

Article

A Study of Landslide Susceptibility Assessment and Trend Prediction Using a Rule-Based Discrete Grid Model

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Abstract: Landslides are common natural disasters in mountainous regions, exerting considerable influence on socioeconomic development and city construction. Landslides occur and develop rapidly, often posing a significant threat to the safety of individuals and their property. Consequently, the mapping of areas susceptible to landslides and the simulation of the development of such events are crucial for the early warning and forecasting of regional landslide occurrences, as well as for the management of associated risks. In this study, a landslide susceptibility (LS) model was developed using an ensemble machine learning (ML) approach which integrates geological and geomorphological data, hydrological data, and remote sensing data. A total of nine factors (e.g., surface deformation rates (SDF), slope, and aspect) were used to assess the susceptibility of the study area to landslides and a grading of the LS in the study area was obtained. The proposed model demonstrates high accuracy and good applicability for LS. Additionally, a simulation of the landslide process and velocity was constructed based on the principles of landslide movement and the rule-based discrete grid model. Compared with actual unmanned aerial vehicle (UAV) imagery, this simulation model has a Sørensen coefficient (SC) of 0.878, a kappa coefficient of 0.891, and a total accuracy of 94.12%. The evaluation results indicate that the model aligns well with the spatial and temporal development characteristics of landslides, thereby providing a valuable reference basis for monitoring and early warning of landslide events.

Keywords: landslide simulation; landslide susceptibility (LS); ensemble machine learning (ML); rule-based discrete grid model



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1. Introduction

Landslides are among the most devastating natural disasters, causing fatalities, destruction of property, and ecological disruption [1]. China, particularly in its western, northwestern, and Tibetan Plateau regions, frequently experiences severe landslide disasters [2]. From 1999–2019, landslides in China caused a cumulative total of 4742 fatalities, with an annual average of 226 deaths [3–7]. The occurrence of landslides is influenced by both natural and human factors. In terms of natural factors, landslides are influenced by the local topography, geological environment, and hydrometeorological conditions and often occur in areas with complex geological formations, fractures and folds, strong neotectonic activity, and sudden rainfall. In addition, population growth has led to further expansion into mountainous areas, a reduction in vegetation coverage, an increase in land desertification, ecological damage, and an increase in the frequency of extreme rainfall events. Rainfall can raise the amount of moisture in the soil, which increases the downward pressure on loose material along slopes in the mountains and raises the frequency of landslides [8–10]. Studies on the susceptibility and performance of landslide dispersion

simulations can help us predict the development process of landslides and ensure the safety of people's lives and property and help us comprehend the key factors influencing the occurrence of landslides, with implications for disaster prevention, mitigation strategies, and emergency management practices [11].

Many studies have focused on the susceptibility and performance of landslide dispersion simulations [12]. The assessment of landslide susceptibility (LS) can be broadly categorized into three categories: traditional statistical methods, simulations based on physical theory, and machine learning (ML) methods. The traditional statistical methods usually use a specific function to fit the process of landslide occurrence and evaluate the possibility of landslide occurrence by preset influencing factors [13]. Commonly used traditional statistical methods include the factor analysis method [14], the information entropy method [15], the coefficient of determination method [16], and the hierarchical analysis method [17]. Traditional statistical methods are always site-dependent since the geological and geomorphological environments of different study areas are quite different and the preset evaluation factors are often region-specific, making them difficult to apply across wide areas [18]. LS can be optimally assessed through a comprehensive understanding of the fundamentals of landslide occurrence and by mastering the critical elements that influence its occurrence and development. As a result of further investigations into the mechanism of landslide movement, a series of software programs have been developed [19]. An increasing number of researchers have begun to use existing software models for susceptibility analysis. For example, FLO-2D is an application that employs the single strip block model and finite difference method [20]; MassFlow is software using the generalized depth integral model [21]; MatDEM is based on the discrete cell method [22]; and DAN3D is based on the equivalent fluid assumption and continuity assumption [23,24]. However, there are too many parameters involved in these models, so reflecting real landslide occurrence scenarios by relying on empirically set parameters is difficult [25]. In recent years, the continuous progress of 3S technology (remote sensing, GIS, and GNSS) and the wider use of ML technology have led to an increase in the number of researchers who have combined ML technology with susceptibility analysis. The random forest [26], support vector machine (SVM) [27], convolutional neural network (CNN) [28], and other machine learning methods are frequently employed in landslide susceptibility analysis. In contrast to traditional statistical and modelling methods, ML methods have a high degree of generalizability and are broadly applicable across numerous study domains. These methods are capable of nonlinear fitting, which enhances the accuracy of the susceptibility results [29–31]. Although the existing methods provide a useful framework for LS studies, the complexity of the factors involved in mudslides means that they must be developed to facilitate precise susceptibility analyses.

Landslide simulation constitutes a fundamental aspect of landslide studies. The most commonly used simulation methods include physical modelling and numerical simulation [32,33]. Typically, landslides are multiphase events comprising solid particulate matter and fluids. The quantity of particles in motion during a landslide, the number of solid–liquid interactions, and the percentage of solid–fluid phases can influence the movement process [34]. A range of physical models have been introduced for landslide simulation, which include the empirical impact model based on field observations [35], the two-phase model of landslides based on the assumption of constant porosity and equal velocities of fluids and solids [36], and the depth-averaged two-fluid model based on the two-fluid equation [37]. Nonetheless, in practice, it is difficult to obtain accurate physical and mechanical parameters for landslides and parameters characterizing their movement, making it difficult for physical models to reflect the exact situation of landslide movement [38]. Numerical simulations are capable of modeling complex terrains, reflect the anisotropy of the environment in the study area, and more comprehensively consider the various factors affecting the movement of landslides [39]. The application of numerical simulations is another effective alternative method for landslide prediction. These models represent the dynamic mudslide movement process by solving the equations of conservation of

mass, momentum, and energy, as well as depth-averaging methods [40–42]. Numerical simulation methods can be broadly classified into two categories: continuous medium methods and discrete cell methods. Continuous medium approaches are founded on the theory of fluid dynamics and employ the conservation equation of matter–motion–energy dissipation to describe the motion process of landslides [43,44]. In contrast, discrete unit methods involve decomposing landslides into a collection of elements that satisfy the equations of motion. These elements are then solved using iterative methods to simulate landslides [45,46]. Although existing landslide simulation methods can simulate the movement trends of landslides and the challenge of acquiring validation data, it is necessary to explore new methods for landslide simulation.

Although much work has been conducted in the fields of LS and landslide modelling, numerous challenges remain. First, the occurrence of landslides is influenced by various factors including geological landforms (e.g., soil type, riverine influences, and geological conditions) and hydrological conditions (e.g., fluvial influences and precipitation influences) [47,48]. The selection of these factors is crucial for LS. However, the geological and hydrological conditions of study areas are often not fully considered in the selection of factors for LS analysis, making susceptibility analyses less accurate. Second, many parameters are involved in landslide modelling. Acquiring precise data for parameters such as geotechnical parameters, solid–liquid mixing ratios, and the composition of landslide solids is challenging owing to the limitations of existing technology. Consequently, most of these parameters are estimated through field surveys, resulting in relatively low-accuracy landslide simulations [49–52]. Third, since landslides occur rapidly, typically within a few minutes, the ability to rapidly model and predict these events is a crucial aspect of landslide modelling. The majority of existing landslide simulation models (e.g., the Voellmy model, rainfall intensity–duration model, and Bingham fluid model) focus on the physics of landslide spreading, with complex models and slow computational speeds. In addition, the acquisition of validation data for landslides is fraught with difficulties and most studies have not verified the accuracy using real data [15,53–56]. Therefore, the development and validation of rapid simulation models for landslides is highly important.

To address the above issues, this paper takes Wenchuan County in Sichuan Province as an example to carry out LS assessment as well as landslide movement simulations and validations. Section 1 presents the research background and current status of studies on LS and landslide simulations. Section 2 presents an overview of the study area, data sources, and processing methods. The construction of both the ensemble ML-based LS model and the rule-based discrete grid model for landslide simulation can be found in Section 3. Section 4 provides the results and validation of the LS assessment and the landslide simulation in Wenchuan County. The results obtained in the study are discussed in Section 5. Finally, a brief summary of the conclusions of this study is provided.

