

Article

Enhancing Earthquake-Induced Landslide Susceptibility Mapping Through Integration of Climatological Soil Moisture: A Hybrid CNN–Swin Transformer Approach

Mustafa Kamal ¹, Yi Wang ^{1,*}, Tao Chen ¹, Luca Brocca ², Muhammad Rashid ¹ and Abbas Abbaszadeh Shahri ³

¹ School of Geophysics and Geomatics, China University of Geosciences, Wuhan 430074, China; 2202390019@cug.edu.cn (M.K.); taochen@cug.edu.cn (T.C.) rashid@cug.edu.cn (M.R.)

² Institute of Geosciences, National Research Council, 06128 Perugia, Italy; luca.brocca@cnr.it

³ Faculty of Engineering and Technology, Bircham International University, 28691 Madrid, Spain; shahri.abbas@bircham.edu

* Correspondence: cug.yi.wang@gmail.com

Highlights

What are the main findings?

- A Hybrid CNN-SwinT model achieved high accuracy in earthquake-induced landslide susceptibility mapping and outperformed individual deep learning models.
- Integrating long-term mean soil moisture as a static hydrological conditioning factor improved model performance of earthquake-induced landslides.

What are the implications of the main findings?

- Climatological Soil moisture information should be considered as complementary hydrological conditioning factors to improve the reliability of hazard mapping.
- The proposed framework provides an effective approach for high-resolution landslide susceptibility mapping and risk management in seismically active areas.

Abstract

Assessing earthquake-induced landslide (EQIL) susceptibility is essential for hazard mitigation in mountainous regions. While background hydrological variations influence slope stability, long-term mean soil moisture is rarely incorporated into deep learning-based landslide susceptibility mapping (LSM). This study proposes a hybrid Convolutional Neural Network and Swin Transformer (CNN-SwinT) framework that integrates long-term mean soil moisture as a static covariate to represent persistent background moisture conditions. The model couples the local spatial feature extraction of CNNs with the hierarchical contextual representation of Swin Transformers to capture multi-scale spatial dependencies. Using Minxian County of China as the study area, thirteen conditioning factors were selected via multicollinearity and information gain ratio analyses. The dataset was split into training (70%) and validation (30%) sets. Performance comparison against standalone CNN and SwinT models revealed that the hybrid CNN-SwinT achieved the highest accuracy (0.856) and AUC (0.95), with predicted high-susceptibility zones closely aligning with historical inventories. However, these reported metrics reflect a random, spatially non-independent split, and spatial block cross-validation is recommended for future operational deployment. The results demonstrate that incorporating long-term mean soil moisture provides critical complementary hydrological information that enhances predictive performance. These findings indicate that the proposed hybrid framework is reliable and effective for high-resolution EQIL susceptibility mapping.

Academic Editor: Dusan Gleich

Received: 5 June 2026

Revised: 22 July 2026

Accepted: 25 July 2026

Published: 31 July 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: earthquake-induced landslide; susceptibility mapping; soil moisture; hybrid CNN-SwinT; Minxian County

1. Introduction

Landslides are catastrophic geomorphic hazards in mountainous regions worldwide, causing extensive damage to infrastructure, economic disruption, and fatalities [1,2]. In tectonically active mountainous areas, earthquake-induced landslides serve as a secondary hazard that can severely intensify the social consequences of seismic events. A comprehensive understanding of the geographic occurrence and controlling mechanisms of earthquake-induced landslides is therefore crucial for effective hazard reduction, land-use planning, and sustainable regional development [3]. Consequently, Landslide Susceptibility Mapping (LSM) has become a widely adopted analytical technique for identifying landslide-prone regions by evaluating the spatial relationships between geo-environmental variables and historical landslide inventories [4].

Surface roughness and high-resolution topographic features have shown significant improvement in landslide susceptibility assessments [5,6]. Ultimately, climate fluctuations, hydrological conditions, geology, and topography interactively influence the occurrence of landslides. According to [7–9], soil moisture exerts a profound impact on slope stability by controlling pore-water pressure and lowering effective shear strength. Slope stability depends heavily on soil moisture because it directly affects pore-water pressure, soil cohesion, and effective stress. Rainfall penetration increases soil moisture content, which weakens soil shear strength and elevates the risk of slope failure [9]. Because hydrological processes exert a dominant influence on landslide occurrence, soil moisture provides crucial information regarding subsurface instability [10].

Furthermore, the use of high-resolution remote sensing data enhances the accuracy of landslide susceptibility modeling by better representing spatial variability [11]. Thus, integrating soil moisture into landslide susceptibility modeling enhances the reliability of the assessment and provides a more physically realistic depiction of slope hydrological processes [12]. Recent studies indicate that combining traditional influencing factors with high-resolution soil moisture data can significantly enhance landslide susceptibility modeling, resulting in more accurate susceptibility maps [13].

Even in the absence of adverse rainfall events, climate variability can significantly aid in identifying the preconditioning slope states susceptible to failure by altering climatological moisture conditions. Climate variability influences long-term hydrological conditions that affect slope susceptibility by modifying the spatial distribution of soil moisture and groundwater storage. Consequently, spatial long-term mean soil moisture information provides valuable insights into the hydrological controls driving slope instability, even when event-specific climatological soil moisture observations are unavailable [14–16]. Therefore, the predictive reliability of landslide susceptibility analysis depends heavily on the integration of hydrological data, particularly in seismically active regions.

During the last two decades, methodological approaches to landslide susceptibility assessment have substantially shifted from traditional statistical methods to sophisticated machine learning (ML) and deep learning (DL) frameworks [17–21]. It has been demonstrated that ML-based techniques are highly effective at capturing intricate, nonlinear relationships between landslide events and environmental influencing factors. Deep learning approaches demonstrate superior performance in landslide susceptibility mapping by effectively capturing complex spatial patterns [8]. In particular, Convolutional Neural Networks (CNNs) have been increasingly integrated into DL architectures due to their

capacity to automatically extract spatial features from multi-dimensional datasets pertinent to slope instability [22,23]. Concurrently with CNN-based advancements, the field of geospatial analysis has embraced Swin Transformer-based architectures. These architectures offer advanced capabilities for modeling contextual interactions and long-range spatial dependencies within environmental data [2,24,25].

Building on these developments, hybrid and ensemble learning techniques have emerged as a viable means of enhancing the generalizability and robustness of landslide susceptibility models [26–28]. In landslide susceptibility mapping, hybrid frameworks have shown remarkable stability and predictive accuracy by combining complementary learning mechanisms, such as convolutional feature extraction and attention-based contextual refinement [29]. Furthermore, recent studies have highlighted the significance of ensemble and explainable AI approaches for addressing the spatial heterogeneities and uncertainties inherent in geohazards [30–32].

Despite these noteworthy analytical advancements, the application of remotely sensed soil moisture data in EQIL susceptibility mapping remains highly limited. Fewer studies have examined soil moisture as an influencing factor for seismic landslide susceptibility, even though it has been thoroughly investigated in connection with rainfall-induced landslides [33]. From a geotechnical perspective, increased soil moisture can reduce effective stress and shear strength, thereby increasing slope susceptibility under seismic loading [34–37]. Although event-specific climatological soil moisture may influence earthquake-triggered landslides, the present study focuses on evaluating whether long-term spatial soil moisture information provides additional predictive value as a static hydrological conditioning factor in landslide susceptibility mapping. The present study overcomes the limitations of previous work by establishing a novel deep learning framework that utilizes a CNN, a Swin Transformer, and a proposed hybrid CNN-SwinT model, while incorporating long-term mean soil moisture as a regulating influencing factor for landslide susceptibility mapping. Accordingly, the objective of this study is not to quantify the effect of transient climatological soil moisture immediately before an earthquake, but rather to investigate whether incorporating long-term spatial soil moisture information can improve EQIL susceptibility predictions. The performance of each model was investigated using an identical experimental environment. To quantify the impact of soil moisture, each model was evaluated under two distinct scenarios: with and without the inclusion of soil moisture data. Ultimately, this study aims to increase the reliability of landslide susceptibility mapping in Minxian County, Gansu, China, and to provide sound scientific guidance for regional land-use strategies and risk mitigation. As a consequence of the technical review presented, the following contributions can be highlighted:

1. **Methodological innovation:** Developed a novel hybrid CNN-SwinT deep learning framework that successfully integrates localized convolutional feature extraction with attention-based, long-range spatial dependency modeling for LSM.
2. **Hydrological integration gap-filling:** Pioneered the application of remotely sensed long-term spatial soil moisture data as a static hydrological conditioning factor within earthquake-induced LSM, addressing a critical oversight in conventional seismic hazard frameworks.
3. **Controlled Empirical Validation:** Quantified the predictive significance of soil moisture through a controlled, dual-scenario comparative analysis (modeled with and without hydrological data) under uniform experimental conditions, demonstrating a marked improvement in classification accuracy and spatial consistency.

The proposed approach has been successfully applied to provide a reliable, high-resolution susceptibility map for Minxian County, Gansu, China, establishing a scalable, transferable framework to guide regional land-use planning and disaster risk reduction strategies in seismically active mountainous terrains.

