukamakmur Sub-district.

Keywords: Google Earth Engine; Landslide; Random Forest; Spatial Analysis

ABSTRAK

Penelitian ini bertujuan untuk memetakan potensi bencana tanah longsor di Kecamatan Sukamakmur, Kabupaten Bogor, menggunakan metode Random Forest melalui platform Google Earth Engine. Kecamatan Sukamakmur merupakan daerah dengan risiko tanah longsor yang tinggi karena curah hujan yang tinggi dan kondisi topografi yang curam. Metode Random Forest dipilih karena kemampuannya untuk menangani data yang kompleks dan menghasilkan prediksi yang akurat. Dalam penelitian ini, data yang digunakan meliputi kemiringan lereng, Indeks Kelembaban Topografi (TWI), jarak dari sungai, tekstur tanah, curah hujan, tipe geologi, dan tutupan lahan, yang diolah *menggunakan platform Google Earth Engine. Hasil penelitian menunjukkan bahwa model Random Forest mampu memetakan potensi tanah longsor di Kecamatan Sukamakmur dengan akurasi tinggi. Model tersebut berhasil mengidentifikasi area dengan potensi tanah longsor sangat tinggi, tinggi, sedang, rendah, dan sangat rendah. Luas area yang termasuk dalam kategori potensi tanah longsor sangat tinggi mencapai 1.331,39 Ha, sedangkan kategori tinggi mencakup 8.524,05 Ha. Faktor yang paling berpengaruh dalam memprediksi tanah longsor adalah kemiringan lereng dan curah hujan. Penelitian ini berkontribusi pada upaya mitigasi bencana dengan menyediakan peta potensi tanah longsor yang akurat. Hasil penelitian ini dapat digunakan oleh Badan Penanggulangan Bencana Daerah (BPBD) Kabupaten Bogor sebagai dasar pengambilan keputusan dalam upaya mengurangi risiko tanah longsor di Kecamatan Sukamakmur.*

Kata Kunci: Random Forest; Google Earth Engine; Tanah Longsor

INTRODUCTION

Indonesia is located in an area with a high potential to experience various types of natural disasters, such as earthquakes, volcanic eruptions, tsunamis, landslides and floods. Indonesia's geographical position between the confluence of three major tectonic plates, Indo-Australia, Eurasia and the Pacific, makes it vulnerable to such events. Meeting these plates often results in earthquakes, volcanic eruptions and tsunamis (Rahmat & Alawiyah, 2020). Volcanic pathways known as the Pacific Ring of Fire and the Mediterranean Circumference run through Sumatra, Java, Nusa Tenggara and North Sulawesi, amplifying the disaster risk (Qodrifuddin et al., 2022). Landslides are the movement of masses of soil or rock down a slope due to the force of gravity. This phenomenon can occur suddenly or slowly, especially on steep slopes. Landslides are a severe threat in Indonesia, mainly due to high rainfall. Water that seeps into the ground due to intense rainfall can reduce slope stability and increase the risk of landslides (Widagdo & Khasanah, 2023).

According to the national disaster risk assessment data of West Java Province from the National Disaster Management Agency (BNPB) in 2022, Bogor Regency is one of the areas categorized in the high class of landslides. This is due to a disturbance in the stability of the slope and can be triggered by rainfall, ground motion events and vibration (BNPB, 2021). Based on data from BPBD Bogor Regency, there were 487 landslides in 2023 (BPBD Kabupaten Bogor, 2023). Sukamakmur Sub-district is one of the eight Bogor Regency sub-districts prone to landslides (Wardhana et al., 2023). This is in accordance with the Bogor Regency Spatial Plan 2016–2036, which designates Sukamakmur Sub-district as a landslide-prone area (Peraturan Daerah Kabupaten Bogor Nomor 11 Tahun 2016 Tentang Rencana Tata Ruang Wilayah Kabupaten Bogor Tahun 2016-2036, 2016).

Remote sensing technology enables quick and accurate monitoring and identification of the Earth's surface conditions, providing significant benefits in the analysis of potential landslide disasters (Lasaiba, 2023). The Google Earth Engine (GEE) platform provides various datasets, such as satellite imagery, topographic data and meteorological data, which can be effectively accessed and integrated for mapping potential landslide disasters. GEE also supports the use of Machine Learning algorithms, which enables more complex data processing and more in-depth analysis (Lindsay et al., 2022).

Disaster mitigation efforts are in accordance with the Minister of Home Affairs Regulation No. 33 Year 2006, one of which is the availability of information and disaster vulnerability maps for each type of disaster (Gedangsari, 2020). In an effort to reduce the risk of landslides, it is important to map disaster potential by utilizing the latest technology. One solution that can be applied is utilizing remote sensing technology to determine the potential of landslides (Ezrahayu et al., 2024).