2. Study Area and Data

2.1. Study Area

Wenchuan County, situated within the Aba Tibetan and Qiang Autonomous Prefectures of Sichuan Province, located in the northwestern part of Sichuan Province, at the intersection of the Northwest Sichuan Plateau and the southeastern part of Aba Tibetan and Qiang Autonomous Prefectures, is a geographically very important location. The territory of Wenchuan County is characterized by towering peaks and profound canyons, dominated by steep slopes and steep riverbeds. The area is situated within the Sichuan Longmen Mountain fracture area, an area noted for a complex geological structure, frequent seismic activity, and the presence of loose surface material, which provides a sufficient source of material for the occurrence of landslides [57–59].

The combination of rugged terrain, copious water resources, friable surface materials, and seismic disturbances renders Wenchuan County highly susceptible to landslide events. The 2008 earthquake in Wenchuan, which occurred on May 12, caused rock fragmentation followed by frequent heavy rainfall, resulting in numerous landslides. According to the

results of the 2021 Detailed Geological Hazards Survey, there are as many as 126 potential landslide sites in Wenchuan County. The recurrent earthquakes and resultant landslide calamities have had a profound impact on the safety of people, property, and economic development [60–62]. Therefore, Wenchuan County was selected as the study area for LS and landslide simulations in this study.

2.2. Data and Data Preprocessing

The data on the landslide dataset were obtained from the Geographic Remote Sensing Ecological Network Platform (GISRS) (www.gisrs.cn (accessed on 20 August 2023)), established by the Ministry of Land and Resources through the organization of geohazard survey units and professionals through the integration of remote sensing imagery and field investigations. This dataset illustrates the spatial distribution of over 250,000 geological disaster sites across the country divided into seven major categories: avalanches, subsidence, mudslides, ground settlement, ground cracks, landslides, and slopes. The data on landslide disaster sites in the study area were extracted from the aforementioned source and are presented in Figure 1. The study area encompasses 1754 landslide disaster sites, with a combined area of 206.5 km². These include the well-known Arzhai and Maoxian landslide sites [63,64].

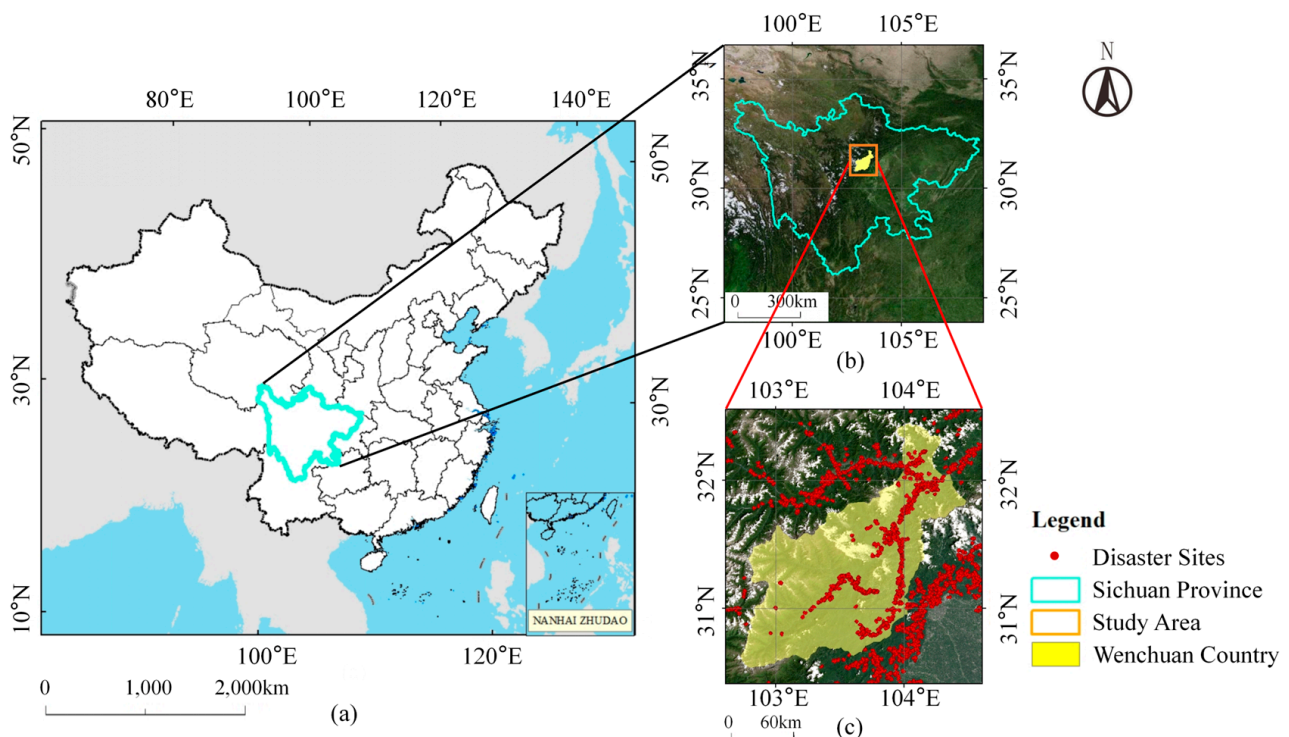


Figure 1. Geographic location of the study area and distribution of landslide disaster sites: (a) geographic location of Sichuan Province; (b) geographic location of Wenchuan County and the study area from Landsat 8 OLI; (c) distribution of landslide disaster sites from Landsat 8 OLI.

The Sentinel-1 and Landsat 8 OLI data, obtained from the Geospatial Data Cloud (GDC) (www.gscloud.cn (accessed on 12 October 2023)) of the Computer Network Information Center of the Chinese Academy of Sciences, provided the primary high-resolution satellite imagery data. Lithology data were obtained from the Resource and Environmental Science Data Platform (RESDP) (www.resdc.cn (accessed on 19 October 2023)) of the Institute of Geographic Sciences and Resources, Chinese Academy of Sciences. The data sources used in the experiment are listed in Table 1. Geological elements like lithology, aspect, and roughness influence the quantity of loose material on a hillside. Additionally, hydrological factors, including distance to a river, impact the stability of the ground surface,

soil moisture levels, and other variables, which in turn affect the likelihood of landslides happening. Slope, aspect, degree of undulation, depth of surface incision, and roughness were extracted from the DEM using ArcGIS 10.2. Surface deformation rates were obtained by preprocessing, differential interference, and phase de-entanglement operations on the Sentinel-1 data from 2020–2022. Landsat 8 OLI data were used as the base map.

Table 1. Sources of different applied factors.

Data Type	Factors	Resolution/Scale	Source
Topography	DEM	30 m	GDC
	Slope	30 m	GDC
	Aspect	30 m	GDC
	Roughness	30 m	GDC
	Degree of undulation	30 m	GDC
	Depth of surface incision	30 m	GDC
Hydrology	River	--	GDC
Geology	Lithology	--	RESDP
	Surface deformation rates	30 m	Sentinel-1
	Landslide disaster data	--	GISRS

3. Methodology

3.1. Landslide Susceptibility

Ensemble machine learning algorithms are insensitive to outliers and achieve high accuracy in many fields. These methods are based on multiple ML algorithms that are combined through specific strategies to create a strong learner to improve the accuracy of the model [65–67]. An ensemble machine learning algorithm was employed in this study to simulate the susceptibility of landslides. The algorithm is based on seven ML algorithms: the Convolutional Neural Network (CNN) [68], Random Forest (RF) [69], K-Nearest Neighbors (KNN) [70], Support Vector Classifier (SVC) [71], Gaussian Naive Bayes (GNB) [72], Gradient Boosting Decision Tree (GBDT) [73], and Logistic Regression (LR) [74].

