

Article

Predicting Change in Adaptation Strategies of Households to Geological Hazards in the Longmenshan Area, China Using Machine Learning and GIS

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Abstract: Hydrological changes combined with earthquakes easily trigger secondary disasters, including geological hazards. The secondary hazard of precipitation is the main disaster type in the Longmenshan Area (China). The 2008 Wenchuan earthquake caused more than 60,000 landslides, severely affecting rural households. This study aimed to answer two questions: (1) How did households adapt to the landslide-prone post-earthquake environment? (2) How will the households' adaptation strategies change if landslide frequency changes? Different post-disaster adaptation strategies of households in Longmenshan Town, Sichuan, China were identified through a questionnaire survey and then clustered into groups based on similarity using a K-means algorithm. Afterward, a gradient boosting decision tree (GBDT) was used to predict change in adaptation strategies if there was a change in the frequency of landslides. The results show that there are three types of landslide adaptation strategies in the study area: (1) autonomous adaptation; (2) policy-dependent adaptation; and (3) hybrid adaptation, which is a mixture of the first two types. If the frequency of landslides is increased, then around 5% of households previously under the autonomous adaptation type would be converted to policy-dependent and hybrid adaptation types. If the frequency of landslides is reduced, then around 5% of households with policy-dependent adaptation strategies would be converted to the autonomous adaptation type. This exploratory study provides a glimpse of how machine learning can be utilized to predict how adaptation strategies would be modified if hazard frequency changed. A follow-up long-term study in Longmenshan Town is needed to confirm whether the predictions are indeed correct.



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Keywords: landslide; adaptation strategy; GBDT; machine learning; mountain hazards

1. Introduction

Geological hazards occur frequently in China and are driven by many factors, including hydrological conditions, geological conditions, climate change, etc. From 2009 to 2019, about 133,899 geological hazards occurred in China, including 94,321 landslides, 24,981 mudslides, 10,284 debris flows, and 3209 surface collapses [1]. Landslides account for 71% of the total geological hazards in China and are mainly due to changes in geological and hydrological conditions. Water-related factors, such as heavy rainfall and ground water change, easily trigger landslides, especially after an earthquake. The 2008 Wenchuan earthquake along the Longmenshan fault and the change in hydrological conditions triggered more than 60,000 landslides, which resulted in about 20,000 fatalities [2]. Xu et al. reported an even higher estimate: almost 200,000 landslides distributed over an area of more than

110,000 square kilometers [3]. Among the recent strong earthquakes around the world, the 2008 Wenchuan earthquake set off the largest number of landslides [4], which caused extensive damage to houses, factories, offices, schools, farms, highways, bridges, irrigation channels, power plants, and lifeline infrastructure. More than 30 dammed lakes were also created by the landslides, threatening the residents living downstream of those lakes [5–9].

Strong earthquakes, like the M_S 8.0 Wenchuan earthquake, can lead to increased slope instability, which can persist for a long period of time [5,10]. After the 2008 Wenchuan earthquake, abundant loose landslide debris remained on slopes; this debris can later serve as source material for rainfall-induced landslides and endanger reconstructed settlements [5,9,11]. Post-earthquake landslides will continue to be a significant concern in the future [10,12]. Without vegetation cover, the topsoil and sediment in denuded areas and other high-risk areas will continue to be unstable in the coming years. Previous researchers have mainly concentrated on how long it will take for the landslide activity to stabilize after the 2008 Wenchuan earthquake [4]. In previous studies, researchers have noted that there was a high level of landslide activity for more than 15 years after the 1923 Kanto earthquake (with comparable magnitude of M_S 7.9) in Japan, and it took more than 40 years for landslide activity to dwindle to a stable condition. According to Chen et al. [13], it will take about 81 years for the denudation rate in the area affected by the 2008 Wenchuan earthquake to return to the pre-earthquake rate. Debris-flow disasters can only be expected to become infrequent 22 years after the earthquake, or around 2030.

Whether by choice or by necessity, people in earthquake-affected areas must adapt to new landscape that has become vulnerable to landslides. However, rare studies focus on community-based approaches related to landslide risk reduction, and even fewer on household-scale interventions. Anderson et al. [14] enumerated some factors that limit the capacity of communities to manage landslide risk in the Caribbean: lack of technical awareness related to landslides (e.g., what mechanisms trigger landslides); lack of access to finance; lack of organization for the provision of public good; and high levels of poverty and unemployment. As a consequence, homeowners built retaining walls based on the perception that it was best to address immediate and visible threats (soil erosion and slope failures) rather than invisible causes (surface water infiltration). The construction of retaining walls was rarely effective without addressing inadequate drainage first.