Based on previous research using machine learning algorithms for mapping landslide potential, the Random Forest method has demonstrated significant reliability. For instance, a study that utilized Random Forest to predict landslide potential in the Cililin Subdistrict achieved an accuracy rate of 73%, with 49% of the area being identified as prone to landslides (Azam & Fardani, 2022). Similarly, research that applied Random Forest through the Google Earth Engine platform in Pacitan, East Java, using variables such as elevation, slope, and topographic aspects, resulted in an AUC value of 0.80 and a Kappa value of 0.79, further confirming the model's efficacy for mapping disaster potential (Ilmy et al., 2021).

Additionally, research that compared various machine learning algorithms, including Random Forest, demonstrated that this method excels in landslide mapping, achieving an AUC of 0.988 in Shexian County, China—significantly outperforming other models such as Support Vector Machine (SVM) and Logistic Regression (LR) (Wang et al., 2020). Weather factors have also been highlighted as crucial in landslide prediction models. A study in Rwanda revealed that incorporating rainfall data enhanced model accuracy, with AUC reaching 0.995. These studies affirm the importance of incorporating topographic, geological, and weather-related data in landslide risk modelling. The Random Forest method, in particular, has been proven capable of managing the complexity inherent in such diverse data sets (Kuradusenge et al., 2020).

Based on previous research, the Random Forest method, with the support of data from remote sensing, is very effective in mapping landslide potential in various regions. This provides a strong foundation for research in Sukamakmur Sub-district to model landslide risk and provide important information for disaster mitigation efforts in the area.

PROBLEM STATEMENT

1. How can the Random Forest model be applied using a combined set of variables derived from previous landslide studies to analyze potential landslide areas in Sukamakmur District?
2. How well does the Random Forest model perform in predicting landslide potential when these integrated variables are applied to the Sukamakmur region?
3. Which variable contributes the most to the Random Forest model in predicting landslide potential in Sukamakmur District?

LITERATURE REVIEW

Previous studies have demonstrated the effectiveness of machine-learning algorithms, particularly Random Forest, in landslide susceptibility modelling. Akhsani et al. (2022) applied the Random Forest method using multiple geospatial variables including slope, elevation, curvature, NDVI, land cover, rainfall, and soil type and achieved an accuracy of 73%. Their results showed that nearly half of the Cililin Sub-district was categorized as landslide-prone, highlighting the capability of Random Forest to handle complex terrain-related factors in susceptibility mapping.

Similarly, Ilmy et al. (2022) utilized Random Forest on the Google Earth Engine platform in Pacitan, East Java, using elevation, slope, and aspect as predictors. The study achieved strong performance with an accuracy of 0.94, a kappa of 0.79, and an AUC of 0.80, while identifying elevation as the most influential variable. This indicates that topographic characteristics play a crucial role in determining landslide susceptibility, especially in mountainous regions.

Wang et al. (2020) conducted a comparative analysis of several machine-learning algorithms including Random Forest, Support Vector Machine (SVM), Multilayer Perceptron (MLP), Gradient Boosting Machine (GBM), and Logistic Regression (LR) for landslide susceptibility mapping in Shexian County, China. Their results ranked Random Forest as the best performing algorithm (AUC 0.988), demonstrating its superiority over other classification models in handling nonlinear and high-dimensional geospatial datasets.

Rainfall has also been emphasized as an important factor influencing landslides. Kuradusenge et al. (2020) incorporated rainfall into machine-learning models in Rwanda and reported that both Random Forest and Logistic Regression achieved exceptional AUC values of 0.995 and 0.997. This finding reinforces the strong correlation between rainfall intensity and slope instability, especially in regions with frequent extreme weather events.

In the Indonesian context, Ummah et al. (2022) applied Random Forest to model landslide susceptibility in Malang Regency using elevation, slope, aspect, soil type, geological type, distance to river, and NDVI. The model produced high predictive accuracy (0.884) with a kappa of 0.749 and identified elevation as the most influential variable. This study further confirms the importance of integrating topographic, geological, hydrological, and vegetation-related factors when modeling landslide susceptibility.

Overall, these studies demonstrate that Random Forest consistently performs well for landslide susceptibility mapping and that a combination of variables particularly topography, rainfall, geology, soil type, distance to river, and land cover can improve predictive accuracy. Building upon these findings, the present study integrates key variables identified across the literature and applies them specifically to Sukamakmur District, an area with unique geomorphological characteristics that has not yet been extensively examined using Random Forest on the Google Earth Engine platform. This approach contributes to both methodological and regional novelty by assessing the combined influence of multiple variables and producing a five-class susceptibility map tailored to the local landscape.