First, based on the influence of geological and geomorphological factors and hydrological factors on the occurrence of landslides, this study selected nine factors as predisposing factors for landslides. Figure 2 illustrates a plot of nine predisposing factor diagrams in the study area: DEM, slope, aspect, roughness (R), degree of undulation (U), distance to the river (Dis), depth of surface incision (Depth), surface deformation rates (SDF), and lithology (L). After the input variables were selected, the model was created according to Equation (1). These factors underwent preprocessing that included outlier removal, resampling, and normalization. Second, all predisposing factors of landslides were divided into 70% for the training data and 30% for the testing data. The training data were used to train the above ML models, and the test data were used to evaluate their performance. Third, the accuracy of these models was evaluated by plotting receiver operating characteristic (ROC) curves. The optimal ML model was selected, and the results of each model were used as inputs to obtain the susceptibility level of the study area. Finally, the LS of the study area was graded based on the obtained values, with regions exhibiting higher values designated as areas of high landslide susceptibility.

$$LS = f_{ml}(DEM, Slope, Aspect, R, U, Dis, Depth, SDF, L) \quad (1)$$

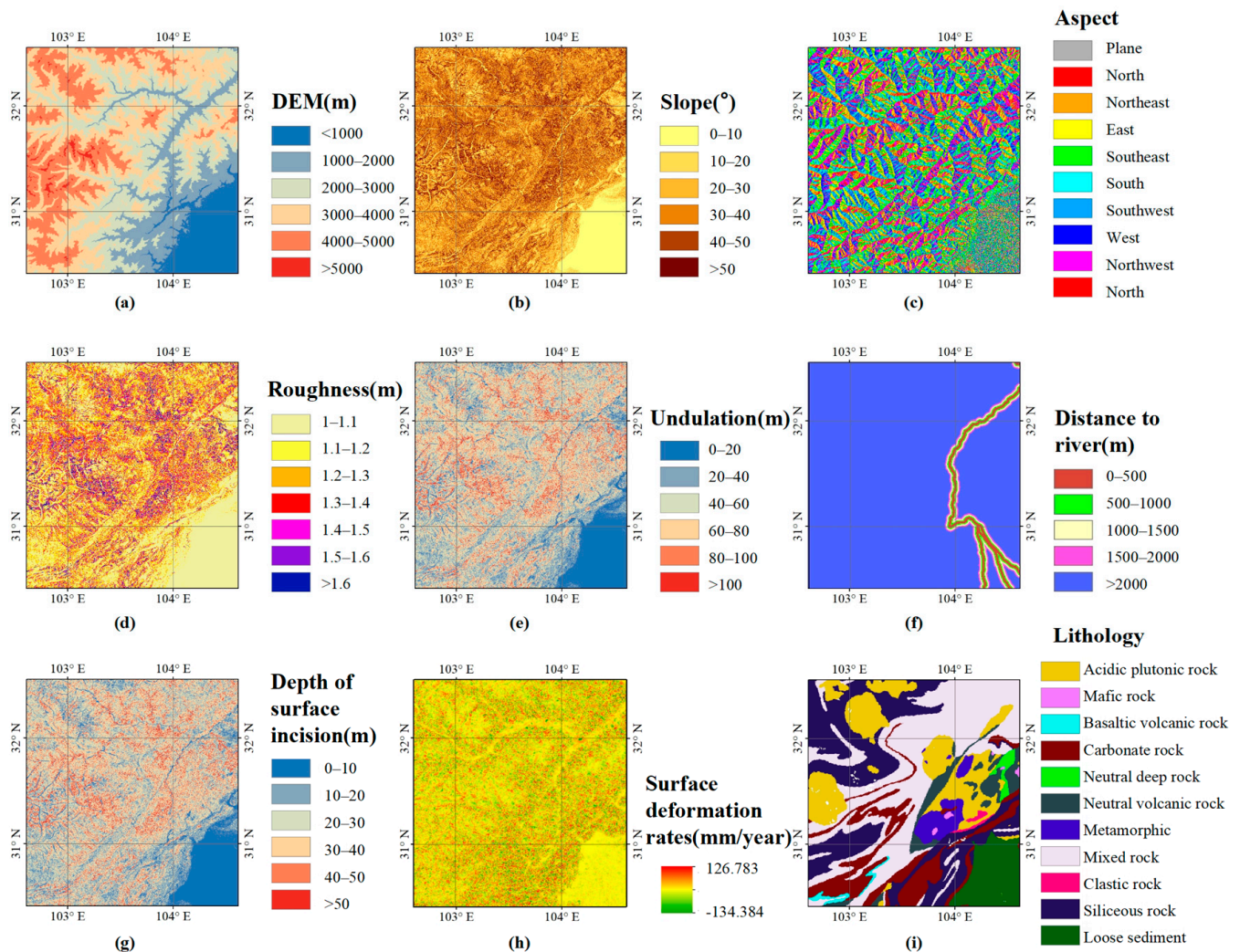


Figure 2. Nine predisposing factors of landslide diagrams in the study area: (a) DEM; (b) slope; (c) aspect; (d) roughness; (e) degree of undulation; (f) distance to the river; (g) depth of surface incision; (h) surface deformation rates; (i) lithology.

3.2. The Rule-Based Discrete Grid Model

LS analysis can assist in the identification of areas within the study area that are susceptible to landslides, thereby informing the selection of areas for subsequent landslide simulations. The technique of simulating landslides is intricate and subject to numerous variables that vary greatly across different regions. For example, the attributes of various mountainous terrains, such as slope and aspect, can vary considerably. Therefore, this paper initially delineates the mudslide-prone region derived from the ensemble machine learning model and subsequently selects two mountains within the region for landslide simulation aiming to replicate the actual dynamics of landslide movement.

The CA model is a discrete grid-based model governed by a set of rules that has gained importance as a method for researching complex systems. Following a lengthy period of development and research, the CA model has been widely utilized across various disciplines such as forest fire simulation, land use analysis, urban sprawl research, infectious disease spread analysis, transportation planning, and numerous other applications. It simulates the progression of the complete system by employing basic principles and interactions at a local level, thereby elucidating the fundamental laws and characteristics of the system [75,76]. The CA model is composed of discrete cells with finite states, where each cell is initially assigned a specific state. By applying predefined rules, these cells transition between states, allowing for the modelling of intricate systems. The state of each

cell in the CA represents the initial attributes, characteristics, or behaviors of individuals at time $t = 0$. The future state of a cell is determined by its current state in conjunction with the states of its neighboring cells. This can be summarized using Equation (2):

$$S_i^{t+1} = R(S_i^t, S_M^t) \quad (2)$$

where S_i^{t+1} is the state of the cell at the next time; S_i^t is the state of the cell at the current time; S_M^t is the combination of neighborhood states at time t ; and R is the state update rule.

A two-dimensional grid system was selected as the most suitable way to depict the features of landslide simulations. Since landslide diffusion is a continuous process and can occur in various directions, this study employed a square grid area to divide the study region's surface. Eight cells around each center cell serve as the cell's neighbors. These neighbors are of the Moore type, allowing for more accurate modelling of landslide diffusion. In the model, the diffusion process can be represented by the change in the landslide material content in the cell [77,78]. The quantity of landslide material present in the central cell is connected to the initial landslide material content found in that cell and in the nearby surrounding cells.

First, the surface elevations of the central cell and the neighboring cells were obtained. If the elevation of the neighboring cell was lower than that of the central cell, it was labelled a diffusible cell. Second, the slope, aspect, soil moisture content, water pressure, and pressure of the solid sources on the slope were calculated. Based on the diffusion characteristics of landslides, if the static friction between the solid source and the slope is lower than the downwards force of the solid source on the slope, the solid source begins to move, resulting in the formation of a landslide. In other words, when Equation (7) is met, the landslide starts to move [79,80]. Finally, the adjacent direction of landslide dispersion is established according to the slope, and landslides can potentially travel in eight directions: north, northeast, east, southeast, south, southwest, west, and northwest [42,77]. Considering the impact of friction and gravity on the movement of landslides, the landslide diffusion equation is shown in Equations (3)–(7):

$$\tau = \sigma(1 - y_u) \tan \alpha \quad (3)$$

$$F_W = m_w i V - \rho g V \quad (4)$$

$$F_{slope} = \tau \cot \alpha + F_W \cos \alpha \quad (5)$$

$$F_{max} = \mu(\tau + F_W \sin \alpha) \quad (6)$$

$$F_{max} < F_{slope} \quad (7)$$

where F_{max} represents the maximum static friction of the solid source against the slope; F_W represents the pressure of water in the soil; F_{slope} represents the total pressure of the solid source along the slope; τ represents the shear stress at the bottom of the solid source; σ represents the positive pressure of the solid source; y_u represents the pore water pressure ratio; α represents the gradient of the landslide-producing slope; m_w represents the gravitational force of the water in the solid source; i represents the hydraulic gradient; V represents the volume of the solid source; g represents the coefficient of gravity, g (9.8 m/s^2); η represents coefficient of friction; and ρ represents the fluid density.

The propagation of landslides adheres to the principles outlined in Equation (8). The transfer of landslide material within the central cell ceases once the amount of landslide material in the central cell no longer satisfies Equation (7).

$$M_{i,j}^{t+1} = M_{i,j}^t + R_{i,j}^t \quad (8)$$

where $M_{i,j}^{t+1}$ represents the landslide material content of the central cell at moment $t + 1$; $M_{i,j}^t$ represents the landslide material content of the central cell at moment t ; and $R_{i,j}^t$

represents the landslide material content transferred from the central cell to surrounding neighboring cells at moment t .