In the case of the areas affected by the 2008 Wenchuan earthquake, some studies have examined the recovery strategies of communities and households after the earthquake and the secondary hazard events that followed [15–18]. Han [16] focused on five livelihood assets: human capital, social capital, financial capital, natural capital, and physical capital. Jin et al. [17] reported that households adjusted their income-generating strategies through crop diversification, non-agricultural self-employment, and increased working time of male household members. Feng et al. [18] examined the effectiveness of government aid and concluded that financial aid for housing reconstruction accounted for less than 60% of the total cost. Song et al. [12] reviewed local recovery plans created in response to the 2008 Wenchuan earthquake, which suggested ways for planners to incorporate sustainability into the recovery process. According to Peng et al. [19], the risk perception of farmers affected their post-disaster reconstruction strategies and, eventually, the sustainability of the overall disaster recovery of their area. Andersson-Sköld et al. [20] provided an overview of the analytical steps in systematic landslide risk management: risk identification; risk inventory; risk assessment and risk mitigation requirements; defining risk management strategy; and implementation, follow-up, control, and monitoring.

Machine learning techniques are widely utilized to scientifically predict the location and timing of disaster developments and potential impacts [21]. Chen et al. utilized six machine learning techniques to investigate the development of floods based on flood risk evaluation: support vector machine (SVM), random forest (RF), gradient boosting decision tree (GBDT), eXtreme gradient boosting (XGBoost), multi-layer perceptron (MLP), and convolutional neural network (CNN) [22]. The GBDT model is a widely used approach in machine learning based on establishing various weak classifiers for accumulation to a

strong classifier with diverse iterations that improve the accuracy of predictions [23]. It has advantages in forecasting, which are strongly predictive abilities, and it is insensitive to outliers, flexible for processing multiple types of data, and does not pre-determine the correlation between predictor variables and predicted variables [22,24]. Yang et al. applied GBDT to study the non-linear impacts between bus rapid transit and traffic accidents [25]. In terms of landslides, an increasing amount of research has applied machine learning techniques to assess landslide susceptibility and predict changes due to landslides, providing a feasible outcome for decision making. Pourghasemi and Rahmati [26] gave examples of previous studies published between 2004 and 2017 and used machine learning for landslide susceptibility mapping. They identified 14 commonly used machine learning techniques and utilized 10 techniques in their own comparative study. The output landslide susceptibility maps are very useful for planners and decision makers in formulating land use, developing landslide early warning systems, and prioritizing areas for mitigating landslide risks [21,26]. Shirzadi et al. [27] mentioned several other studies applying machine learning to landslide research, especially in risk analyses. In a quantitative assessment of landslide susceptibility, machine learning approaches performed better and were regarded as more efficient than expert opinion-based and analytic approaches [28]. He et al. compared the performances of two methods, gradient boosting decision tree (GBDT) and AdaBoost, in vulnerability appraisals of landslides and wildfires in Southeast Asia, which showed that GBDT had outstanding performances in assessment processes, offering precise assessment results by combining several weak classifiers [24,29]. Rong et al. also applied GBDT to assess the susceptibility of landslides and produce landslide susceptibility mappings [30].

At present, little is known about bottom-up recovery strategies of households in areas exposed to post-earthquake mountain hazards. This study aims to address this knowledge gap by using machine learning, which has been increasingly employed in disaster risk management related to landslides. Most machine learning studies related to landslides deal with the first two steps (e.g., gaining knowledge of triggering factors and landslide susceptibility mapping), but very few machine learning studies deal with subsequent steps. Landslides are the most frequent geological hazards in the Longmenshan area. This study will focus on the landslide adaptation strategies of households. The two objectives of this study are: (1) to investigate how households adapt to the landslide-prone post-earthquake environment and (2) to predict using machine learning how the adaptation strategies of households change if landslide frequency changes.

2. Methodology

This study followed the methodology flowchart shown in Figure 1. The research was divided into three parts: data collection, cluster analysis of adaptation strategies, and prediction of change in adaptation strategies. Details are provided in the following subsections.