METHODOLOGY

Research Location and Time

This research was conducted in 2024 and involved two primary locations. The first location is Sukamakmur Sub-district, Bogor Regency, West Java, where field surveys were conducted to collect landslide and non-landslide points based on historical data. The second location is the Geospatial Information Technology Laboratory at the Faculty of Engineering and Science, Ibn Khaldun University of Bogor, where data processing and model analysis were carried out using the Google Earth Engine platform.

Data Collection

The data used in this study consisted of both primary and secondary sources. Primary data was obtained through field surveys in the form of landslide and non-landslide occurrence points, which served as reference points for model training and validation. Meanwhile, secondary data was obtained from various datasets available on the Google Earth Engine platform. The secondary variables included slope, Topographic Wetness Index (TWI), distance from river, soil texture, maximum rainfall, geological type, and land cover. These variables were selected based on their known relevance in influencing landslide occurrences.

Data Processing

The data processing stage was carried out entirely within the Google Earth Engine platform. The first step involved defining the research boundary by extracting the administrative area of Sukamakmur Sub-district. Next, spatial datasets corresponding to each variable were imported and processed. All layers were resampled to a uniform resolution of 10 meters to ensure consistency. Once all variables were prepared, they were combined with the primary point data, where each landslide and non-landslide point was assigned corresponding values from each variable. This process produced a comprehensive dataset in which each sample point contained complete input feature information required for the modelling phase.

Random Forest Modelling

The modelling phase employed the Random Forest algorithm to classify landslide susceptibility. This machine learning method was selected for its strength in handling nonlinear relationships and high-dimensional geospatial data. The model was trained using the compiled dataset, with the dependent variable representing landslide presence or absence, and the independent variables consisting of the geospatial factors collected previously. Prior to training, the dataset was split into training and validation subsets. A hyperparameter tuning process was then carried out to determine the optimal number of trees for the model, ensuring maximum prediction performance. The modelling process generated a probability output representing the likelihood of landslide occurrence for each point in the study area.

Model Accuracy Evaluation

After the modelling process, the model's predictive performance was evaluated using several accuracy metrics. These included Overall Accuracy (OA), Kappa coefficient, and Area Under the Curve (AUC) from the Receiver Operating Characteristic (ROC) curve. These metrics provided insight into how well the model distinguished between landslide and non-landslide areas. In addition, a variable importance analysis was conducted to quantify the contribution of each input variable toward the model's decision-making process. The resulting percentage values indicated which variables had the most influence in predicting landslide potential.

Mapping and Classification

Following evaluation, the trained Random Forest model was applied across the entire Sukamakmur Sub-district to generate a continuous landslide susceptibility map. The model output, expressed as probability values, was reclassified into five distinct classes: very low, low, medium, high, and very high susceptibility. This classification allowed for a more interpretable visual representation of landslide risk in the region. Subsequently, an area analysis was performed to quantify the extent of each susceptibility class within each village, providing valuable insights for regional disaster preparedness and mitigation planning.

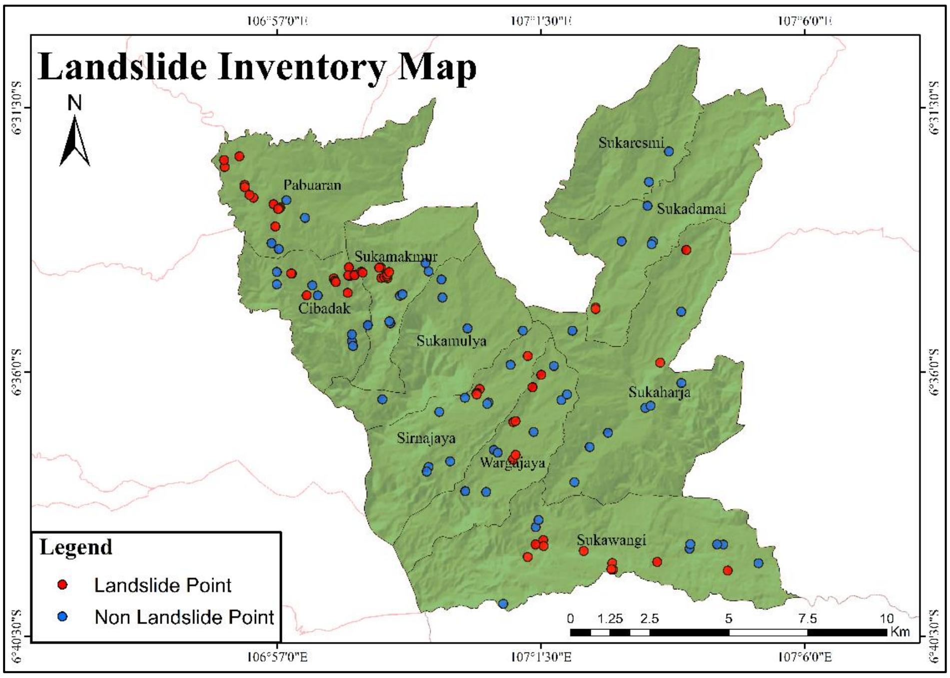
FINDING AND DISCUSSIONS

This section presents the results of the entire research process, encompassing data collection, data processing, and the application and evaluation of a landslide potential prediction model using the Random Forest algorithm. The obtained results include the mapping of landslide potential based on geospatial variables and the model's performance in predicting the likelihood of landslide occurrences in the Sukamakmur area, Bogor Regency. All collected data were subsequently analyzed to generate relevant insights for understanding the region's potential risk of natural disasters.