4. Results and Analysis

4.1. Landslides Susceptibility in the Study Area

The nine identified predisposing factors for landslides in the study area were integrated into seven ML models, resulting in the generation of an LS map of the study area. The LS results for the study area of each ML algorithm are presented in Figure 3. An LS value close to 1 indicates a high risk of landslides, while a value close to 0 indicates a low risk. As shown in Figure 3, areas with elevated risk of landslides align closely with the distribution of historical landslide disaster sites. To further understand the differences between the susceptibility estimates from ML and the actual historical records of landslide disasters, a detailed analysis of the number of disaster sites in high-risk ($LS = 0.6–0.8$) and very high-risk ($LS > 0.8$) areas within the LS resulting from the seven ML algorithms was conducted. These findings are summarized in Table 2 for comprehensive comparison. Table 2 revealed that more than 80% of disaster sites are situated within high-risk areas. The GNB method has the lowest accuracy, with 81.93% of the disaster sites in high-risk areas, while the GBDT method has the highest accuracy, with 89.28% of the disaster sites in high-risk areas. Additionally, over 60% of disaster sites are found in very high-risk areas, with the GNB method having the lowest accuracy at 61.35% and the GBDT method showing the highest accuracy at 67.34%.

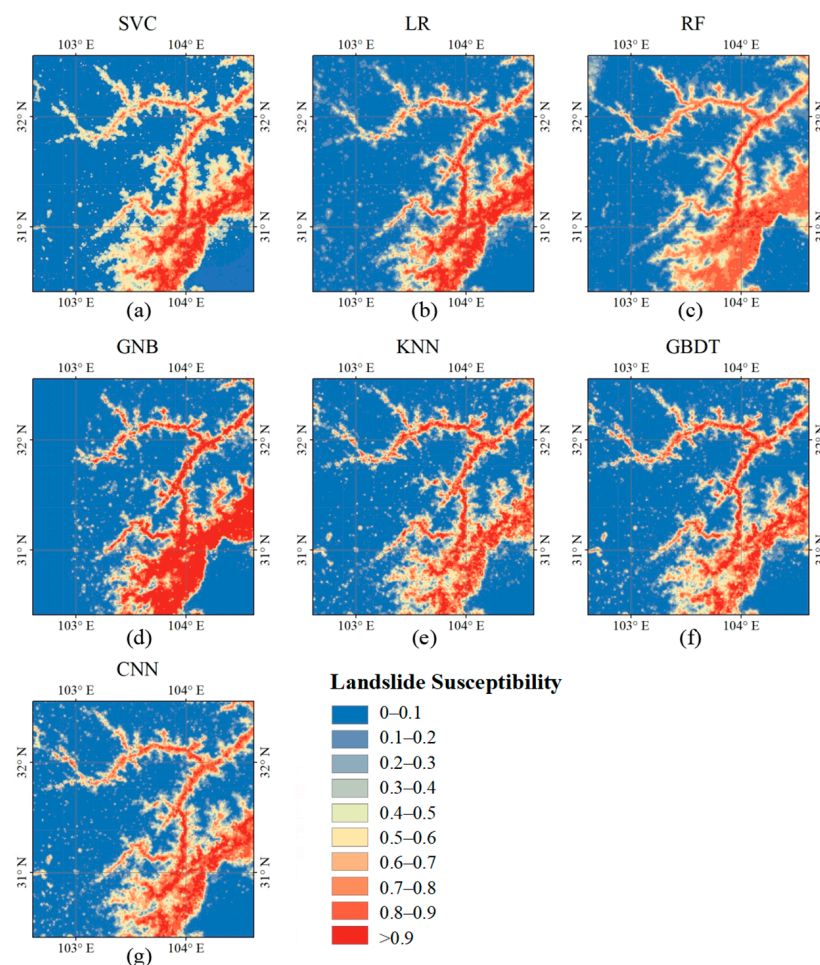


Figure 3. LS results of seven ML methods in the study area: (a) LS results of SVC; (b) LS results of LR; (c) LS results of RF; (d) LS results of GNB; (e) LS results of KNN; (f) LS results of GBDT; (g) LS results of CNN.

Table 2. Comparative analysis of the accuracy of ensemble ML and single ML.

Methods	Disaster Sites in Very High-Risk Area	Percentage (%)	Disaster Sites in High-Risk Area	Percentage (%)
SVC	1107	63.11	1498	85.40
LR	1129	64.37	1518	86.55
RF	1161	66.19	1553	87.40
GNB	1076	61.35	1437	81.93
KNN	1138	64.88	1524	86.89
GBDT	1181	67.34	1566	89.28
CNN	1152	65.68	1512	86.20
Ensemble ML	1352	77.08	1649	94.01

The receiver operating characteristic (ROC) curves for each model were plotted to assess their discriminative accuracy. The ROC curve serves as a tool for evaluating the generalization performance of the ML models. In the ROC curve, the vertical axis represents the true-positive rate (TPR), and the horizontal axis represents the false-positive rate (FPR) [73,81]. The horizontal axis and the area enclosed by the ROC curve are called the area under the ROC curve (AUC), and the closer the value is to 1, the better the algorithmic model [82]. The ROC curve for each method is depicted in Figure 4. The figure shows that GBDT has the highest AUC value of 0.9497, indicating the most effective classification. In contrast, GNB has the lowest AUC value of 0.9172, suggesting the least effective classification among the tested methods.

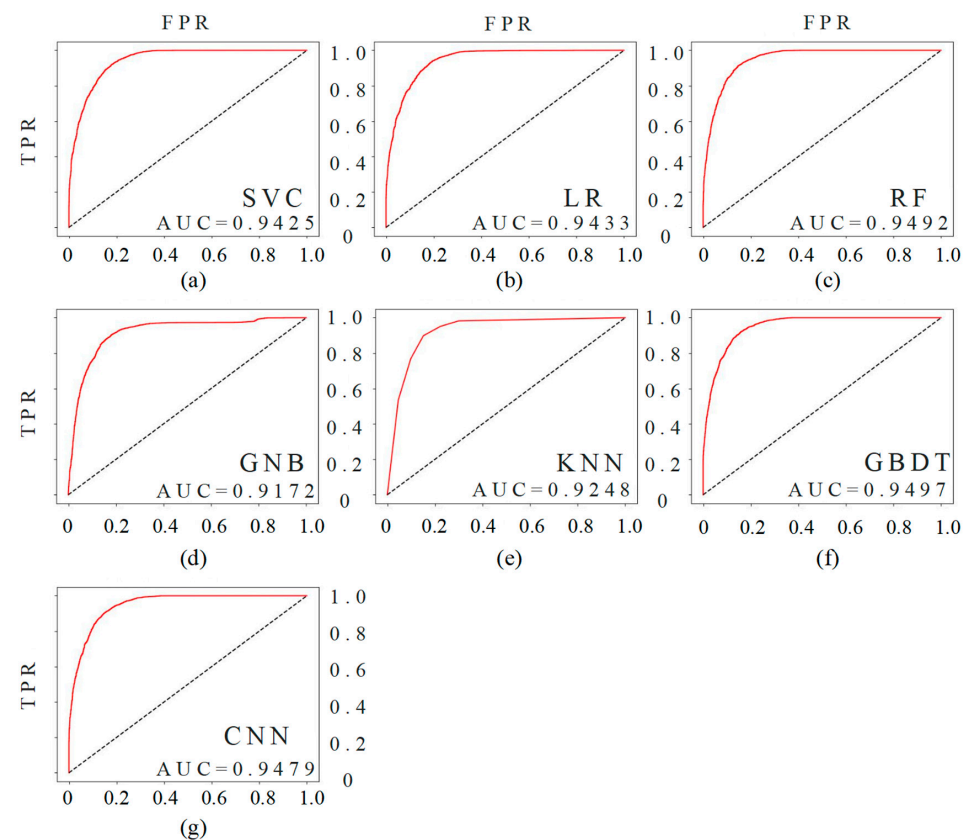


Figure 4. ROC curves of seven ML methods: (a) ROC curve of SVC; (b) ROC curve of LR; (c) ROC curve of RF; (d) ROC curve of GNB; (e) ROC curve of KNN; (f) ROC curve of GBDT; (g) ROC curve of CNN.