2.1. Study Area

The study area is located along the Jianjiang River in Longmenshan Town, Sichuan, China, specifically in the section between Xujiagou Town and Dahaizigou Town approximately 89 km northwest of Pengzhou County (Figure 2). Longmenshan Town is located in the Longmenshan (Longmen Mountain) area, which geographically lies in the transition zone between the Tibetan Plateau and the Chengdu Plains. It is a mountainous area with steep topography, and it has a very complex geology and geomorphology with elevation ranges from 1073 to 4812 m and a north–south decline. The climate is subtropical with a mean annual temperature of about 12 °C, and the yearly rainfall in the study area ranges from 635 to 1281 mm, with a large part of the precipitation falling between May and October [31]. With the 2008 Wenchuan earthquake and the subsequent 2013 Lushan earthquake both hitting this region, the households in the area have been under severe threat of potential landslides. Frequent geological disasters in the area have caused repeated reconstruction of infrastructure and housing in previous years. Mountain hazards continue

to occur, especially during the rainy monsoon season, indicating that huge losses are still likely in the future.

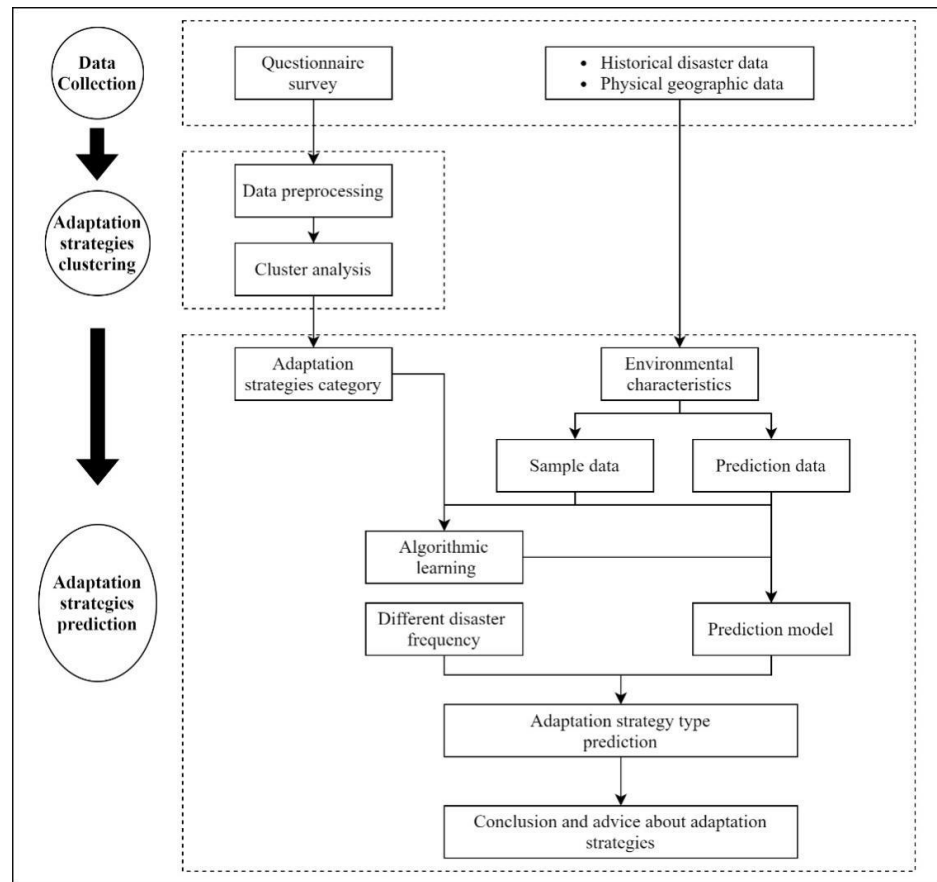


Figure 1. Methodology flowchart.