2. Materials and Methods

2.1. Study Area and Created Landslide Inventory Map

Minxian belongs to the south of Dingxi city, Gansu province, which lies between the latitudes of 34°0'N and 34°50'N and the longitudes of 103°40'E and 105°0'E. It is located on the eastern edge of the Tibetan Plateau, which is tectonically very active due to ongoing collision between the Indian and Eurasian plates, and is affected by the East-Kunlun and West Qinling strike-slip faults. Among these faults is the Lintan-Dangchang fault, which was ruptured on 22 July 2013 by a Mw 5.9 earthquake [38]. The area is distinguished by rough mountainous terrain and a deep carved river-valley system connected to the Tao River. The elevation varies between 2208 and 3351 m with steep slopes and noticeable relief. Climatically, the region lies in a humid to cold semi-humid transitional zone with an average of 600 mm of precipitation annually, which promotes earthquake-induced landslides. A week before the 2013 earthquake, a noteworthy accumulation of 10–20 mm rainfall was measured, which could have impacted the pre-event slope saturation conditions [39].

The spatial distribution of landslides in a susceptible area can be exposed using a landslide inventory. Therefore, landslide inventory is essential for landslide susceptibility assessment [40]. The landslide inventory of Minxian-Zhangxin [41] was acquired from USGS. Using the landslide inventory, 871 landslide samples were extracted as shown in Figure 1c, and about the same number of non-landslide samples were chosen randomly for further analysis. To create a balanced dataset, an equal number of non-landslide locations were randomly selected within the study area where no landslide incidents were documented. Random sampling of non-landslide locations is a widely adopted strategy in landslide susceptibility mapping because reliable inventories of stable slopes are generally unavailable, making random selection from documented non-landslide areas a practical and commonly accepted approach [42,43]. To reduce potential sampling bias and improve spatial independence between the positive and negative samples, a 1 km buffer was generated around the mapped landslide polygons using the Buffer tool in ArcGIS Pro. Non-landslide samples were then randomly selected only from areas outside the buffer zone, thereby minimizing the inclusion of potentially unstable transitional areas and improving the reliability and representativeness of the training dataset.

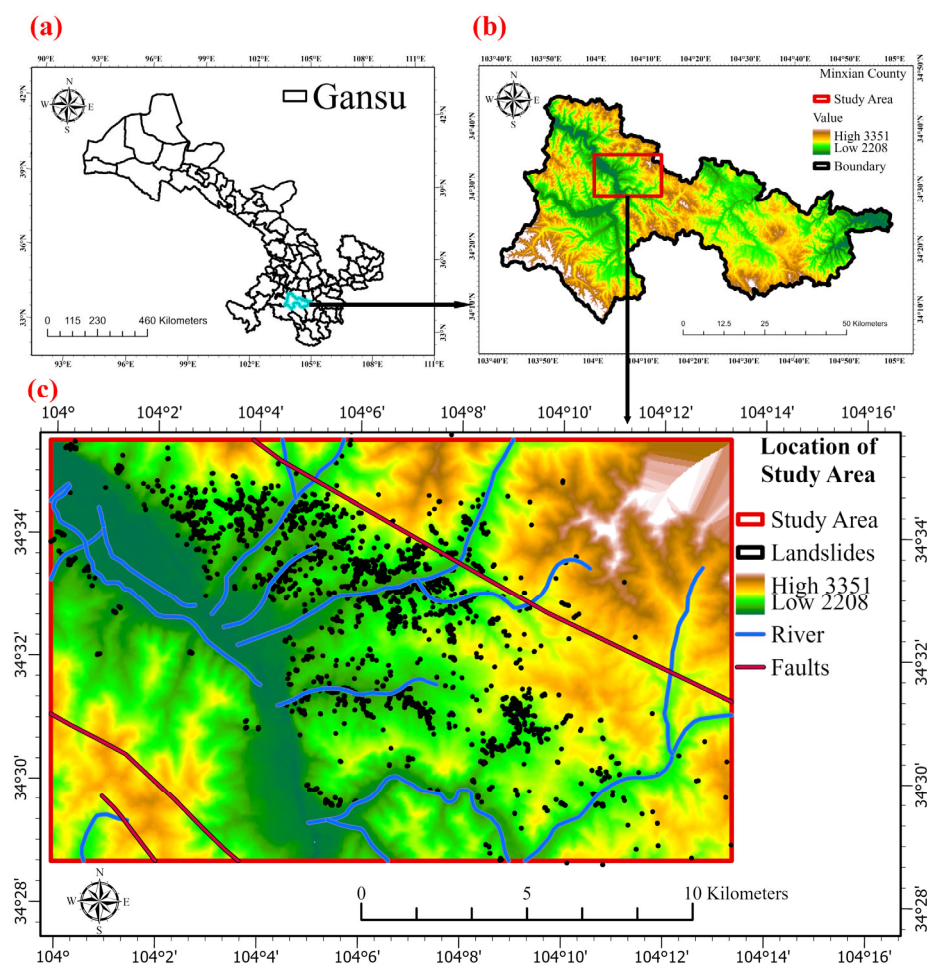


Figure 1. Overview of region (a), the location of the study area (b), and the generated landslide inventory map (c).

2.2. Landslide Causative Factors

LSM operates on the premise that future slope failures are likely to occur under environmental conditions similar to those that triggered past events. Consequently, the meticulous selection of landslide causative factors is essential to enhance model reliability and interpretability. Even though landslides are influenced by numerous factors [4], it makes sense to focus on the most important ones to reduce uncertainty. Thirteen causative factors, including elevation, aspect, plane curvature (PLC), slope, hillshade, lithology, peak ground acceleration (PGA), normalized difference vegetation index (NDVI), dominant soil (DOM), land use, distance to river (DTR), rainfall, and soil moisture supported by resources, were considered in this study (Table 1). The soil moisture data provide spatially consistent information on long-term soil moisture conditions and are considered an important hydro-environmental factor influencing post-seismic slope instability.

Table 1. Detailed information on the employed landslide causative factors.

LIFs	Source	Values	Scale/Resolution
Elevation (m)	http://www.gscloud.cn (accessed on 20 October 2024)	2208–3351 m	30 × 30 m
Lithology	http://gsd.cgs.cn/ (accessed on 15 November 2023)	Gneiss, Schist	1:50,000
Land Use	http://www.resdc.cn/ (accessed on 30 November 2023)	MH, HH, HM	30 × 30 m
Dominant Soil	http://www.resdc.cn/ (accessed on 30 November 2023)	Haplic, Calcic, Luvisol, Dystric, Eutric	1:1,000,000

DTR (km)	https://www.webmap.cn/mapDataAction.do (accessed on 31 December 2023)	1–5 km	1:10,000
Rainfall	https://doi.org/10.5281/zenodo.7949858 (accessed on 8 January 2024)	65–197.52 mm	30 × 30 m
Soil Moisture	http://dx.doi.org/10.11888/Terre.tpd.272415 (accessed on 8 January 2024)	0.272–0.376 m ³ /m ³	30 × 30 m
PGA	http://earthquake.usgs.gov/shake/earthquakeexplore/ (accessed on 25 October 2023)	0.02–0.18 g	30 × 30 m
NDVI	Landsat-8	−0.275–0.689	30 × 30 m
PLC (1/m)	DEM (USGS EarthExplorer)	−4.954–4.998	30 × 30 m
Slope (°)	DEM (USGS EarthExplorer)	0–64°	30 × 30 m
Aspect	DEM (USGS EarthExplorer)	North, East, South, West, North-west	30 × 30 m
Hillshade	DEM (USGS EarthExplorer)	0–254	30 × 30 m

2.3. Methodology and Modeling Procedure

The methodology of this research was based on deep learning techniques using Convolutional Neural Network (CNN), Swin Transformer (SwinT), and hybrid CNN-SwinT. Multicollinearity tests were conducted on all influencing factors to assess data reliability before modelling [34]. The significance of soil moisture was then demonstrated by quantifying factor importance using the information gain ratio (IGR) approach, which is explained in Section 2.3.2. Landslide and non-landslide samples were used under comparable environmental circumstances to generate a balanced landslide inventory. Figure 2 depicts the overall methodological flow.

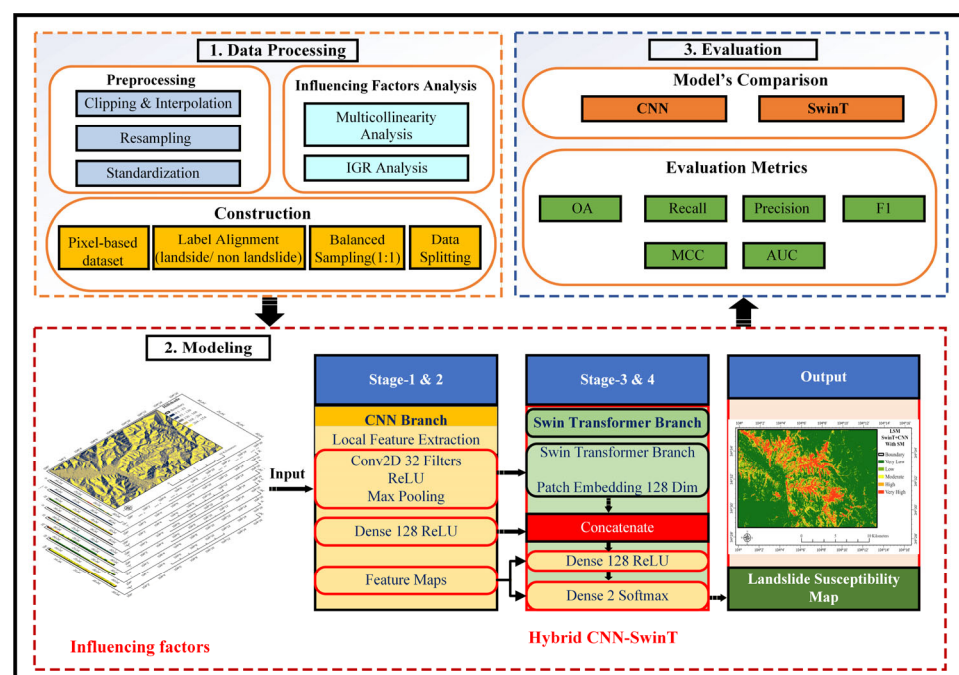


Figure 2. Proposed methodology workflow.