Subsequently, the seven ML results obtained were integrated into the GBDT model and subsequently retrained to generate a map of LS for the study area, as illustrated in Figure 5a. The numerical values represent the likelihood of landslide events, with values tending towards 1 signifying an elevated probability of occurrence. Specifically, areas colored in red denote a high probability of landslides, whereas areas depicted in blue reflect a low probability of such events. This study categorizes susceptibility levels based on the magnitude of the susceptibility results, designating the range of 0–0.2 as very low susceptibility, 0.2–0.4 as low susceptibility, 0.4–0.6 as medium susceptibility, 0.6–0.8 as high susceptibility, and greater than 0.8 as very high susceptibility. The classification of LS is illustrated in Figure 5b.

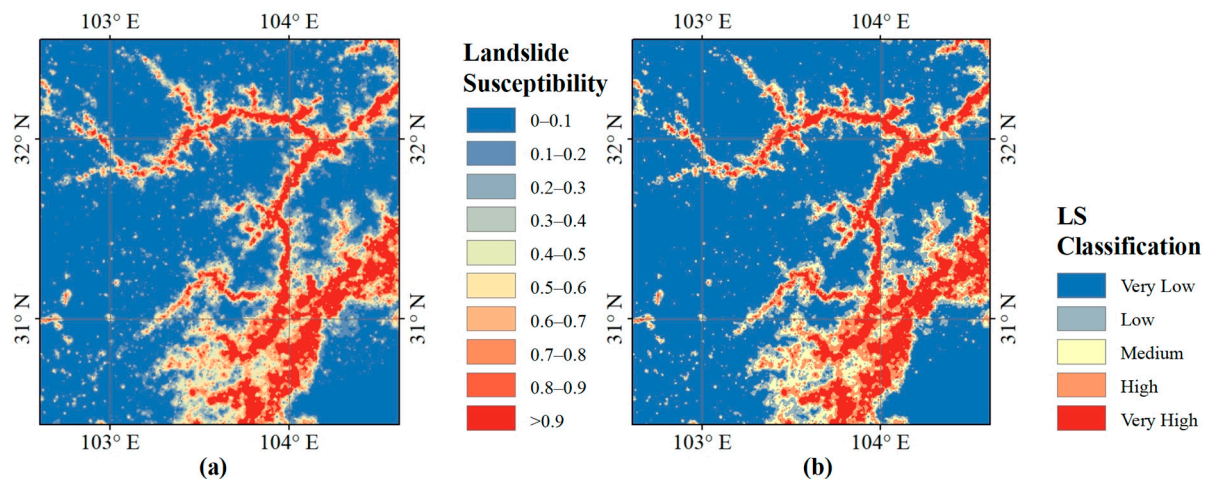


Figure 5. LS results of the ensemble ML method in the study area: (a) LS of the study area; (b) LS classification.

To further validate the accuracy of the LS results, this study conducted a comparison between the LS results and the distributions of disaster locations. The results are presented in Figure 6. The comparison reveals that the spatial distribution of areas with a high probability of landslides in the study area closely resembles the spatial distribution of disaster locations. The majority of the high-risk areas are situated near the Minjiang River, where the geological conditions are complex and characterized by intense neotectonic movements, fault development, frequent seismic activity, and geological disasters. Due to the action of river flow, the surface debris content increases and the river water system infiltrates the surrounding soil, leading to an increase in the soil water content. During seismic events or heavy rainfall, the accumulation of surface debris accumulation and soil water content increases, causing a decrease in friction and consequently increasing the likelihood of landslides.

To compare the accuracy of ensemble machine learning methods and single machine learning methods, this study analyzed the distribution of disaster sites in mudslide-prone areas within the study area for both ensemble machine learning and single machine learning methods, as presented in Table 2. A total of 1754 landslide disaster sites were identified in the study area. Table 2 demonstrates that the ensemble machine learning method has the highest accuracy in identifying landslide susceptibility, while the GNB method has the lowest accuracy. In the ensemble machine learning method, 1352 disaster sites are situated within the very high-risk area, accounting for 77.08% of the total number of disaster sites in the study area, while the high-risk area contains 1649 disaster sites, accounting for 94.01% of the total number. In the GNB method, there are only 1076 sites in the very high-risk area, representing 61.35% of the total number of sites in the study area, and 1437 sites in the high-risk area, representing 81.93% of the total number of sites in the study area. The total number of landslide disaster sites in very high-risk and high-risk areas in the ensemble ML method is significantly greater, indicating that the model is more accurate than the single

machine learning approach. Finally, the top 5% of the area with the highest susceptibility value was designated the landslide susceptibility area. The results are depicted in Figure 7.

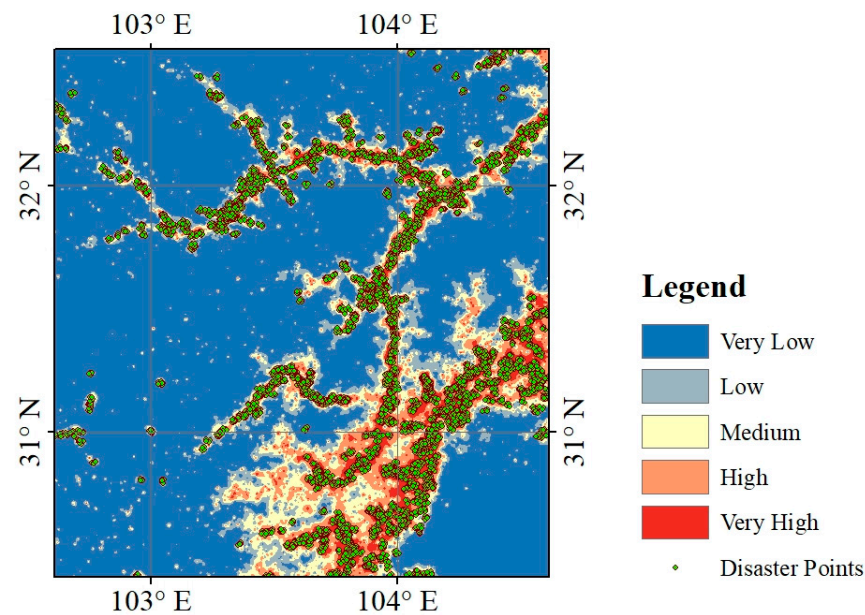


Figure 6. Landslide disaster sites and LS classification in the study area.

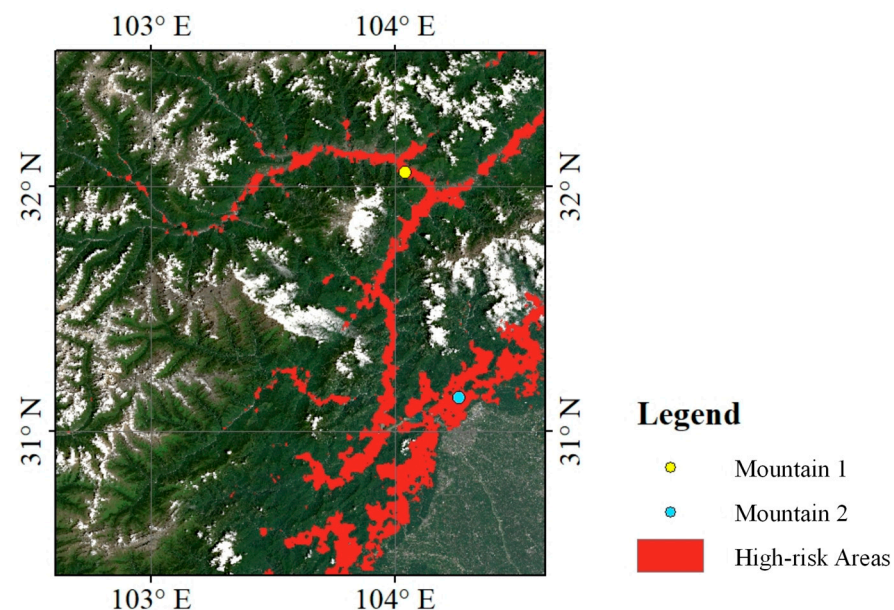


Figure 7. High-risk areas for landslides and selected mountains from two landslide simulations.

4.2. Landslide Movement Prediction

In this study, LS analysis was carried out using an ensemble ML model to obtain LS areas for the study area. Two landslide simulation experiments were subsequently conducted in the high-risk landslide area, with two mountains selected as the study area for each of the two experiments. The chosen mountains, mountain 1 and mountain 2, are shown in Figure 7. These mountains are situated at actual landslide disaster sites and are characterized by abundant sources of surface solids, steep hills, and high precipitation levels, increasing their vulnerability to landslide hazards. A landslide event in mountain 1, located within the high-risk area of Wenchuan County, Sichuan Province, was simulated via the developed CA model. Figure 8 illustrates the diffusion process of the landslide over

a 90 s period, with the red areas in subfigures a–j indicating the spread of the landslide within the 0–90 s interval. The simulation results revealed that the landslide gradually moved towards the base of the mountain over time, with its trajectory influenced by topographical and geomorphological features. Quantitative analysis of the data revealed that the maximum velocity of the landslide was 16.327 m/s, while the average velocity was calculated to be 6.392 m/s during movement.