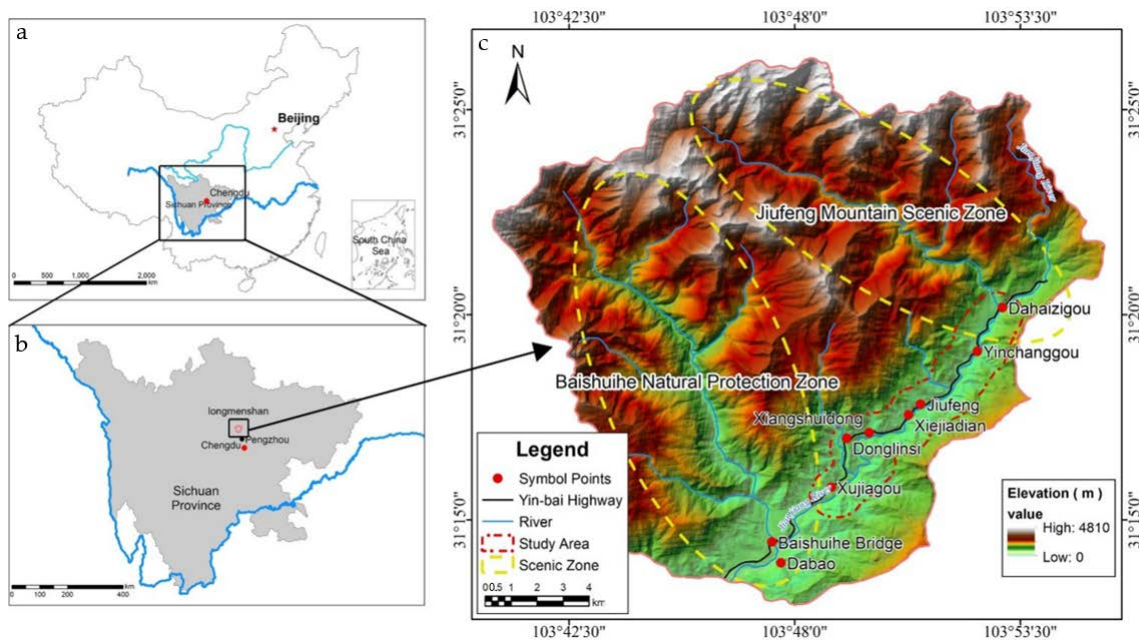


Figure 2. Maps showing the location in (b) Sichuan Province of (a) China, where (c) the study area is situated.

Longmenshan Town has a total area of about 368 km² and is located at about 30 km from the epicenter of the 2008 Wenchuan earthquake. The Jianjiang River, which is a tributary of the Yangtze River, flows through the length of this valley. About 56% of this mountainous town is covered with forest, and the area is rich in mineral resources (mainly copper and nickel) and pharmaceutical raw materials. Due to abundant water resources, there are also many small hydropower stations. The Yin-bai Highway (a province-level road) is the main connection between the area and the rest of the country. At the end of 2020, Longmenshan Town had a population of 24,912 distributed in 8629 households [32].

According to the disaster information data from detailed investigations and zoning reports of geological disasters in Pengzhou in 2009, 2012, 2013, and 2020 by the Sichuan Geological Engineering Investigation Institute, a total of 159 potential geohazards were identified in Longmenshan Town (Table 1). Based on the 1978 Varnes classification system, the identified potential geohazards included 51 debris flows, 66 landslides, 40 debris falls, and 2 slope failures. The geohazards were classified according to their impact radius into four levels: small (500 m), medium (1000 m), large (1500 m), and extra-large (2000 m). For the study area of this work, there were 77 potential geohazards, including 34 debris flows, 30 landslides, 12 debris falls, and 1 slope failure. The distribution of potential geohazards in the study area is visualized in Figure 3a using ArcGIS software.

Table 1. Co-seismic and post-seismic potential geohazards in Longmenshan Town.

Category	Levels				Total
	Small	Medium	Large	Extra-Large	
Debris flow	20	18	11	2	51
Landslide	60	6	0	0	66
Debris fall	26	10	4	0	40
Slope failure	1	1	0	0	2
Total	107	35	15	2	159

Note: Source: Sichuan Geological Engineering Investigation Institute reports.