CNNs are deep learning architectures designed to process grid-structured data through integrated convolutional, pooling, and fully connected layers [44]. By leveraging stacked convolutional layers with local receptive fields, CNNs effectively extract localized spatial features while maintaining parameter efficiency [45,46]. Consequently, they are widely utilized in LSM for their capacity to computationally efficiently capture fine-scale geomorphological and hydrological patterns—such as slope morphology and soil moisture variations—from multi-channel conditioning factors [47]. This makes CNN-based

models highly effective when local spatial features dominate landslide-triggering mechanisms.

CNN is a deep learning architecture with a specific ability to process images [46]. A CNN comprises one or more layers, including convolutional, pooling, and fully connected layers. This arrangement allows for the effective extraction of localized spatial data while keeping parameter efficiency [45,46].

Transformer-based approaches have recently gained substantial traction in geospatial analysis due to their capacity to capture global spatial features beyond the restricted receptive fields of conventional CNNs [48]. The Swin Transformer addresses this by utilizing window-based self-attention with a shifted-window mechanism, creating a hierarchical architecture that learns contextual features while avoiding the quadratic computational costs of global self-attention [43]. While Swin Transformer base models excel at capturing large-scale spatial interactions and show significant potential in integrating landslide-influencing factors for susceptibility mapping [25], they may underperform when landslide initiation is heavily governed by fine-scale, localized variables.

Recent studies have shown that frameworks based on Swin Transformers are sufficiently adaptable to capture the spatial dependence hierarchy in LSM without compromising computational viability [25]. Inspired by the hierarchical mechanism, this study proposes a hybrid CNN-SwinT architecture that blends window-based attention with convolutional feature learning. In the proposed model, the CNN branch is responsible for extracting fine-scale local characteristics from multi-channel landslide-influencing factors. While the Swin Transformer employs hierarchical shifted-window attention for global-scale spatial dependencies. This hybrid architecture improves learning robustness in prediction under the same experimental environment while avoiding the computational cost of global attention mechanisms and enabling effective multi-scale feature learning.

2.3.1. Data Processing, Factor Evaluation, and Multicollinearity Test

Spatial consistency was ensured by reprojecting all thematic layers to WGS84/UTM Zone 47, resampling them with bilinear interpolation to 30×30 m resolution [17,49], and clipping them to the research boundary. Using ArcGIS Pro, the layers were created and aligned with the DEM grid to maintain pixel-level coherence. The invalid values were handled in accordance with [1]. This process facilitates faster and more reliable model convergence by reducing scale disparities across features.

Selecting the appropriate influencing factors is crucial for accurate modelling. Establishing unimportant or marginally significant factors could increase noise and obscure the signal from significant landslides, reducing prediction accuracy. On the other hand, high factor correlations can lead to data redundancy, reducing model performance and introducing bias in the weights assigned to features during training. To address these issues, a collinearity test and factor importance analysis were conducted before creating the landslide sample dataset.

A strong relationship between the influencing factors that cause landslides is referred to as multicollinearity in statistics. Predictive modelling may be biased because of this relationship, which can lead to an imbalanced parameter estimation between the predictors and the outcome [50]. The multicollinearity test was employed to examine the presence of a linear relationship between variables [24]. The variance inflation factor (VIF) and Tolerance were used to assist in this evaluation. VIF was computed as shown in Equation (1), and the reciprocal of the VIF was defined as tolerance (TOL). Equation (2) shows the coefficient of determination R^2 , which was used in VIF computation.

$$VIF = \frac{1}{1 - R^2_k} = \frac{1}{TOL} \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (2)$$

R^2 typically falls in the range of 0 to 1. Strong multicollinearity occurs when a factor is explained to a significant extent by the remaining factors, as indicated by values of (R^2) that are close to 1. Higher VIF values signify a level of factor redundancy accordingly. A factor is considered highly collinear with a VIF value greater than 5, or occasionally 10 in less strict criteria, and will not be further examined.

Consequently, a uniform dataset was created for modelling according to the pre-processing step and analysis of causative factors [17]. Every factor layer was spatially aligned and stacked into a multichannel data structure of size (H, W, C), where C represents the number of causative factors, while H and W, show spatial dimensions. Rather than treating each pixel as an independent training sample, the stacked data cube was used to generate fixed-size image patches centered on labeled pixels. Each patch, therefore, contained both the central pixel and its surrounding neighborhood, allowing the CNN–SwinT model to learn local spatial structures together with contextual information. To improve sample quality, only patches whose dominant class label was consistent with the central pixel label were retained for model training, while inconsistent patches were discarded. The historical landslides yielded 871 landslide locations in total. To create a balanced dataset, an equal number of non-landslide locations were randomly created inside the study area where no landslide incidents were documented. To prevent spatial overlap with actual landslides, the non-landslide points were randomly selected only from areas outside the 1 km buffer established around the mapped landslide polygons, thereby reducing the inclusion of potentially unstable transitional zones and improving spatial independence between the two classes. To reduce sampling bias, a balanced dataset was generated with comparable environmental circumstances. Following that, the dataset was then randomly split into 70% training and 30% validation respectively. The same patch-level random partition was applied consistently to all CNN, SwinT, and Hybrid CNN–SwinT experiments, both with and without soil moisture, to ensure a fair comparison of the contribution of soil moisture under identical experimental conditions. The performance of the model was then evaluated using the validation dataset.

2.3.2. Information Gain Ratio (IGR) Analysis

Attribute mean (AM) values were computed using Gain Ratio analysis to evaluate the importance of the conditioning factors [51]. Higher AM values indicate a stronger correlation with landslide occurrence, signifying greater relevance to susceptibility modeling. Because all selected factors exhibited positive AM values, they were retained for subsequent analysis and modeling stages. Figure 4 shows the AM factor values.

2.3.3. Optimal Model and Experimental Hyperparameter Setting

All the experiments were conducted using Python 3.10 and the TensorFlow 2.X framework on a Linux workstation equipped with an Intel chip, a multi-core CPU, 128 GB RAM, and four NGPUs (GPUs). The model was optimized using the Adam optimizer, which provides stable and effective convergence, and the cross-entropy loss function was used for the binary classification of landslides. The network architecture and training hyperparameters were selected based on commonly adopted configurations reported in previous CNN–Swin Transformer-based landslide susceptibility studies, together with preliminary experiments to achieve stable convergence and minimize overfitting [52]. To make sure that the models converged without overfitting, a batch size of 32 was employed, and each model was trained for 200 epochs. Early stopping, batch optimization, dropout,

and L2 regularization were incorporated during training to further improve model generalization and reduce the risk of overfitting [53]. CNN employed 3×3 convolutional kernels, with 32 and 64 filters, followed by 2×2 max pooling, as well as a fully connected layer of 128 neurons with a ReLU activation function. The SwinT used the GELU activation function with 2 transformer blocks, 8 attention heads, 3×3 patch size, and an embedding dimension of 128 to learn global-spatial information. Under the training settings, the hybrid CNN-SwinT feature fusion technique was carried out by concatenating the joint local and global feature learners (Figure 3, Tables 2 and 3). To ensure a fair comparison, the same network architecture and hyperparameter settings were consistently applied to all CNN, Swin Transformer, and hybrid CNN-SwinT models, including the experiments with and without soil moisture.

Table 2. Details of Computer Hardware.

Items	Parameters
CPU	Intel(R) Core (TM) i5-(server-class processor)
GPU	4 × NVIDIA GeForce RTX 3090 (24 GB VRAM each, PCIe)
Memory	128 GB RAM
Hard Disk	High-capacity local storage (multi-terabyte)

Table 3. Managed hyperparameters for the optimal setting.