Data Collection

Primary data was collected through a field survey in Sukamakmur Sub-district, Bogor District. The survey aimed to obtain information on landslide and nonlandslide occurrence points based on historical data from BPBD Bogor District. The primary data obtained is in the form of a map with information on landslide and non-landslide sites indicated by points.

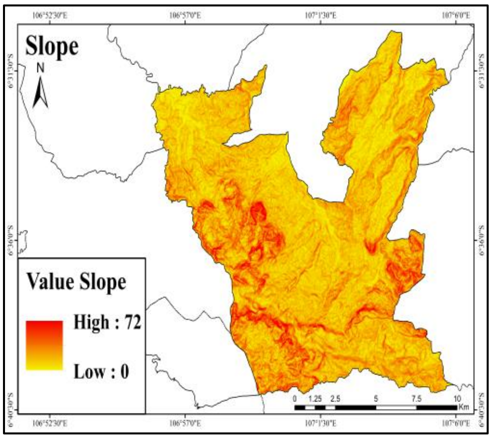
Figure 1: Landslide Inventory Data



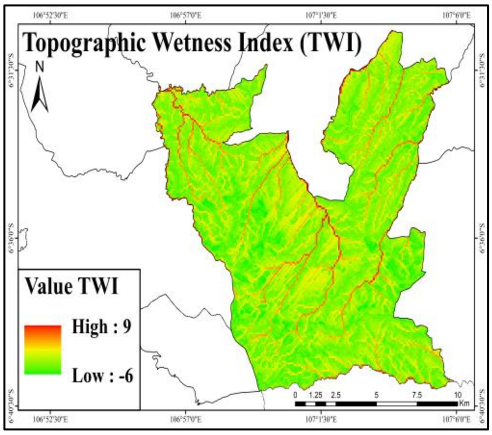
In addition to primary data, secondary data is also used to obtain variables that are causal factors of landslides. Secondary data was obtained from various dataset sources on Google Earth Engine to determine the variables that cause landslides, including slope, Topographic Wetness Index (TWI), distance from river, soil texture, max rainfall, geological type, and land cover. Secondary data in the form of maps are shown in detail as follows.

Figure 2: a. Slope Map; b. Topographic Wetness Index; c. Soil Texture Map; d. Distance from River Map; e. Maximum Rainfall Map; f. Geology Type Map; g. Landcover Map