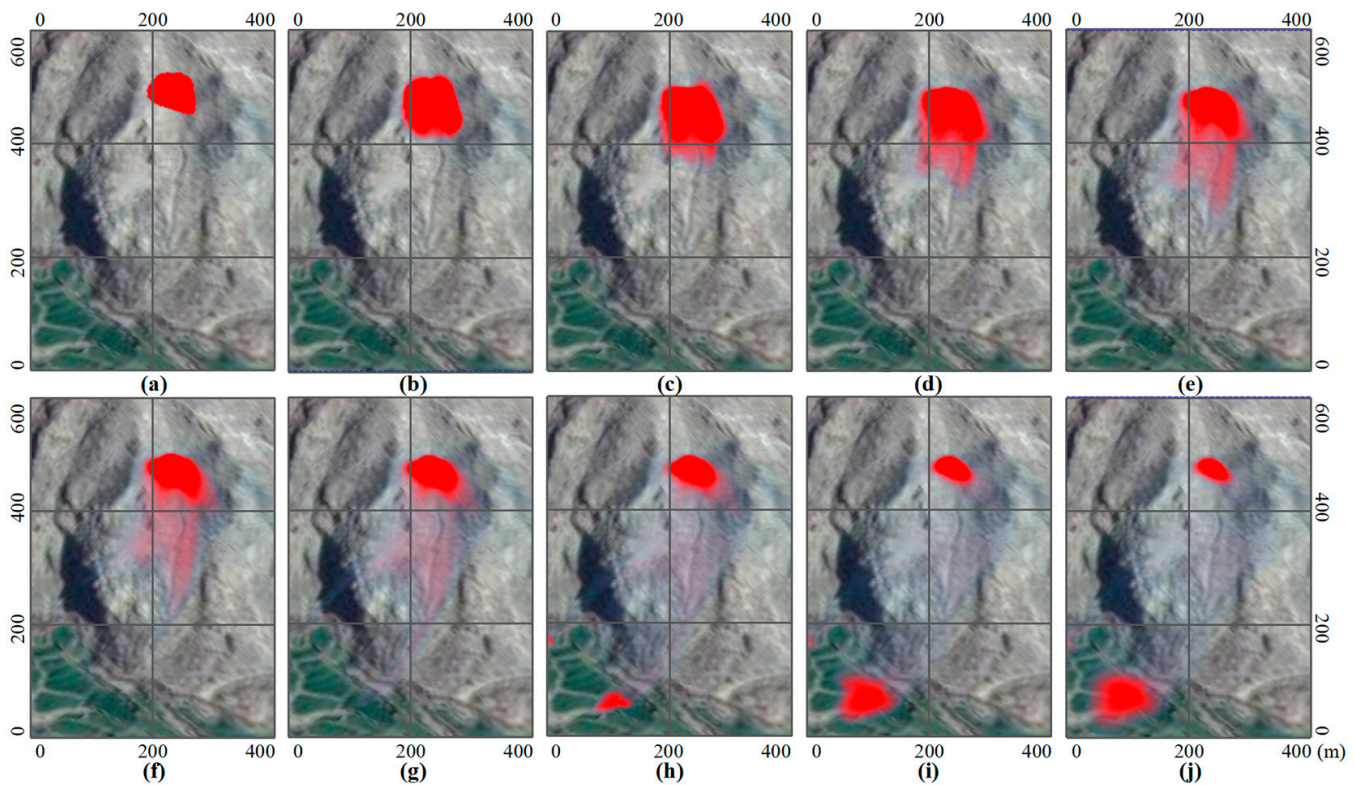


Figure 8. Landslide dispersion process for mountain 1: (a) initial landslide region; (b–j) 10–90 s landslide spread region.

In addition, a simulation experiment for landslides was conducted for mountain 2, an area identified as high risk. The results are presented in Figure 9. The red region delineates the path of the landslide as it advances down the valley and collects at the base of the mountain. The maximum velocity recorded for the landslide was 18.143 m/s, while the average velocity was calculated to be 6.912 m/s.

To increase the accuracy of the CA model, this study validated it via unmanned aerial vehicle (UAV) imagery from a landslide incident that occurred in Shuicheng County, Guizhou Province, in 2019. On 23 July 2019, a significant landslide disaster struck the Shuicheng District of Liupanshui City in Guizhou Province. The landslide had an estimated volume of around 2 million cubic meters, impacting nearly 1600 individuals, resulting in 43 fatalities and 9 people reported missing. Over 100 homes were completely destroyed, while more than 2300 sustained varying degrees of damage, leading to direct economic losses amounting to approximately CNY 190 million. To validate the CA model, data from the landslide site, encompassing topographic, geomorphological, and remote sensing imagery, were subsequently utilized to simulate the event. The results of the simulation are depicted in Figure 10, which shows the progression of the landslide from its initiation to the 90 s mark. In this figure, the red region signifies the area affected by the landslide, which is expected to gradually expand as the flow moves towards the base of the mountain.

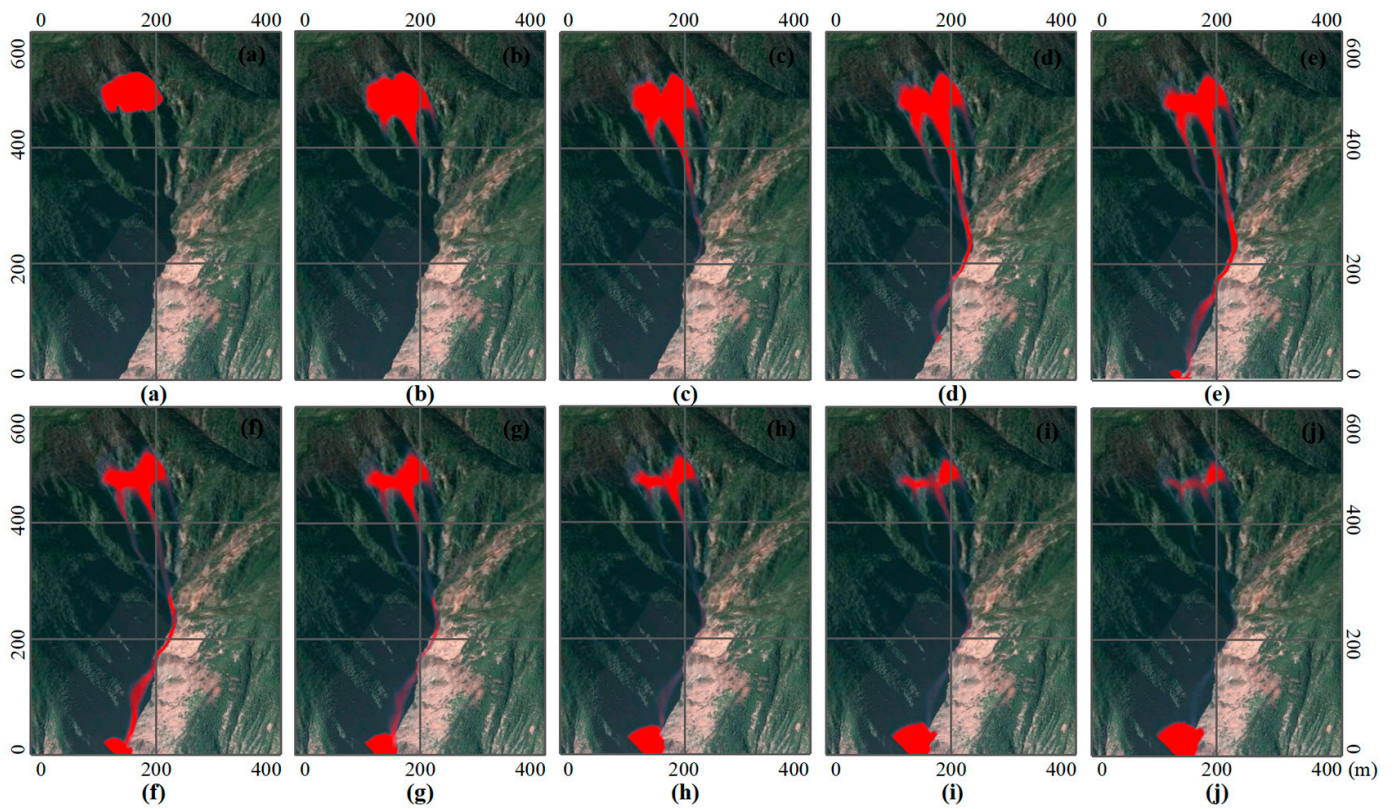


Figure 9. Landslide dispersion process for mountain 2: (a) initial landslide region; (b–j) 10–90 s landslide spread region.