Models	Parameter Settings
Convolutional Neural Network (CNN)	Convolutional Kernel size: 3×3 ; filters: 32, 64; max pooling size: 2×2 ; dense layer size: 128; activation function: ReLU; optimizer: Adam; batch size: 32; number of epochs: 200
Swin Transformer (SwinT)	Patch size: 3×3 ; embedding dimension: 128; swin transformer blocks: 2; attention heads: 8; activation function: GELU; optimizer: Adam; batch size: 32; number of epochs: 200
Hybrid CNN-SwinT	CNN branch: convolutional kernel size: 3×3 ; filters: 32, 64; max pooling size: 2×2 ; dense layer size: 128 SwinT branch: patch size: 3×3 ; embedding dimension: 128; swin transformer blocks: 2; attention heads: 8; feature fusion: concatenation; activation function: ReLU; optimizer: Adam; batch size: 32; number of epochs: 200

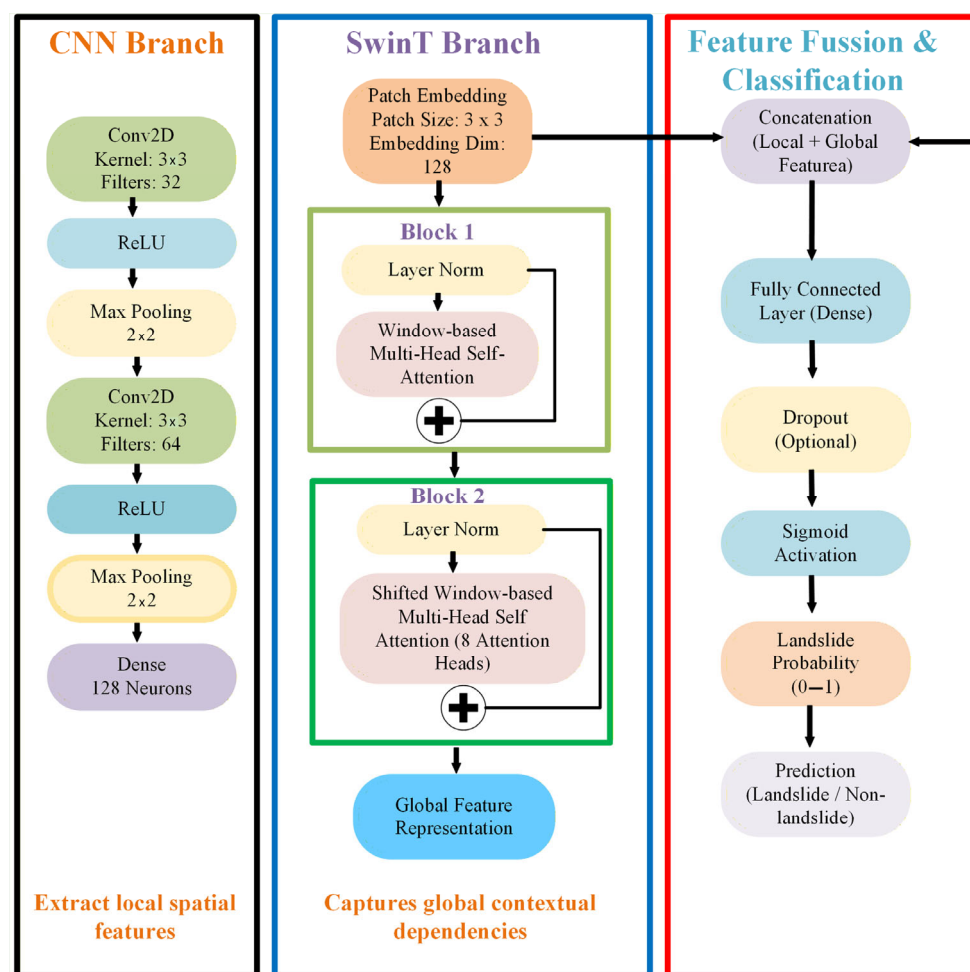


Figure 3. Procedure of hyperparameter settings of the proposed model.

To quantify the impact of soil moisture, three models, including CNN, SwinT, and hybrid CNN-SwinT, were trained twice with and without soil moisture while keeping the same training procedure, architecture, and hyperparameters. This controlled ablation design enables a fair contribution of soil moisture across different model architectures under identical experimental conditions.

3. Results

3.1. Multicollinearity Analysis

Every influencing factor in the research domain was evaluated for collinearity. Table 4 displays VIF and tolerance, demonstrating no substantial multicollinearity. Therefore, all the factors can be included in LSM analysis as they exhibit VIF scores lower than 5.

Table 4. Multicollinearity analysis results.

Influencing Factors	Tolerance	VIF
Elevation	0.238	4.20
Rainfall	0.512	1.95
Soil Moisture	0.531	1.88
Dominant Soil	0.548	1.82
NDVI	0.589	1.70
PGA	0.603	1.66
Land Use	0.611	1.64
Aspect	0.668	1.50

Distance to the river	0.762	1.31
Curvature	0.796	1.26
Slope	0.803	1.25
Hillshade	0.815	1.23
Lithology	0.931	1.07

3.2. AM-Based Importance Analysis

The relative importance of influencing factors ranked by AM is shown in Figure 4. The elevation contributes the most with the AM value 0.066. It is noteworthy that soil moisture ranks second with the AM value 0.049, indicating its significance and independent influence on landslide occurrence, and that it is not solely influenced by conventional topographic and geologic factors. The AM values of PGA and rainfall are 0.043 and 0.037, which show the combined effect of hydrological and seismic activity. Alongside the moderate influence of lithology, hillshade and aspect have secondary influence with the AM values 0.031, 0.018, and 0.012 respectively. In contrast, the remaining factors have a relatively small impact on performance, with the distance to the river having the lowest AM value of 0.004. Overall, these findings collectively highlight the significance of soil moisture for landslide susceptibility.

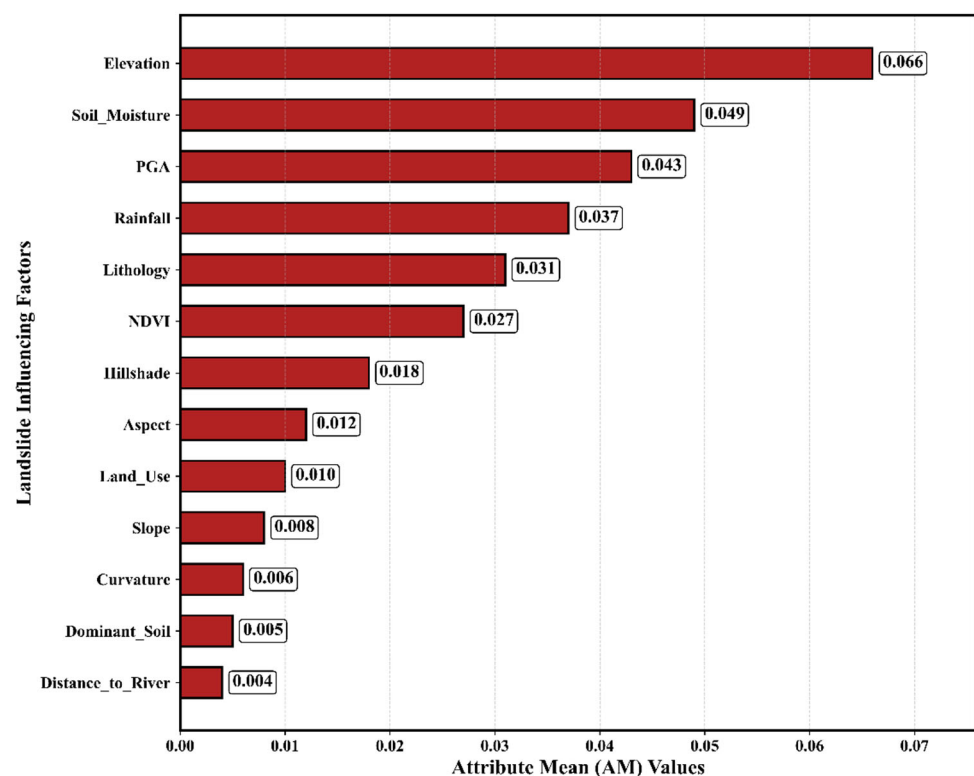


Figure 4. Relative importance of Influencing Factors.

3.3. Comparison of Generated LSM

Using CNN, SwinT and hybrid CNN-SwinT, landslide susceptibility maps were created and classified (Figure 5). The results showed that the high-risk zones are near known landslide sites, while moderate-risk zones are transition belts that shift into low-hazard areas corresponding to thematic spatial areas. Comparison of CNN, SwinT, and hybrid CNN-SwinT exhibited different spatial patterns, i.e., CNN characterized class boundaries and precise spatial features, while SwinT showed a weak class transition and regional distribution of susceptibility on coarse scales. Integrated CNN-SwinT then generated higher connectivity in transition zones and reduced fragmentation of high susceptibility

zones, leading to the most spatially coherent maps and consistent quantitative performance with spatial trends.