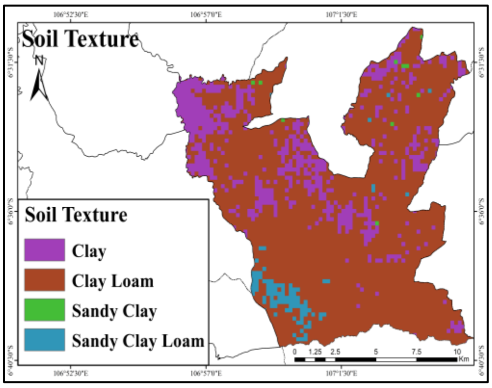
a. Slope Map



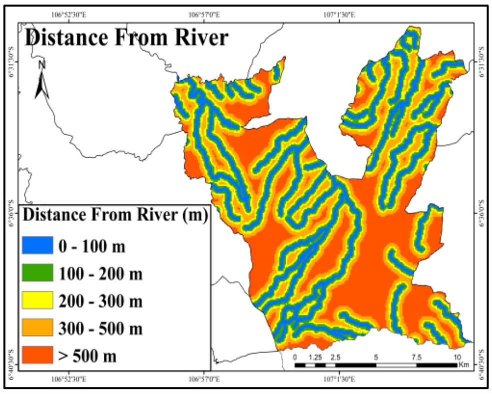
b. Topographic Wetnes Index Map



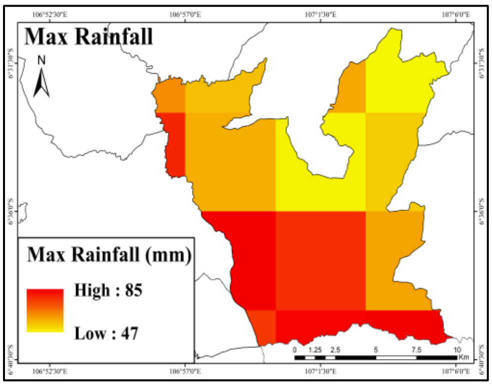
c. Soil Texture Map



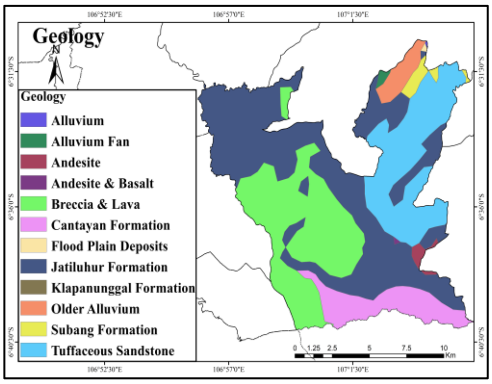
d. Distance from River Map



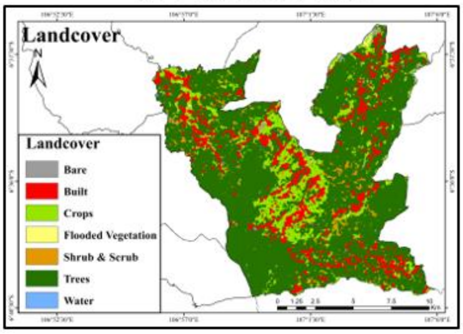
e. Maximum Rainfall Map



f. Geology Type Map



g. Landcover Map



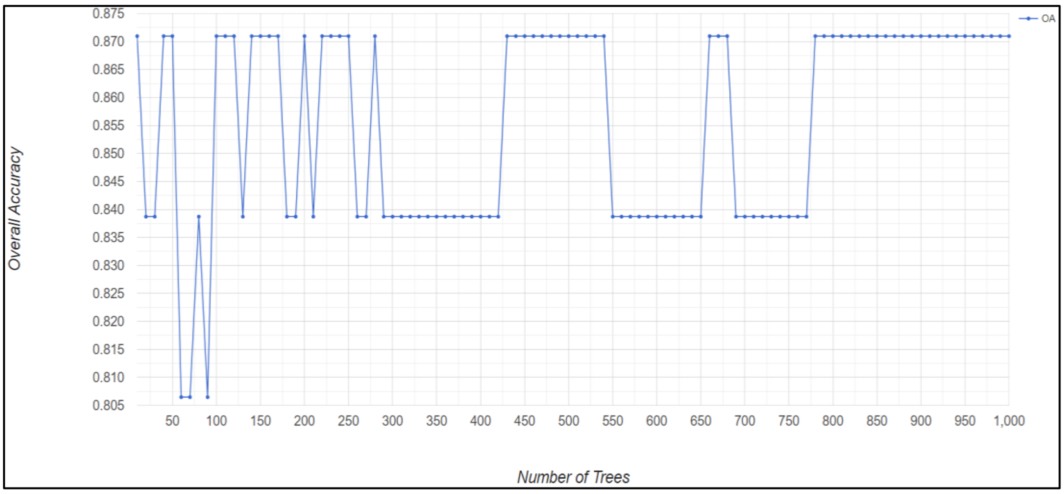
Data Processing

Data processing in this research uses the Google Earth Engine platform. Some of the stages of data processing include determining the study area to focus the analysis only on relevant spatial data within the administrative boundary, importing geological type data, importing soil texture data, importing distance from river data, calculating and adding Topographic Wetness Index, importing land cover data, adding rainfall data, calculating and adding slope data, resampling data to 10 meter resolution to equalize the resolution of all variables used, and the last step is to create a dataset for landslide potential analysis by adding all variable data that has been added previously and giving a class value to each point. The result of this process is sampled points collection that contains all points with values of all variables, which will be used for modeling landslide potential analysis.