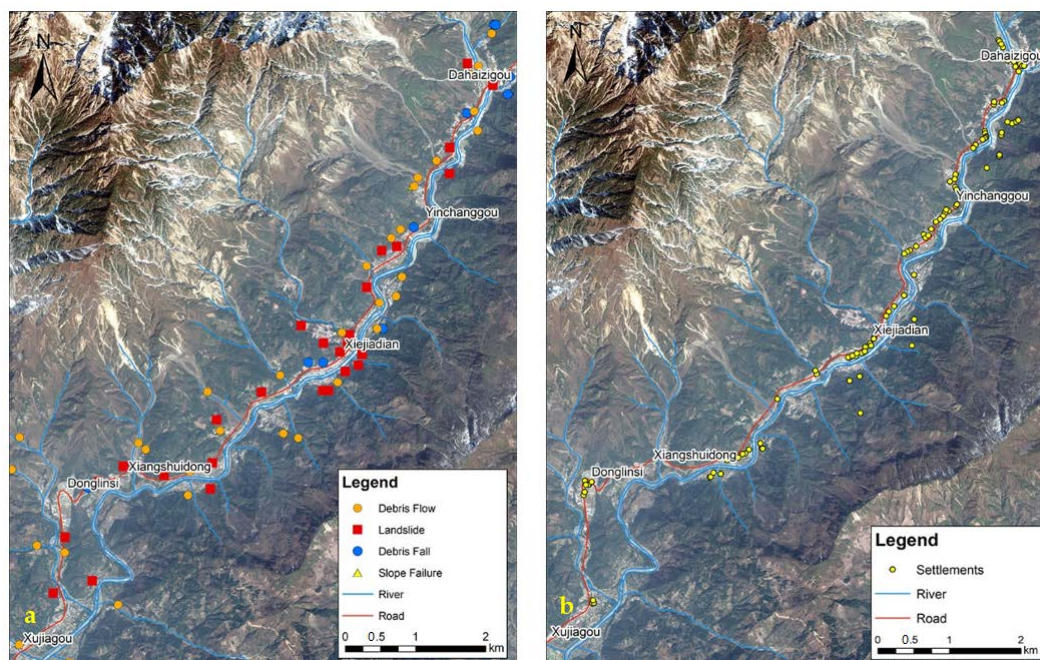


Figure 3. Distribution of co-seismic and post-seismic potential geohazards (a) and settlements investigated (b) in the study area.

2.2. Data Collection

2.2.1. Landslide Adaptation Strategies

Adaptation strategies employed by the households were obtained through face-to-face questionnaire surveys with a participatory rural appraisal (PRA) that evaluated the changes in settlement patterns after the 2008 Wenchuan earthquake. The surveys were conducted with different people during three time periods (October 2012, August 2013, and July 2014) in six villages of Longmenshan Town: Xujiagou, Donglinsi, Xiangshuidong, Xiejiadian, Yinchanggou, and Dahaizigou (Figure 3b). The interview with each survey respondent lasted between 30 to 60 min. The questionnaire covered issues pertaining to (1) economic adaptability, (2) physical adaptability, (3) dependence on government policies, (4) information accessibility, and (5) psychological adaptability. These five dimensions were used to determine the adaptation strategies of the households. The list of indicators under each dimension is shown in Table 2.

Table 2. List of indicators for each dimension of household adaptation strategies.

Dimensions	Indicators	Values
Economic adaptability	Living condition	Worse = -1; No change = 0; Better = 1
	Type of job	No change = 0; Changed = 1
	Number of jobs	Decreased = -1; No change = 0; Increased = 1
	Number of household members with job	Decreased = -1; No change = 0; Increased = 1
Physical adaptability	Place of work	Contracted = -1; No change = 0; Expanded = 1
	House floor area	Decreased = -1; No change = 0; Increased = 1
	House construction material Relocated	No change = 0; Changed = 1 Yes = 1; No = 0
Dependence on government policies	Government assistance	Yes = 1; No = 0
	Communal facilities	Yes = 1; No = 0
Information accessibility	Information access	Yes = 1; No = 0
	Understanding degree	High = 1; Low = 0
	Educational level	High = 1; Low = 0
Psychological adaptability	Adaptation perception	Bad = -1; No change = 0; Good = 1

A total of 112 valid responses were obtained using convenience sampling. Random sampling was not possible due to the frequent unavailability of target respondents at their houses during the survey. Verbal informed consent was obtained from each survey participant.

2.2.2. Model Parameter Data

In this study, a variety of data were used in the GBDT model to predict how the adaptation strategies would change under different landslide frequencies. The GBDT model considered different parameters, including historical disaster data, terrain data, vegetation data, landform data, vector data (road, river, and settlement points), and the adaptation strategies obtained from the questionnaire survey. The historical disaster data were obtained from investigations and zoning reports on geological disasters by the Sichuan Geological Engineering Investigation Institute. The terrain data were provided by the Sichuan Bureau of Surveying, Mapping, and Geoinformation. The vegetation data were obtained from the United States Geological Survey (USGS). The landform data were obtained from the Atlas of Mountain Hazards and Soil Erosion in the Upper Yangtze. The vector data (road, river, and settlement points) are remote sensing images derived from Google Earth images and photos taken from drones. However, as the type of land use in the study area was all settlements and the study site spanned a small area (i.e., the meteorological data and geological data were the same), the researchers only chose parameters with obvious differences when selecting the features of the model. Table 3 shows the list of data used in the model for predicting change in household landslide adaptation strategies.

Table 3. Data used in the prediction model.