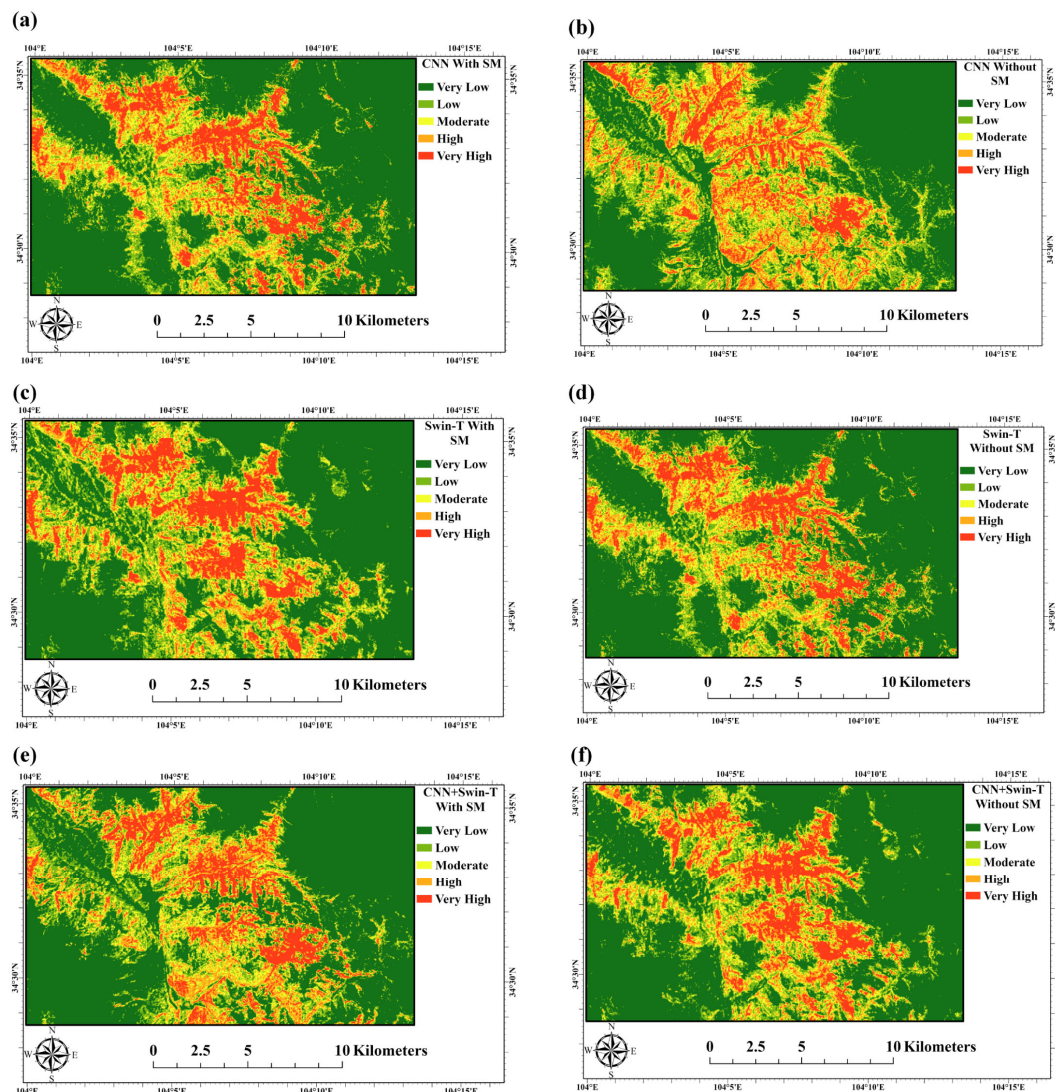


Figure 5. Landslide susceptibility map including (a,c,e) and excluding (b,d,f) soil moisture alongside other causative factors.

The predictability of the model was then evaluated using the area under the curve of the receiver operating characteristic (AUC-ROC) as well as overall accuracy (Equation (3)), precision (Equation (4)), recall (Equation (5)), F1-score (Equation (6)), and Matthew's correlation coefficient (MCC) (Equation (7)).

$$OA = \frac{TP + TN}{TP + FP + TN + FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

$$F1 = 2 * \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}} \quad (7)$$

where TP (True Positive) and TN (True Negative) denote the accurately identified landslide and non-landslide samples. False Positive (FP) is a non-landslide that is predicted as a landslide, whereas False Negatives (FN) are the landslides that are predicted to be non-landslides. Overall accuracy (OA) shows the percentage of samples that were accurately identified out of all the predictions by the model. Precision is the percentage of accurately predicted landslide samples out of all that were identified as landslides. Recall denotes the percentage of accurately predicted landslide samples out of all actual landslides. F1-Score shows the harmonic mean of precision and recall, providing a single metric balancing both metrics. MCC spans from −1 to 1 and accounts for TP, TN, FP, and FN. Accurate predictions have an MCC of 1, random predictions have an MCC of 0, while complete discrepancies between predictions and observations have an MCC of −1.

Based on these metrics, integrating the soil moisture with the proposed hybrid CNN-SwinT dedicated the highest OA values of 0.856 and 0.950 among the evaluated models under the adopted experimental framework. CNN consistently outperforms SwinT in single modelling, with OA and AUC values of 0.835 and 0.92. The hybrid model improved prediction ability and higher spatial continuity are consistent with the IGR analysis, which identified soil moisture as an important regulator of the potential information of landslides. This demonstrates that using soil moisture as a causative factor improves both the classification robustness and spatial representation under the adopted experimental condition.

3.4. Model Evaluation

Table 5 presents a performance comparison of the evaluated models, demonstrating that the hybrid CNN-SwinT model achieves superior performance when soil moisture data is incorporated. This hybrid configuration yielded the highest overall accuracy (OA = 0.856) and area under the receiver operating characteristic curve (AUC = 0.950), outperforming the standalone CNN (OA = 0.835, AUC = 0.920) and SwinT (OA = 0.823, AUC = 0.901) models. Additionally, the hybrid model achieved a recall of 0.902, an F1-score of 0.867, and a Matthews correlation coefficient (MCC) of 0.712, indicating enhanced robustness and class discrimination. The notable increase in AUC (from 0.930 to 0.950) underscores the model's heightened sensitivity to hydrological variables.

Table 5. Model Evaluation Metrics.

Models	OA	Precision	Recall	F1	MCC	AUC
CNN with SM	0.835	0.811	0.873	0.841	0.672	0.92
CNN without SM	0.824	0.805	0.867	0.838	0.659	0.903
SwinT with SM	0.823	0.803	0.858	0.829	0.643	0.901
SwinT without SM	0.814	0.802	0.827	0.816	0.628	0.893
Hybrid CNN-SwinT with SM	0.856	0.852	0.902	0.867	0.712	0.95
Hybrid CNN-SwinT without SM	0.836	0.842	0.881	0.845	0.668	0.93

This superior predictive performance is further supported by the receiver operating characteristic (ROC) curves in Figure 6. While the integration of soil moisture consistently improved metrics across all architectures, each model was evaluated using a single training realization. Consequently, these improvements indicate consistent performance gains within the specific experimental framework rather than statistically significant differences. Future research should validate the robustness of these findings through repeated experiments across multiple random seeds and formal statistical significance testing.

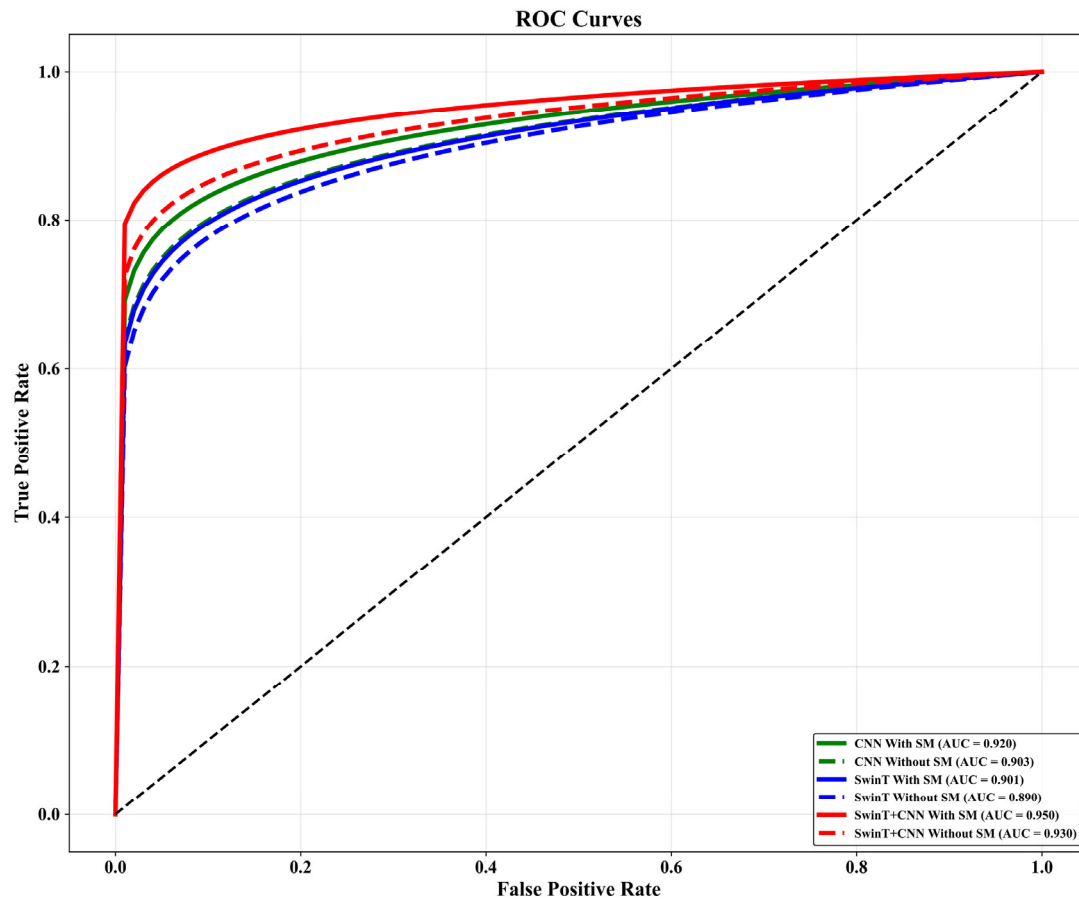


Figure 6. Comparison of the ROC curves among examined models with/without soil moisture.