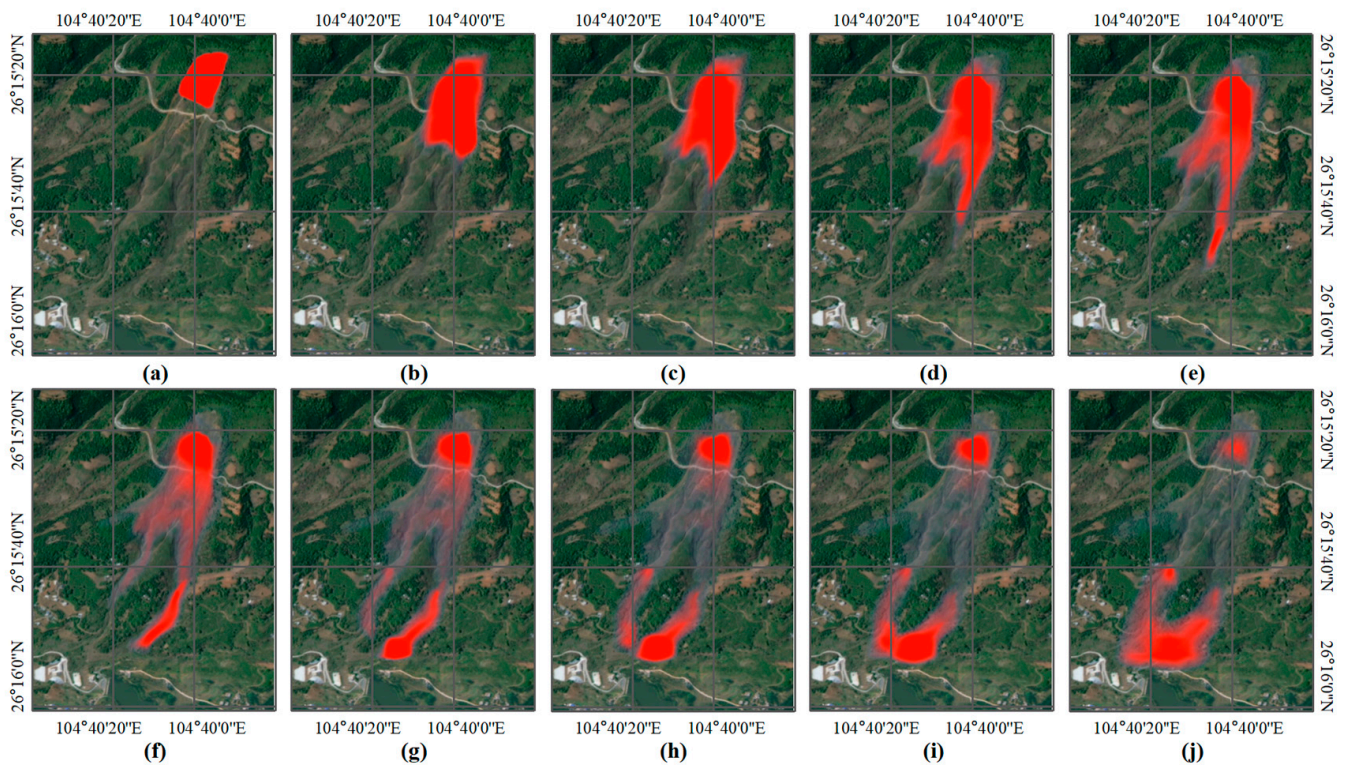


Figure 10. Landslide dispersion process in Shuicheng: (a) initial landslide region; (b–j) 10–90 s landslide spread region.

To gain a deeper insight into the landslide movement process, the landslide velocity was calculated using Equations (9) and (10). Initially, the distance of landslide movement in the direction of the hillside, denoted as L , was determined by assessing the displacement between the initial cell and the current cell of the landslide. Then, the landslide movement distance in the vertical direction, denoted as h , was calculated in accordance with Equation (9). Finally, during landslide motion, the gravitational potential energy is converted into the kinetic energy and frictional potential energy. The velocity of the landslide movement was calculated based on Equation (10).

$$h = L \sin \alpha \quad (9)$$

$$Mgh = \frac{Mv^2}{2} + L\rho Mg \cos \alpha \quad (10)$$

where M represents the landslide quality; v represents the velocity of the landslide; g represents the coefficient of gravity, $g = 9.8 \text{ m/s}^2$; h represents the distance of landslide movement in the vertical direction, that is, the distance of landslide movement in the direction of gravity; L represents distance of landslide movement in the direction of the hillside, that is, the distance between the initial cell location of the landslide and the current cell location; ρ represents the fluid density; and α represents the gradient of the landslide-producing slope.

The velocity during the first 0–90 s is illustrated in Figure 11. The landslide can achieve a maximum velocity of 30 m/s, which occurs at the midpoint of its movement, as indicated by the red section of the figure. In contrast, the motion velocity in both the initiation and accumulation areas of the landslide is lower, approximately ranging from 0 to 10 m/s.

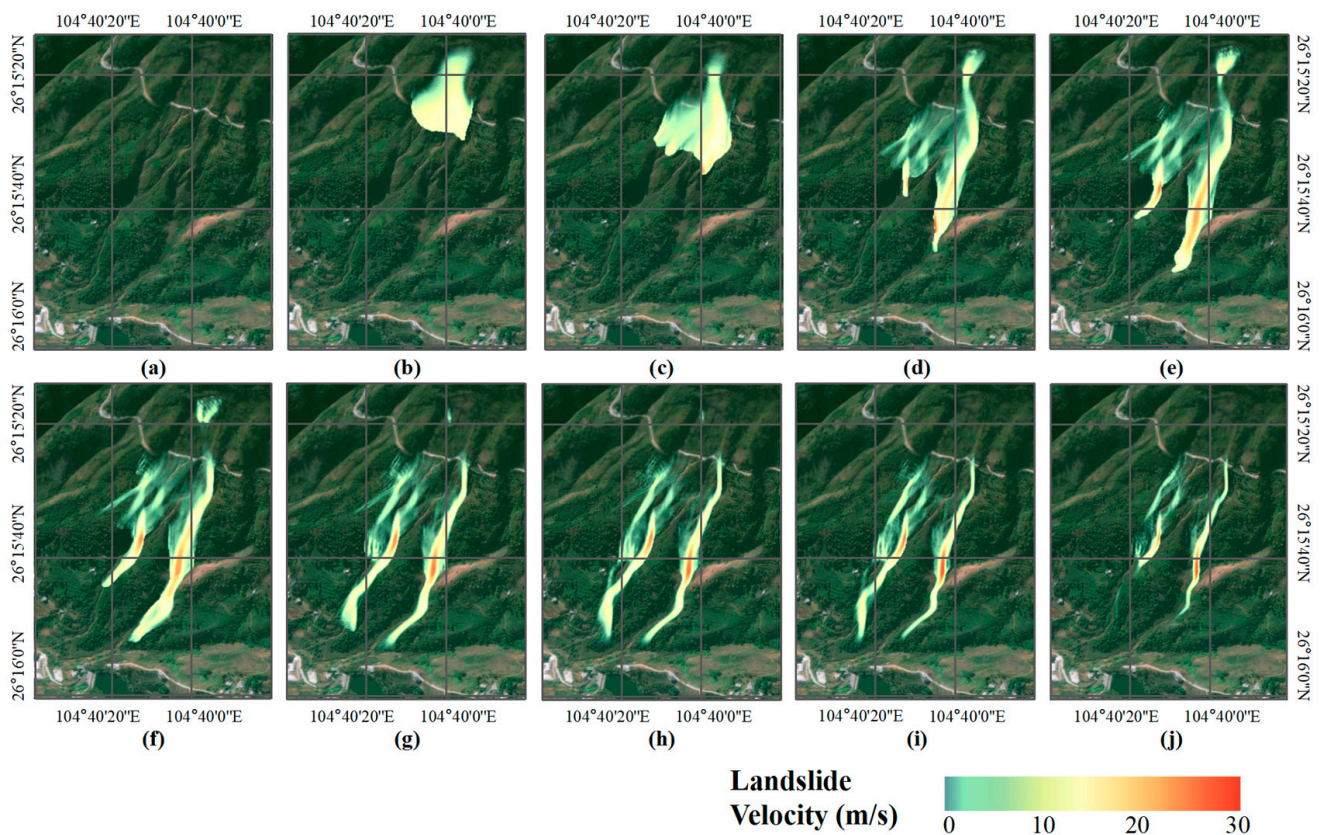


Figure 11. Landslide velocity of Shuicheng landslide: (a) initial landslide velocity; (b–j) 10–90 s landslide velocity.