Elements	Description	Data Source
Historical disaster data	The distribution of collapses, landslides, debris flows, and unstable slopes in the study area	Investigations and zoning reports of geological disasters, Sichuan Geological Engineering Investigation Institute
Terrain data	Digital elevation model, 30 m resolution; basic topographic map of Sichuan, scale 1:50,000	Sichuan Bureau of Surveying, Mapping, and Geoinformation
Vegetation data	NDVI data of the study area in September and October of 2011, 2013, and 2015 obtained from LANDSAT images	LANDSAT satellite digital products from the USGS (https://earthexplorer.usgs.gov/ , accessed at 19 November 2016)
Landform data	The landform data in the study area	Atlas of Mountain Hazards and Soil Erosion in the Upper Yangtze (http://ir.imde.ac.cn/handle/131551/18263 , accessed at 20 September 2016)
River	Vector data of the river in the study area (distance from river in meters)	Remote sensing image interpretation
Road	Vector data of the road in the study area (distance from road in meters)	Remote sensing image interpretation
Residential area points	Vector data of residential points in the study area	Remote sensing image interpretation
Questionnaire survey data	Survey of landslide adaptation strategies of households in the study area	Questionnaire survey
Remote sensing image	QuickBird high resolution picture, 2.4 m resolution; UAV photographs, 0.6 m resolution	Google Earth images, unmanned aerial vehicle photography

2.3. Clustering Method of Landslide Adaptation Strategies

As each household implemented different landslide adaptation strategies based on its situation, it was expected that there would be a large number of distinct adaptation strategies. To reduce the number of strategies considered in the study, the researchers clustered similar strategies together.

In the past, researchers have mainly relied on experience and professional knowledge in classification and clustering processes and have seldom used mathematical methods, causing many classifications to be subjective and arbitrary. Nowadays, cluster analysis, which classifies objects in association with their degrees of similarity, is based on multivariate statistical analysis, making the classification results more objective. In machine learning, clustering is a method of unsupervised learning where a set of inputs is divided into subsets (called clusters) so that observations within the same cluster are similar according to some predesignated criterion or criteria, while observations drawn from different clusters are dissimilar [33]. Unlike classification, the subsets in clustering are not known beforehand.

A K-means algorithm was used to cluster the 112 landslide adaptation strategies collected from the questionnaire survey. A comparison study shows that K-means algorithms had a much higher operational efficiency in clustering among five clustering algorithms investigated by Abbas [33]. Based on the Calinski–Harabasz Index, $s(k)$ was used for clustering model evaluation. The index describes the ratio of the discrete mean between clusters to the discrete mean within a cluster. The higher index is, the better the clustering model. The main steps involved were:

- (1) Randomly initializing K-cluster centroids based on the data ranges of N data objects;
- (2) Assigning each object to the group that had the closest centroid;
- (3) Updating the locations of each centroid by calculating the mean value of the objects assigned to it;
- (4) Repeating Steps 2 and 3 until the maximum number of iterations was reached or until the centroids no longer moved;
- (5) Finding the best clustering effect of the model based on the value of $s(k)$;
- (6) Conducting computations using scikit-learn and NumPy Python packages.

2.4. Prediction Method of Change in Adaptation Strategies

Based on the clustering results, a gradient boosting decision tree (GBDT) machine learning technique was used to predict change in household adaptation strategies in the study area (721 households total) with three scenarios of landslide frequency: Scenario 1 (no change in landslide frequency); Scenario 2 (an increase in landslide frequency); and Scenario 3 (a decrease in landslide frequency). To predict changes in landslide adaptation strategies, we adopted the GBDT approach due to its superior anticipation ability [34,35]. GBDT yields a predictive model in the form of an ensemble of decision trees and exhibits strong predictive power with a differentiable loss function [36].

GBDT, as an integrated model, uses a classification and regression trees (CART) model as a weak learner [34]. Its basic idea is to iteratively build a decision tree with a gradient of residual reduction and, finally, to obtain a model composed of multiple decision trees. When comparing 11 state-of-the-art classification algorithms, Zhang et al. [37] observed that GBDT can achieve impressive classification prediction performance, as it was the fastest in testing and prediction. Natekin and Knoll [38] noted that gradient boosting machines are very versatile and can readily be customized to serve different practical purposes.

In performing GBDT in this study, the main steps involved were:

- (1) Model features selection;
- (2) Data preprocessing;
- (3) Model construction and parameter optimization.

The model was constructed with the sample data by taking the following steps: a. import dependencies; b. import sample data; c. apply the sample data to the GBDT function; d. use K-fold cross validation score result to optimize parameters; and e. obtain the best score of the model and related parameters.

- (4) Model prediction

We applied the prediction data to the constructed model to predict adaptation strategies with different landslide frequency scenarios. Scenario 1 (no change in frequency) involved a model frequency that was the same as the historically observed frequency. Scenario 2 (increase in landslide frequency) was set as double the historically observed frequency. Scenario 3 (decrease in landslide frequency) was set as half the historically observed frequency.

A Python code was written to run the model. K-fold cross validation, a technique of dividing the original sample randomly into K sub-samples, was used to avoid model overfitting. Then, a single sub-sample was regarded as the validation data to test the model, and the remaining sub-samples were used as training data. These processes were repeated K times, and each of the K sub-samples was used exactly once as the validation data. It was assumed that the higher the result of the cross-validation, the more accurate the model. In this study, K was set to 10.