4. Discussion

The hybrid CNN-SwinT model outperformed both the standalone CNN and SwinT models, achieving an overall accuracy of 0.856 and an AUC of 0.95, compared with AUC values of 0.92 and 0.901 for the CNN and SwinT models, respectively [54]. This improvement can be attributed to the complementary strengths of convolutional and transformer architectures. CNNs are highly effective at extracting local spatial features and texture information from neighboring pixels. In contrast, Swin Transformers employ hierarchical self-attention to model long-range spatial dependencies and contextual relationships across multiple spatial scales [22,34,48]. The hybrid architecture, therefore, provides a more comprehensive representation of the complex interactions among topographic, geological, seismic, and hydrological conditioning factors, resulting in improved predictive performance. Similar improvements achieved by combining convolutional neural networks with transformer-based architectures have also been reported in recent geospatial and hazard-mapping studies. The standalone Swin-Transformer showed lower performance because the static image-patch inputs favor CNN-based local feature extraction. By combining CNN-based and Swin Transformer, the proposed hybrid model effectively captures both local and global spatial information, leading to improved prediction performance [30,42].

Among the thirteen conditioning factors, long-term mean soil moisture was ranked as the second most informative variable by the IGR analysis ($AM = 0.049$), exceeding both rainfall and PGA. The inclusion of this variable consistently improved model performance, increasing AUC, MCC, recall, and the spatial coherence of the susceptibility maps. It is important to note that the soil moisture dataset used in this study represents the long-

term mean spatial distribution of soil moisture rather than the transient moisture conditions immediately preceding the 2013 earthquake. Consequently, the improved prediction performance should be interpreted as the contribution of a climatological soil moisture covariate that captures persistent spatial variations in hydrological conditions, rather than direct evidence of climatological or event-specific soil moisture effects. Persistent spatial patterns of soil moisture are closely related to terrain, drainage conditions, vegetation cover, soil properties, and long-term climatic conditions, all of which influence slope stability and landslide susceptibility [35,55,56].

The observed improvement is consistent with established geotechnical principles indicating that soil moisture influences slope stability through its control on pore-water pressure, matric suction, and effective stress [35,57]. However, because the present study employed a climatological soil moisture dataset rather than event-specific observations, the results should not be interpreted as quantifying the influence of climatological moisture immediately before the earthquake. Instead, they demonstrate that incorporating long-term spatial moisture patterns provides complementary environmental information beyond conventional topographic, geological, and seismic conditioning factors, thereby improving susceptibility prediction.

Despite the strong predictive performance of the proposed framework, several limitations should be acknowledged. The long-term mean soil moisture dataset was incorporated as a static spatial conditioning factor and subsequently resampled to a spatial resolution of 30×30 m to match the remaining predictor variables. While this approach effectively represents persistent spatial variations in background hydrological conditions, it cannot capture the transient evolution of soil moisture associated with short-term precipitation, seasonal variability, or pre-earthquake hydrological conditions. Therefore, enhanced model performance should be interpreted as reflecting the value of a climatological hydrological predictor rather than the direct influence of climatological soil moisture before the 2013 earthquake.

Future research should incorporate temporally resolved soil moisture observations derived from satellite missions (e.g., SMAP or ESA CCI Soil Moisture) or land surface model products (e.g., GLDAS) to investigate how transient hydrological conditions preceding seismic events influence earthquake-induced landslide occurrence. Integrating dynamic soil moisture information with hybrid deep learning architectures may further improve susceptibility mapping by accounting for both the spatial distribution and temporal evolution of hydrological processes. Furthermore, the proposed framework was evaluated using a single earthquake inventory from the Minxian study area. Although the results demonstrate good predictive performance within this region, the transferability of the proposed framework to other earthquake events or different geological and geomorphological environments has not yet been verified. Future studies should validate the proposed framework using independent landslide inventories from multiple earthquake events and geographically distinct study areas to comprehensively assess its robustness and practical applicability. In addition, the application of hybrid or ensemble deep learning models across multiple earthquake events and different physiographic settings would provide a more comprehensive assessment of model generalizability and robustness [18].

The models were trained and evaluated using a random 70/30 partition, which is commonly adopted in landslide susceptibility mapping to facilitate comparisons among competing models. However, because geospatial observations exhibit spatial autocorrelation, random partitioning samples may place neighboring locations in both the training and validation datasets, resulting in optimistic estimates of predictive performance compared with geographically independent validation strategies. This issue has been widely recognized in spatial prediction and environmental modelling, where conventional random cross-validation can substantially overestimate model generalization performance

due to the violation of the assumption of independent observations [58–61]. Although convergence analysis, early stopping, and training-validation loss monitoring indicated stable model optimization without evidence of conventional overfitting, these procedures do not eliminate the influence of spatial dependence between training and validation samples. Therefore, the reported predictive performance should be interpreted as the performance obtained under a random partitioning strategy. Future studies should evaluate the proposed framework using spatial block cross-validation or geographically disjoint hold-out validation to provide a more rigorous assessment of model transferability and generalization across independent geographic regions [59,60].

Deep learning models exhibit stochastic variability arising from random parameter initialization, data shuffling, and optimization processes. In the present study, model performance was evaluated using a single training realization for each architecture under identical experimental settings. Although the proposed CNN-SwinT consistently outperformed the comparison models on evaluation metrics, the statistical significance of these differences was not formally assessed. Future studies should perform repeated experiments using multiple random seeds and apply appropriate statistical tests, such as DeLong's test for comparing ROC curves, to quantify the robustness of performance improvements [62].

5. Conclusions

In this paper, a hybrid CNN-SwinT technique along with a standalone CNN and SwinT was developed for earthquake-induced LSM in Minxian County, Gansu, China. This technique captures both local and global spatial dependencies. Thirteen influencing factors were considered before modelling, multicollinearity and factor importance analysis were conducted. To quantify the contribution of soil moisture, all the models were trained with and without soil moisture under a similar experimental environment. Based on evaluation metrics, OA, Precision, Recall, MCC, F1 score, and AUC values, the proposed hybrid model outperformed standalone CNN and SwinT. Strong concordance between High and Very High susceptibility zones' spatial distribution and ancient landslides demonstrated reliability and prediction ability. The findings indicate that long-term soil moisture is an important hydrological factor in earthquake-induced landslide susceptibility and that its incorporation consistently improved classification accuracy and spatial consistency under the adopted experimental framework. Overall, this study emphasizes the significance of integrating long-term spatial soil moisture information as a static hydrological conditioning factor with advanced deep learning techniques for earthquake-induced landslide susceptibility mapping. The reported predictive performance was obtained under random patch-level training-validation partitions; therefore, future studies should evaluate the proposed framework using spatially independent validation strategies, such as spatial block cross-validation, as well as independent earthquake inventories from different study areas, to further assess its generalization capability and transferability. The proposed technique offers a scalable, computationally effective approach for modelling geo-hazards.

From a broader perspective, this study is useful in the context of global landslide research, as it highlights the importance of incorporating soil moisture in earthquake-induced landslide susceptibility. As global climatic conditions keep altering soil moisture and precipitation regimes, the relation between pre-event saturation and seismic triggering is predicted to be more crucial in slope instability. As climate variability continues to influence precipitation regimes, incorporating spatial hydrological information into the susceptibility model is expected to become increasingly important for improving regional landslide hazard assessment. Although the proposed methodology demonstrated prom-

ising performance in the Minxian area, its applicability to other mountainous and seismically active regions should be validated using independent earthquake events and geographically distinct study areas before broader generalization can be made. In addition to advancing scientific knowledge of multi-factor landslide susceptibility modelling, this research supports global initiatives in hazard mitigation and disaster risk reduction.

To capture dynamic pre-seismic conditions effectively, future studies should focus on the integration of high-resolution temporal soil moisture data. Future studies should incorporate high-resolution time-series soil moisture datasets to investigate the influence of transient pre-earthquake hydrological conditions on earthquake-induced landslide susceptibility. Prediction accuracy may also improve using advanced deep learning models. The resilience and global applicability of the proposed framework can be improved by testing it in various geological and climatic regions while extending it to multi-hazard scenarios.

Author Contributions: Conceptualization, M.K.; methodology, M.K.; software, M.K. and M.R.; validation, T.C., L.B. and A.A.S.; formal analysis, M.K. and M.R.; investigation, Y.W.; resources, Y.W.; data curation, M.K. and Y.W.; writing—original draft preparation, M.K.; writing—review and editing, M.K., T.C. and Y.W.; visualization, L.B., A.A.S., T.C. and Y.W.; supervision, Y.W.; project administration, Y.W.; funding acquisition, Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Joint Fund of the National Natural Science Foundation of China (U21A2013).

Data Availability Statement: The dataset used during the current study is available from the corresponding author on reasonable request.

Acknowledgments: The authors sincerely thank the anonymous reviewers for their valuable comments and suggestions, which substantially enhanced the quality and presentation of this paper.

Conflicts of Interest: The authors declare that they have no known competing interests.