The results of the simulation were compared with the corresponding UAV image, and the results are illustrated in Figure 12. In this figure, (a) represents the actual inundation extent of the landslide event that occurred in Shuicheng, Guizhou Province, while (b) illustrates the inundation range of the landslide using the CA model. The simulation outcomes were superimposed on the images of the real landslide inundation zone, resulting in the composite representation depicted in (c). The simulation results derived from the CA model in this study closely align with the observed inundation area. The initiation of the landslide occurred at the midpoint of the hillside, subsequently advancing towards the base of the hill, with its movement being influenced by factors such as surface elevation, slope, and aspect. During the progression of the landslide, a localized area of uplift emerged on the hillside which subsequently influenced the landslide to disperse laterally. The simulation closely mimicked the observations captured in the actual imagery. The extent of simulated landslide dispersion was evaluated against the actual dispersion observed in landslides. The accuracy of the model was quantified using the Sørensen's coefficient (SC), a statistical measure employed to assess the similarity between two samples. The SC is quantified on a scale from 0 to 1, where a value approaching 1 signifies a higher degree of similarity between the modelled outcomes and actual results [83,84]. The calculation yielded an SC value of 0.878. To further validate the simulation results, the kappa coefficient and overall accuracy were assessed, resulting in a kappa value of 0.891 and a total accuracy of 94.12%. These metrics indicate that the landslide simulation model established in this research has a high level of accuracy.

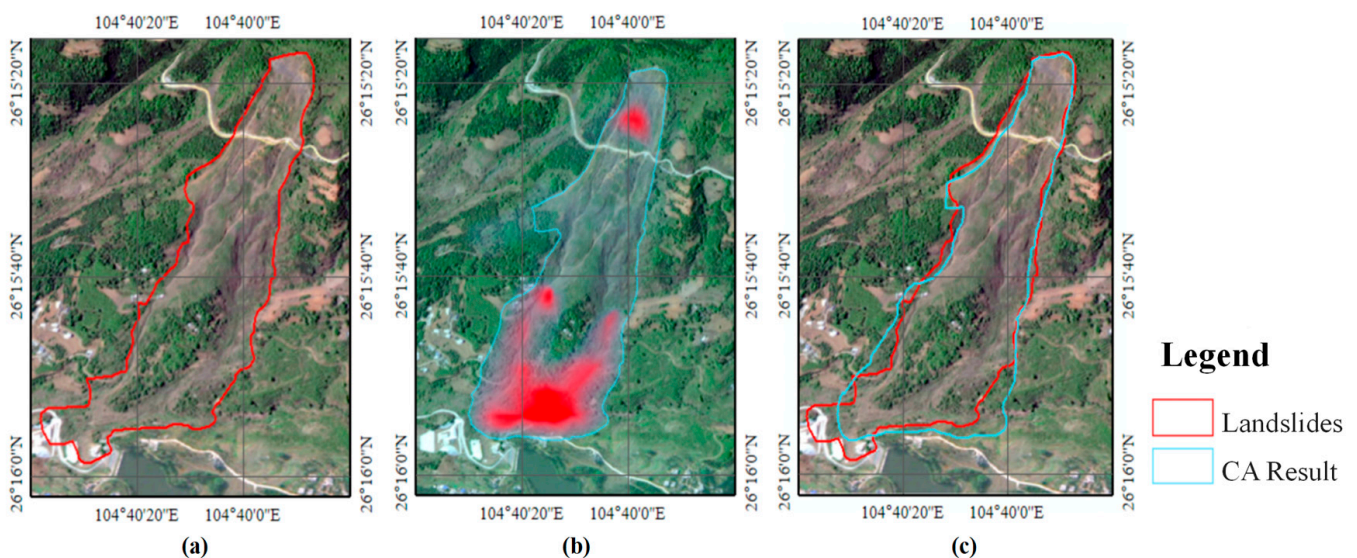


Figure 12. Landslide simulation result and UAV image: (a) actual inundation extent of the landslide event; (b) simulated inundation extent of the landslide event; (c) comparison between actual extent and simulated extent.

5. Discussion

The findings of this study offer important insights into the vulnerability and movement patterns of landslides in the area studied. The ensemble machine learning model shows a high level of accuracy in predicting landslide susceptibility, with many historical landslide sites falling within high-risk zones. This indicates that the chosen predisposing factors effectively represent the main causes of landslide occurrences in the region.

Additionally, the rule-based discrete grid model supports the understanding of the spatial and temporal characteristics of landslides. The simulation outcomes closely match the actual movement patterns seen in past landslide events, highlighting the model's capability to capture the intricate relationships between topography, geomorphology, and hydrology. The model's high accuracy, as demonstrated by the SC, kappa coefficient,

and overall accuracy, suggests its potential for use in landslide monitoring and early warning systems.

There are several inherent limitations to the current study. First, the topography and geomorphology of the study area are complex, and a wide range of factors could influence the occurrence of landslides. However, this study considers only a small number of influencing factors from geological and geometrical features, which may affect the accuracy of the LS assessment. Second, when simulating landslides with the rule-based discrete grid model, the complexity of the landslide movement mechanism and data limits may impose constraints on the design of the movement rules. In the future, we will further our understanding of the mechanism underlying landslide movement and enhance the rule-based discrete grid model to increase the simulation accuracy. Third, extensive examination and assessment of the study area will be carried out to integrate supplementary variables, thereby enhancing the precision of the LS findings and offering a more realistic portrayal of the actual circumstances concerning LS. Finally, there are several varieties of landslide hazards, including rainfall-induced landslides and landslides associated with glacial snowmelt. In the future, based on the distinctive characteristics of each type, an effort will be made to differentiate between the various types of landslides and to develop simulation models that are tailored to the specific characteristics of each type.

The approach used in this research can be utilized in various landslide-prone areas around the globe. By identifying suitable predisposing factors and creating customized simulation models, we can gain important understanding of landslide susceptibility and movement behavior in diverse geological and geomorphological contexts. This knowledge is essential for enhancing disaster risk reduction and emergency management strategies in regions susceptible to landslides.

6. Conclusions

Geological disasters are common in China, with landslides being the most common. Studies on landslide simulations and LS can serve as a foundation for emergency response and rescue operations following a disaster. This study proposes an ensemble machine learning approach that takes nine predisposing factors (e.g., slope, aspect, and SDF) of landslides as inputs to the model and achieves satisfactory performance. An LS grading map and high landslide risk areas were obtained for the study area based on the model's results. The obtained high-risk landslide areas have a high degree of consistency with real landslide disaster sites. A landslide simulation system was established utilizing a rule-based discrete grid model to simulate the occurrence dynamics of landslides in high-risk regions of Wenchuan County, Sichuan Province. The model achieves not only the simulation of the landslide process but also the simulation of landslide velocity. The precision of the landslide simulation model was assessed through UAV imagery pertaining to the Shuicheng landslide incident in Guizhou Province. The model has an SC of 0.878, a kappa coefficient of 0.891, and a total accuracy of 94.12%, providing evidence of its high accuracy. This study, in contrast to analogous research, places a heightened focus on the rationality of the factors that predispose areas to landslide susceptibility. Furthermore, it considers the influence of geological and geomorphological factors, hydrological conditions, and other relevant variables on the occurrence of landslides. Prior research has often focused primarily on simulating the processes involved in landslide development, neglecting to validate the accuracy of these simulations. This is due to the rapid velocity, significant intensity, and restricted range of landslides within the simulation process. Nevertheless, the validity of the established rule-based discrete grid model is substantiated in this study through the integration of actual landslide instances.

This study is important for managing landslides in the Wenchuan region. Recognizing high-risk zones can assist in land-use planning and infrastructure development, thereby reducing the risk of landslide hazards. Local governments and stakeholders can focus on these regions for implementing mitigation strategies like stabilizing slopes, enhancing drainage, and establishing early warning systems. Furthermore, the simulation model

can forecast the possible range of landslide movement, facilitating better evacuation and response strategies if a landslide occurs.

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