3. Results and Discussion

3.1. Clustering of Landslide Adaptation Strategies

Based on 112 survey responses, the Calinski–Harabasz Index was used to evaluate the results of the K-means clustering analysis. The number of clusters with the highest Calinski–Harabasz Index was three (Figure 4). In other words, when the number of clusters was three, the ratio of between-clusters dispersion and within-cluster dispersion was the largest, resulting in the best partition of the data. This means that the cluster analysis obtained the best clustering results.

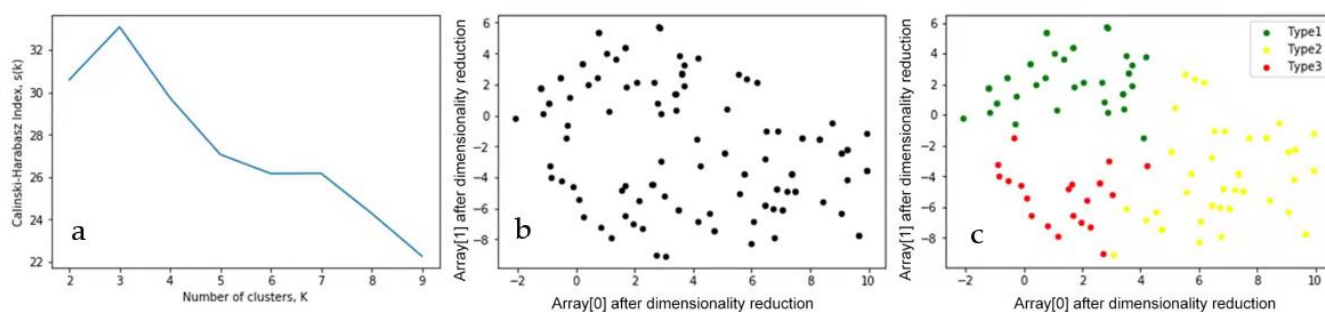


Figure 4. Results of K-means clustering (a), raw data (b), and clustered data (c) of landslide adaptation strategies.

In order to better visualize the clustering results, a t-distributed stochastic neighbor embedding (t-SNE) algorithm [39] was used to reduce the dimensionality of the data from five dimensions to two dimensions, which also was implemented in scikit-learn. Figure 4 shows scatter plots with the raw data and the clustered data after dimensionality reduction. Coordinate overlap existed at different points after dimensionality reduction, so the number of points seen in Figure 4c is smaller than the actual total number of survey responses, especially for the green and yellow points.

We then compared the features of each cluster and named each cluster for convenience as follows:

- Type 1: Government-policy-dependent adaptation strategy (39 green points in Figure 4c, 34.8% of the 112 survey responses);
- Type 2: Autonomous household-initiated adaptation strategy (52 yellow points in Figure 4c, 46.4% of the 112 survey responses);
- Type 3: Hybrid adaptation strategy, which is a mix of Types 1 and 2 (18.8%).

Figure 5 shows the average dimension scores of the three landslide adaptation types plotted on a spider diagram.

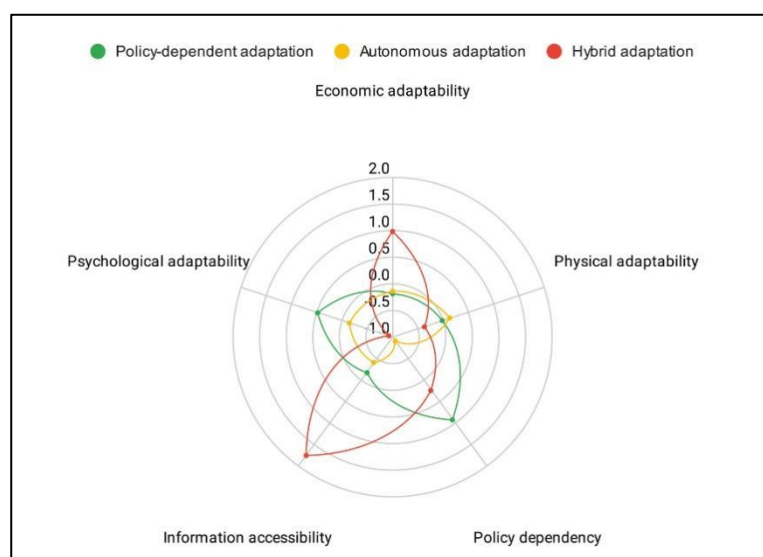


Figure 5. Average dimension scores of the three landslide adaptation types.