Modelling

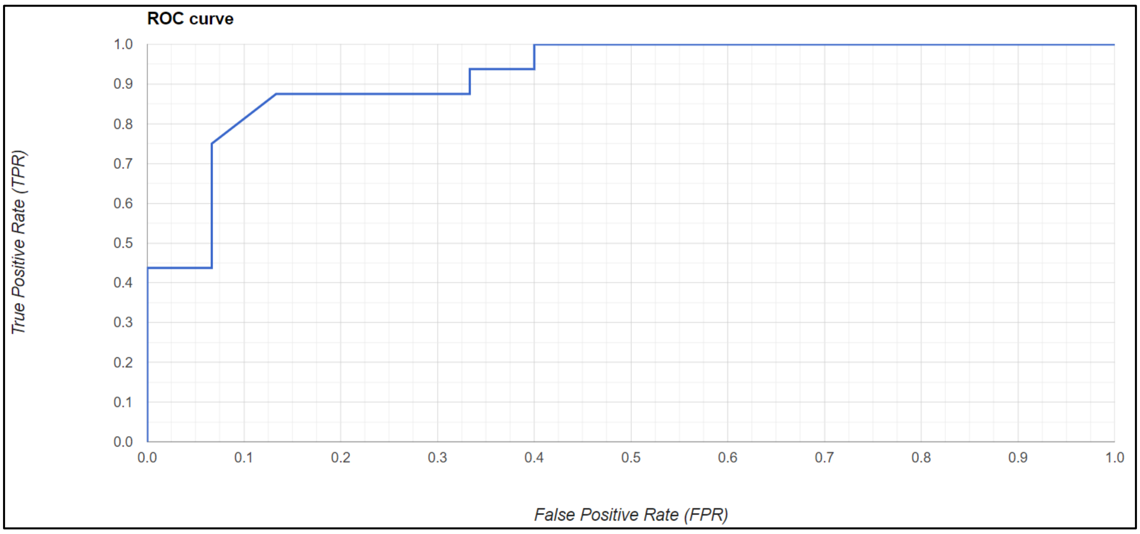
This stage is modeling using a random forest model. This model is used to predict landslide potential based on data that has been collected and processed. The Random Forest model will be trained using data extracted into landslide points and non-landslide points, with various variables such as rainfall, slope, soil texture, geology, distance from the river, etc., as input features. The result of the Random Forest model is a probability value that describes the likelihood of landslide occurrence at each point and is used to generate a map of landslide potential based on its probability level. The data will be divided into two sets of training and validation so that the model is trained and tested with separate data for accurate evaluation. After dividing the data, a tuning process using Google Earth Engine will be conducted to predict landslide potential. The tuning process shows that the overall accuracy (OA) increases as the number of trees increases and stabilizes at a parameter of 10 trees with an OA value of 0.87. The tuning results will be visualized using the features in Google Earth Engine to assist in determining the optimal number of trees for the Random Forest model by selecting the number of trees that provide the highest accuracy. The graph of the tuning result is shown in the figure below.

Figure 3: Random Forest Tuning Result Graph



After modelling using Random Forest is completed, model evaluation is next. This model evaluation assesses the model's ability to predict landslide potential. The evaluation stage starts with making the ROC (Receiver Operating Characteristic) curve and calculating the AUC (Area Under the Curve) to determine the best threshold value. The result is an ROC curve that shows the model's performance in distinguishing landslide and non-landslide classes, with the overall performance measure of the model reaching 0.92, which indicates that the model has an excellent ability for prediction. The ROC curve graph is shown in the figure below.

Figure 4: ROC Curve Graph



Furthermore, model evaluation is carried out based on several evaluation metrics, including Confusion Matrix, Kappa, Sensitivity, and Specificity, with a threshold value of 0.54 obtained from the previous process. These metrics will be calculated and printed to provide an overview of the model's performance in predicting landslide events. The results of the evaluation are shown in the table below as follows.

Table 1: ROC Curve Graph

Confusion Matrix (Threshold 0.54)		Actual	
		0	1
Prediction	0	13	2
	1	2	14
Overall Accuracy	0.87		
Kappa	0.74		
Sensitivity	0.87		
Specificity	0.86		

Discussion

This section discusses the results presented in the previous section, focusing on interpreting the model's performance and the significance of the variables influencing landslide prediction. The Random Forest model's effectiveness in predicting landslide potential is evaluated, highlighting the contributions of various geospatial factors such as slope, soil texture, and distance from rivers. Additionally, the implications of these findings for disaster risk management and mitigation strategies in the Sukamakmur area are explored. The study's limitations and recommendations for future research to enhance model accuracy and applicability in similar regions are also addressed.