References

1. Kamal, M.; Zhang, B.; Cao, J.; Zhang, X.; Chang, J. Comparative study of artificial neural network and random forest model for susceptibility assessment of landslides induced by earthquake in the Western Sichuan Plateau, China. *Sustainability* **2022**, *14*, 13739. <https://doi.org/10.3390/su142113739>.
2. Abbaszadeh Shahri, A.; Maghsoudi Moud, F. Landslide susceptibility mapping using hybridized block modular intelligence model. *Bull. Eng. Geol. Environ.* **2021**, *80*, 267–284. <https://doi.org/10.1007/s10064-020-01922-8>.
3. Li, J.; Wang, W.; Han, Z.; Li, Y.; Chen, G. Exploring the impact of multitemporal DEM data on the susceptibility mapping of landslides. *Appl. Sci.* **2020**, *10*, 2518. <https://doi.org/10.3390/app10072518>.
4. Reichenbach, P.; Rossi, M.; Malamud, B.D.; Mihir, M.; Guzzetti, F. A review of statistically-based landslide susceptibility models. *Earth-Sci. Rev.* **2018**, *180*, 60–91. <https://doi.org/10.1016/j.earscirev.2018.03.001>.
5. Berti, M.; Corsini, A.; Daehne, A. Comparative analysis of surface roughness algorithms for the identification of active landslides. *Geomorphology* **2013**, *182*, 1–18. <https://doi.org/10.1016/j.geomorph.2012.10.022>.
6. Booth, A.M.; Roering, J.J.; Perron, J.T. Automated landslide mapping using spectral analysis and high-resolution topographic data: Puget Sound lowlands, Washington, and Portland Hills, Oregon. *Geomorphology* **2009**, *109*, 132–147. <https://doi.org/10.1016/j.geomorph.2009.02.027>.
7. Carrara, A. Multivariate models for landslide hazard evaluation. *Math. Geol.* **1983**, *15*, 403–426. <https://doi.org/10.1007/BF01031290>.
8. Dou, J.; Yunus, A.P.; Merghadi, A.; Shirzadi, A.; Nguyen, H.; Hussain, Y.; Avtar, R.; Chen, Y.; Pham, B.T.; Yamagishi, H. Different sampling strategies for predicting landslide susceptibilities are deemed less consequential with deep learning. *Sci. Total Environ.* **2020**, *720*, 137320. <https://doi.org/10.1016/j.scitotenv.2020.137320>.
9. Volpe, E.; Ciabatta, L.; Salciarini, D.; Camici, S.; Cattoni, E.; Brocca, L. The impact of probability density functions assessment on model performance for slope stability analysis. *Geosciences* **2021**, *11*, 322. <https://doi.org/10.3390/geosciences11080322>.

10. Peiro, Y.; Volpe, E.; Ciabatta, L.; Cattoni, E. High resolution precipitation and soil moisture data integration for landslide susceptibility mapping. *Geosciences* **2024**, *14*, 330. <https://doi.org/10.3390/geosciences14120330>.
11. Guo, Z.; Zeng, T.; Zhang, Y.; Yu, W.; Wang, L.; Guo, Z.; Glade, T. A novel hybrid model integrating high resolution remote sensing and stacking ensemble techniques for landslide susceptibility mapping: Application to event-based landslide inventory. *Geomorphology* **2025**, *486*, 109886. <https://doi.org/10.1016/j.geomorph.2025.109886>.
12. Li, Y.; Rangarajan, S.; Cheng, Y.; Rahardjo, H.; Satyanaga, A. Random forest-based prediction of shallow slope stability considering spatiotemporal variations in unsaturated soil moisture. *Sci. Rep.* **2025**, *15*, 8751. <https://doi.org/10.1038/s41598-025-92739-6>.
13. Palazzolo, N.; Cancelliere, A.; Zofei, R.D.; Peres, D.J. Use of delayed ERA5-Land soil moisture products for improving landslide early warning. *Nat. Hazards Earth Syst. Sci.* **2025**, *25*, 4907–4919. <https://doi.org/10.5194/nhess-25-4907-2025>.
14. Ardizzone, F.; Gariano, S.L.; Volpe, E.; Antronico, L.; Coscarelli, R.; Manunta, M.; Mondini, A.C. A procedure for the quantitative comparison of rainfall and DInSAR-based surface displacement time series in slow-moving landslides: A case study in southern Italy. *Remote Sens.* **2023**, *15*, 320. <https://doi.org/10.3390/rs15020320>.
15. Salciarini, D.; Brocca, L.; Camici, S.; Ciabatta, L.; Volpe, E.; Massini, R.; Tamagnini, C. Physically based approach for rainfall-induced landslide projections in a changing climate. *Proc. Inst. Civ. Eng.-Geotech. Eng.* **2019**, *172*, 481–495. <https://doi.org/10.1680/jgeen.18.00216>.
16. Vople, E.; Gariano, S.L.; Ciabatta, L.; Peiro, Y.; Cattoni, E. Expected Changes in Rainfall-Induced Landslide Activity in an Italian Archaeological Area. *Geosciences* **2023**, *13*, 270. <https://doi.org/10.3390/geosciences13090270>.
17. Abbaszadeh Shahri, A.; Spross, J.; Johansson, F.; Larsson, S. Landslide susceptibility hazard map in southwest Sweden using artificial neural network. *Catena* **2019**, *183*, 104225. <https://doi.org/10.1016/j.catena.2019.104225>.
18. Goetz, J.; Brenning, A.; Petschko, H.; Leopold, P. Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling. *Comput. Geosci.* **2015**, *81*, 1–11. <https://doi.org/10.1016/j.cageo.2015.04.007>.
19. Merghadi, A.; Yunus, A.P.; Dou, J.; Whiteley, J.; Thaiphom, B.; Bui, D.T.; Avtar, T.; Abderrahmane, B. Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. *Earth-Sci. Rev.* **2020**, *207*, 103225. <https://doi.org/10.1016/j.earscirev.2020.103225>.
20. Sharma, N.; Saharia, M.; Ramana, G. High resolution landslide susceptibility mapping using ensemble machine learning and geospatial big data. *Catena* **2024**, *235*, 107653. <https://doi.org/10.1016/j.catena.2023.107653>.
21. Youssef, A.M.; El-Haddad, B.A.; Skilodimou, H.D.; Bathrellos, G.D.; Golkar, F.; Pourghasemi, H.R. Landslide susceptibility, ensemble machine learning, and accuracy methods in the southern Sinai Peninsula, Egypt: Assessment and Mapping. *Nat. Hazards* **2024**, *120*, 14227–14258. <https://doi.org/10.1007/s11069-024-06769-w>.
22. Huang, F.; Zhang, J.; Zhou, C.; Wang, Y.; Huang, J.; Zhu, L. A deep learning algorithm using a fully connected sparse autoencoder neural network for landslide susceptibility prediction. *Landslides* **2020**, *17*, 217–229. <https://doi.org/10.1007/s10346-019-01274-9>.
23. Yao, J.; Qin, S.; Qiao, S.; Che, W.; Chen, Y.; Su, G.; Miao, Q. Assessment of landslide susceptibility combining deep learning with semi-supervised learning in Jiaohe County, Jilin Province, China. *Appl. Sci.* **2020**, *10*, 5640. <https://doi.org/10.3390/app10165640>.
24. Chen, T.; Wang, Q.; Zhao, Z.; Liu, G.; Dou, J.; Plaza, A. LCFSTE: Landslide Conditioning Factors and Swin Transformer Ensemble for Landslide Susceptibility Assessment. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2024**, *17*, 6444–6454. <https://doi.org/10.1109/JSTARS.2024.3373029>.
25. Tan, J.; Yang, C.; Wang, Y.; Xiong, H.; Ma, C. A hybrid model to overcome landslide inventory incompleteness issue for landslide susceptibility prediction. *Geocarto Int.* **2024**, *39*, 2322066. <https://doi.org/10.1080/10106049.2024.2322066>.
26. Pham, B.T.; Prakash, I.; Dou, J.; Singh, S.K.; Trinh, P.T.; Tran, H.T.; Le, T.M.; Phong, T.V.; Khoi, D.K.; Shirzadi, A.; et al. A novel hybrid approach of landslide susceptibility modelling using rotation forest ensemble and different base classifiers. *Geocarto Int.* **2020**, *35*, 1267–1292. <https://doi.org/10.1080/10106049.2018.1559885>.
27. Tien Bui, D.; Shirzadi, A.; Shahabi, H.; Geertsema, M.; Omidvare, E.; Clague, J.J.; Thaiphom, B.; Dou, J.; Talebpour Asl, D.; Bin Ahmad, B.; et al. New ensemble models for shallow landslide susceptibility modeling in a semi-arid watershed. *Forests* **2019**, *10*, 743. <https://doi.org/10.3390/f10090743>.
28. Wang, C.; Jia, H.; Zhang, S.; MA, Z.; Wang, X. A dynamic evaluation method for slope safety with monitoring information based on a hybrid intelligence algorithm. *Comput. Geotech.* **2023**, *164*, 105772. <https://doi.org/10.1016/j.compgeo.2023.105772>.
29. Ferentinou, M.; Sakellariou, M. Computational intelligence tools for the prediction of slope performance. *Comput. Geotech.* **2007**, *34*, 362–384. <https://doi.org/10.1016/j.compgeo.2007.06.004>.