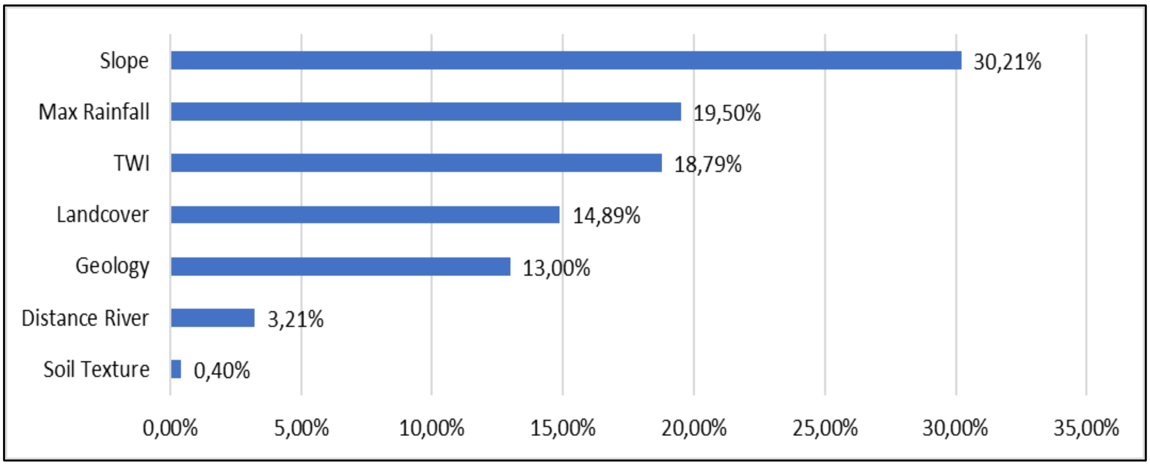
Evaluation of Landslide Potential Modeling Results

In this study, the Random Forest model was applied to predict the landslide potential in the Sukamakmur area, Bogor Regency. The modeling results demonstrate that the model is capable of providing accurate predictions regarding the likelihood of landslides, with an overall accuracy of 87% and Kappa value of 0.74. This indicates that the model has a strong ability to distinguish between points with landslide potential and those without. The AUC (Area Under Curve) value of 0.92 further suggests that the model is highly effective in identifying locations at risk of landslides.

Variable Contribution to Landslide Potential Model

The analysis begins with applying the Random Forest model to identify the variables contributing to landslide prediction, measured as percentages. These variables were assessed by calculating their importance values, which were then converted into percentages using appropriate programming code. The results of this calculation reflect the contribution of each variable, providing a clearer understanding of how much influence each factor has in predicting landslide potential. The percentage contributions of each variable are presented in the figure below, offering a detailed insight into the relative importance of the various geospatial factors in determining landslide risk.

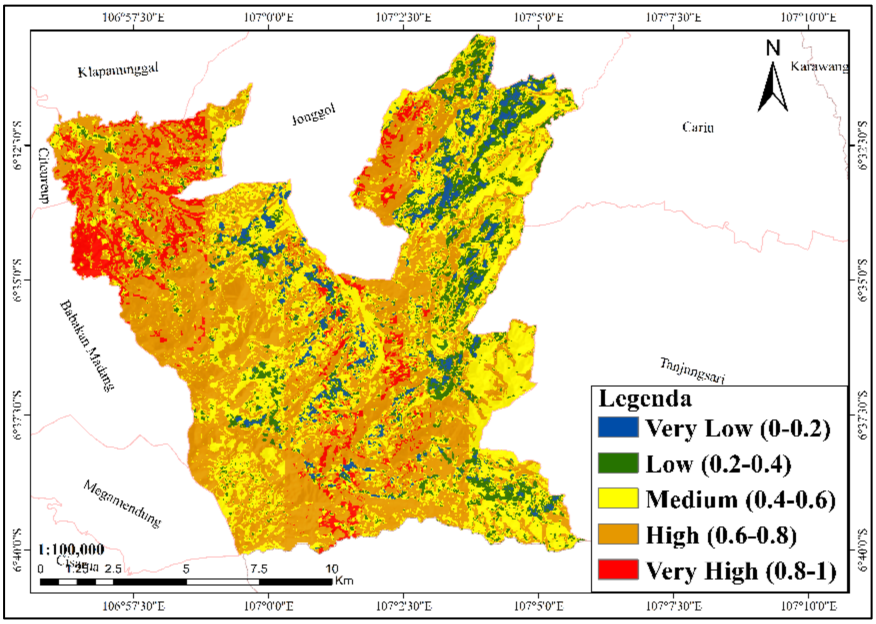
Figure 5: Graph of the contribution of each variable in the Random Forest model



Landslide Potential Mapping and Area Analysis

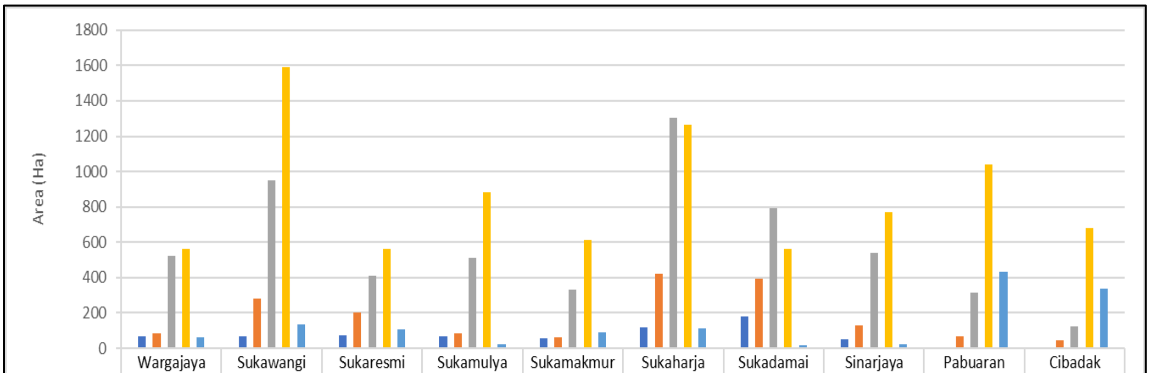
The Random Forest model trained to predict the probability of landslide potential will be applied to the image of the Sukamakmur Sub-district. The application of the model to the image will produce a map of the potential for landslides in the Sukamakmur Sub-district. The landslide potential map is shown in the figure below as follows.

Figure 6: Map of Landslide Potential Modelling Results Sukamakmur Sub-district



An area analysis of the landslide potential level was also conducted to determine how high the landslide potential level is in each village. The landslide potential level analysis results are shown in the figure below, which has been completed with the percentage of each village.

Figure 7: Graph of Total Area of All Landslide Potential Classes



	Wargajaya	Sukawangi	Sukaresmi	Sukamulya	Sukamakmur	Sukaharja	Sukadamai	Sinarjaya	Pabuaran	Cibadak
Very Low	68.73	66.21	73.32	69.78	58.11	119.16	179.94	50.9	2.83	0
Low	83.07	279.82	203.52	82.68	62.29	422.04	392.7	128.78	66.12	45.33
Medium	525.38	948.65	407.96	508.71	333.72	1302.36	792.08	540.95	314.18	121.56
High	563.97	1590.77	564.6	883.81	609.97	1262.04	561.83	767.3	1041.62	678.166
Very High	62.63	134.92	104.58	23.01	88.98	109.87	18.24	20.64	431.57	336.95

From the figure, important points can be noted, including that Sukawangi Village has the highest area in the High category with an area of 1,590.77 Ha, while in the Very Low category, the area is quite small (66.21 Ha). Sukaharja Village also has significant areas in the Medium (1,302.36 Ha) and High (1,262.04 Ha) categories, making it one with high landslide risk. Pabuaran village stands out in the Very High category, with an area of 431.57 Ha, while the High category also covers a large area (1,041.62 Ha). Cibadak village also has a significant area in the Very High category with 336.95 Ha, although the rest is smaller in the Very Low category (0 Ha). In general, villages such as Sukawangi, Sukaharja, and

Pabuaran have significant areas in the High and Very High landslide potential categories, indicating the need for more attention to disaster

CONCLUSION

Based on the results of the Random Forest modelling for landslide susceptibility in Sukamakmur Sub-district, this study successfully produced a five-class landslide susceptibility map using seven influential geospatial variables, including slope, Topographic Wetness Index (TWI), distance from river, soil texture, maximum rainfall, geological type, and land cover. The model shows that the very high landslide susceptibility class covers 1,331.39 Ha, dominated by Pabuaran (32.4%) and Cibadak (25.3%) Villages. The high susceptibility class covers 8,524.05 Ha, with Sukawangi Village contributing the largest area (18.66%). The medium, low, and very low classes cover 5,795.55 Ha, 1,766.35 Ha, and 688.98 Ha, respectively.

The Random Forest model demonstrated excellent predictive performance, with an AUC of 0.92, an optimal threshold of 0.54, overall accuracy of 0.87, Kappa of 0.74, sensitivity of 0.87, and specificity of 0.86. The variable importance analysis showed that slope contributed the most (30.21%), followed by maximum rainfall (19.50%) and TWI (18.79%), while land cover, geology, distance from river, and soil texture contributed smaller proportions. These findings confirm that topographic and hydrological factors play a dominant role in landslide occurrence in the study area.

Limitations of this study include the reliance on the availability and accuracy of secondary datasets from Google Earth Engine, the use of a single machine-learning algorithm, and the limited number of field-verified landslide points. Additionally, the model does not account for anthropogenic influences such as road construction, deforestation, and land-use changes occurring after the data acquisition period.

Future research is recommended to incorporate additional machine-learning algorithms for comparison, expand the landslide inventory using multi-temporal field surveys, integrate higher-resolution terrain data such as LiDAR, and include human-induced factors to improve model accuracy. Time-series rainfall or dynamic soil-moisture data could also enhance the temporal sensitivity of landslide prediction.

Overall, the resulting landslide susceptibility map provides valuable spatial information that can support disaster mitigation efforts in Sukamakmur Sub-district. The outputs of this study can assist local authorities, particularly BPBD Bogor Regency, in prioritizing high-risk areas, planning early warning systems, and guiding land-use management to reduce the future impact of landslides.

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