30. Abbaszadeh Shahri, A.; Chunling, S.; Larsson, S. A hybrid ensemble-based automated deep learning approach to generate 3D geo-models and uncertainty analysis. *Eng. Comput.* **2024**, *40*, 1501–1516. <https://doi.org/10.1007/s00366-023-01852-5>.
31. Edrich, A.-K.; Yildiz, A.; Roscher, R.; Bast, A.; Graf, F.; Kowalski, J. A modular framework for FAIR shallow landslide susceptibility mapping based on machine learning. *Nat. Hazards* **2024**, *120*, 8953–8982. <https://doi.org/10.1007/s11069-024-06563-8>.
32. Novellino, A.; Pennington, C.; Leeming, K.; Taylor, S.; Alvares, I.G.; Micallister, E.; Arnhardt, C.; Winson, A. Mapping landslides from space: A review. *Landslides* **2024**, *21*, 1041–1052. <https://doi.org/10.1007/s10346-024-02215-x>.
33. Tauro, F.; Selker, J.; Van De Giesen, N.; Abrate, T.; Uijlenhoet, R.; Porfiri, M.; Manfreda, S.; Caylor, K.; Moramarco, T.; Benveniste, J. Measurements and observations in the XXI century (MOXXI): Innovation and multi-disciplinarity to sense the hydrological cycle. *Hydrol. Sci. J.* **2018**, *63*, 169–196. <http://doi.org/10.1080/02626667.2017.1420191>.
34. Kamal, M.; Wang, Y.; Fangrui, X.; Ahmed, M. Enhancing landslide susceptibility mapping with the integration of soil moisture and machine learning models in Minxian County, China. *Bull. Eng. Geol. Environ.* **2026**, *85*, 412. <https://doi.org/10.1007/s10064-026-05053-4>.
35. Farahani, A.; Ghayoomi, M. A soil moisture-informed seismic landslide model using SMAP satellite data. *Remote Sens.* **2025**, *17*, 2671. <https://doi.org/10.3390/rs17152671>.
36. Shao, X.; Xu, C. Earthquake-induced landslides susceptibility assessment: A review of the state-of-the-art. *Nat. Hazards Res.* **2022**, *2*, 172–182. <https://doi.org/10.1016/j.nhres.2022.03.002>.
37. Tanyaş, H.; Hill, K.; Mahoney, L.; Fadel, I.; Lombardo, R. The world's second-largest, recorded landslide event: Lessons learnt from the landslides triggered during and after the 2018 Mw 7.5 Papua New Guinea earthquake. *Eng. Geol.* **2022**, *297*, 106504. <https://doi.org/10.1016/j.enggeo.2021.106504>.
38. He, W.; Zheng, W.; Wang, A.; Liu, X.; Zhang, B.; Liu, F.; Pang, W. New activities of Lintan-Dangchang fault and its relations to Minxian-Zhangxian M S 6.6 earthquake. *China Earthq. Eng. J.* **2013**, *35*, 751–760. (In Chinese)
39. Tian, Y.; Xu, C.; Chen, J.; Zhou, Q.; Shen, L. Geometrical characteristics of earthquake-induced landslides and correlations with control factors: A case study of the 2013 Minxian, Gansu, China, Mw 5.9 event. *Landslides* **2017**, *14*, 1915–1927. <https://doi.org/10.1007/s10346-017-0835-6>.
40. Tian, Y.; Xu, C.; Xu, X.; Chen, J. Detailed inventory mapping and spatial analyses to landslides induced by the 2013 Ms 6.6 Minxian earthquake of China. *J. Earth Sci.* **2016**, *27*, 1016–1026. <https://doi.org/10.1007/s12583-016-0905-z>.
41. Xu, C.; Xu, X.; Shyu, J.B.H.; Zheng, W.; Min, W. Landslides triggered by the 22 July 2013 Minxian–Zhangxian, China, Mw 5.9 earthquake: Inventory compiling and spatial distribution analysis. *J. Asian Earth Sci.* **2014**, *92*, 125–142. <https://doi.org/10.1016/j.jseaes.2014.06.014>.
42. Gabriel, V.J.; Wang, R.; Mahato, D.; Wei, C. A novel weighted average ensemble method for landslide susceptibility mapping: A case study in Yuanyang, China. *Egypt. J. Remote Sens. Space Sci.* **2025**, *28*, 436–454. <https://doi.org/10.1016/j.ejrs.2025.07.002>.
43. Yilmaz, I. Comparison of landslide susceptibility mapping methodologies for Koyulhisar, Turkey: Conditional probability, logistic regression, artificial neural networks, and support vector machine. *Environ. Earth Sci.* **2010**, *61*, 821–836. <https://doi.org/10.1007/s12665-009-0394-9>.
44. Wang, Y.; Fang, Z.; Hong, H.; Peng, L. Flood susceptibility mapping using convolutional neural network frameworks. *J. Hydrol.* **2020**, *582*, 124482. <https://doi.org/10.1016/j.jhydrol.2019.124482>.
45. Feng, L.; Zhang, M.; Mao, Y.; Liu, H.; Yang, C.; Dong, Y.; Nanehkaran, Y.A. Convolutional neural network-based deep learning for landslide susceptibility mapping in the Bakhtegan watershed. *Sci. Rep.* **2025**, *15*, 13250. <https://doi.org/10.1038/s41598-025-96748-3>.
46. Yamashita, R.; Nishio, M.; Do, R.K.G.; Togashi, K. Convolutional neural networks: An overview and application in radiology. *Insights Imaging* **2018**, *9*, 611–629. <https://doi.org/10.1007/s13244-018-0639-9>.
47. Wang, Y.; Fang, Z.; Wang, M.; Peng, L.; Hong, H. Comparative study of landslide susceptibility mapping with different recurrent neural networks. *Comput. Geosci.* **2020**, *138*, 104445. <https://doi.org/10.1016/j.cageo.2020.104445>.
48. Khan, S.; Naseer, M.; Hayat, M.; Zamir, S.W.; Khan, F.S.; Shah, M. Transformers in vision: A survey. *ACM Comput. Surv.* **2022**, *54*, 1–41. <https://doi.org/10.1145/3505244>.
49. Chen, L.C.; Papandreou, G.; Kokkinos, I.; Murphy, K.; Yuille, A.L. DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. *IEEE Trans. Pattern Anal. Mach. Intell.* **2018**, *40*, 834–848. <https://doi.org/10.1109/TPAMI.2017.2699184>.
50. He, Y.; Zhao, Z.A.; Zhu, Q.; Liu, T.; Zhang, L.; Wang, Q. An integrated neural network method for landslide susceptibility assessment based on time-series InSAR deformation dynamic features. *Int. J. Digit. Earth* **2024**, *17*, 2295408. <https://doi.org/10.1080/17538947.2023.2295408>.

51. Li, J.; Cheng, K.; Wang, S.; Morstatter, F.; Trevino, R.P.; Tang, J.; Liu, H. Feature selection: A data perspective. *ACM Comput. Surv.* **2018**, *50*, 1–45. <https://doi.org/10.1145/3136625>.
52. Bao, S.; Liu, J.; Wang, L.; Zhao, X. Landslide susceptibility mapping by fusing convolutional neural networks and Vision Transformer. *Remote Sens.* **2023**, *15*, 118. <https://doi.org/10.3390/rs15010118>.
53. Ghaderi, A.; Abbaszadeh Shahri, A.; Larsson, S. A visualized hybrid intelligent model to delineate Swedish fine-grained soil layers using clay sensitivity. *CATENA* **2022**, *214*, 106289. <https://doi.org/10.1016/j.catena.2022.106289>.
54. Wu, L.; Liu, R.; Ju, N.; Zhang, A.; Gou, J.; He, G.; Lei, Y. Landslide mapping based on a hybrid CNN-transformer network and deep transfer learning using remote sensing images with topographic and spectral features. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *126*, 103612. <https://doi.org/10.1016/j.jag.2023.103612>.
55. Vereecken, H.; Huisman, J.A.; Pachepsky, Y.; Montzka, C.; Van der Kruk, J.; Bogen, H.; Weihermüller, L.; Herbst, M.; Martínez, G.; Vanderborght, J. On the spatio-temporal dynamics of soil moisture at the field scale. *J. Hydrol.* **2014**, *516*, 76–96. <https://doi.org/10.1016/j.jhydrol.2013.11.061>.
56. Western, A.W.; Grayson, R.B.; Blöschl, G. Scaling of soil moisture: A hydrologic perspective. *Annu. Rev. Earth Planet. Sci.* **2002**, *30*, 149–180. <https://doi.org/10.1146/annurev.earth.30.091201.140434>.
57. Iverson, R.M. Landslide triggering by rain infiltration. *Water Resour. Res.* **2000**, *36*, 1897–1910. <https://doi.org/10.1029/2000WR900090>.
58. Brenning, A. Spatial prediction models for landslide hazards: Review, comparison and evaluation. *Nat. Hazards Earth Syst. Sci.* **2005**, *5*, 853–862. <https://doi.org/10.5194/nhess-5-853-2005>.
59. Roberts, D.R.; Bahn, V.; Ciuti, S.; Boyce, M.S.; Elith, J.; Guillera-Arroita, G.; Hauenstein, S.; Lahoz-Monfort, J.J.; Schroder, B.; Thuiller, W. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* **2017**, *40*, 913–929. <https://doi.org/10.1111/ecog.02881>.
60. Valavi, R.; Elith, J.; Lahoz-Monfort, J.J.; Guillera-Arroita, G. blockCV: An R package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. *Methods Ecol. Evol.* **2019**, *10*, 225–232. <https://doi.org/10.1111/2041-210X.13107>.
61. Ploton, P.; Mortier, F.; Réjou-Méchain, M.; Barbier, N.; Picard, N.; Rossi, V.; Dormann, C.; Cornu, G.; Viennois, G.; Bayol, N.; et al. Spatial validation reveals poor predictive performance of large-scale ecological mapping models. *Nat. Commun.* **2020**, *11*, 4540. <https://doi.org/10.1038/s41467-020-18321-y>.
62. De Long, E.R.; De Long, D.M.; Clarke-Pearson, D.L. Comparing the areas under two or more correlated receiver operating characteristic curves: A nonparametric approach. *Biometrics* **1988**, *44*, 837–845. PMID: 3203132.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.