3.2. Prediction of Change in Landslide Adaptation Strategies

After running the prediction model, Table 4 shows changes in landslide adaptation strategies depending on changes in landslide frequency. Explanations for each of the three scenarios are provided below.

Table 4. Results of the prediction model with 721 households.

Adaptation Types	Scenario 1 No Change	Scenario 2 Frequency Increases	Scenario 3 Frequency Decreases
Type 1: Policy-dependent adaptation	72 (10%)	121 (17%)	40 (5%)
Type 2: Autonomous adaptation	551 (76%)	490 (68%)	583 (81%)
Type 3: Hybrid adaptation	98 (14%)	110 (15%)	98 (14%)
Total	721 (100%)	721 (100%)	721 (100%)

3.2.1. Scenario 1: No Change in Landslide Frequency

When the frequency of landslides remained the same, only one in ten of the 721 households was classified as having adaptation strategies dependent on government policy. Three out of every four households exercised autonomous adaptation strategies. Around 100 households had strategies that were split between government-led and household-driven. These classifications of households were used as the baseline for comparison with the other two scenarios.

3.2.2. Scenario 2: Increase in Landslide Frequency

There are many natural and human-induced factors that can increase the frequency of landslides. Logging of trees, irrigation, mining, quarrying, slope cutting, construction of roads, water impoundment in reservoirs, and increased seismic activity are believed to cause the incidence of landslides to rise [35,40].

If the frequency of landslides increased, previously Type 1 households increased by 7%, while Type 2 households decreased by 8%. There was a slight increase in the number of Type 3 households (1%). Some households previously following autonomous adaptation strategies shifted to government-policy-dependent adaptation. Although landslide disasters can destroy built environment, countries with a strong central government, such as China, may finance most of the reconstruction of the built environment [41], hence the increase in government policy dependence. National policies and plans, similar to the “Regulation on Post-Wenchuan Earthquake Disaster Recovery and Reconstruction” and the “State Overall Plan for Post-Wenchuan Earthquake Restoration and Reconstruction”, may be issued to guide recovery and reconstruction after increasing landslides. When a large number of houses are destroyed by landslides, the government prefers mass housing construction to take advantage of economies and scale to reduce unit cost [41]. In the areas seriously impacted by the 2008 Wenchuan earthquake, there was overwhelming government support for eligible affected households [42]. Subsidies provided in 2008 were so large that the poverty rate actually declined from 34% to 19%; in contrast to the Chinese experience, government subsidies to those affected by a tsunami in Aceh, Indonesia in 2004 and by the Kobe earthquake in 2005 were very modest [42]. Chinese government assistance was so well-targeted to those who suffered great losses that no aid dependency was observed [42]. State-managed allocation of reconstruction resources was driven by damage assessments [43]. In China, the government plays an important role in leading post-disaster reconstruction [8].

Figure 6 shows an example of an area experiencing Scenario 2, or an increase in the frequency of landslides. The area, called Yingchanggou, is a location where areas covered only by grass have become denuded. One of the biggest debris flows happened in Yingchanggou in 2012, as can be seen in the photo for that year. Due to the high frequency of landslides, recovery and reconstruction in this area were slow, which caused the local residents to prefer to work in places other than in the living place. The adaptation strategies depended on local policies to cover the difficulties in life. The prediction results indicated an increasing number of autonomous adaptation strategies shifting to government policy-dependent adaptation, which were concentrated in the Yingchangou area.



Figure 6. Example of an area experiencing Scenario 2 (Source: Photos taken by the authors from Google Earth and an unmanned aerial vehicle (November 2009).

3.2.3. Scenario 3: Decrease in Landslide Frequency

Deliberate interventions, such as geotechnical solutions for stabilizing slopes (such as drainage systems, retention structures, and soil reinforcement), can lower the number of landslides. Gariano and Guzzetti [44] reviewed the existing literature on the combined study of landslides and climate change and observed the impacts on the stability of slopes of changes in temperature, precipitation, wind, and weather systems. Some studies have reported an expected increase in the number of landslides due to climate change, while others have reported a deceleration of landslide activity. Disasters in landslide-prone areas can be avoided by restricting human settlement and activities through land-use zoning, forced and voluntary relocation, and similar controls. Disasters can only occur when natural hazards, such as landslides, interact with human vulnerability [45]. This is best-exemplified by the government's decision to relocate the entire town of Beichuan to a new location 23 km away, eliminating the threat of landslides [46]. The old town was designated as an earthquake memorial site.

If the frequency of landslides decreased, previously Type 1 households decreased by 5% (from 10% to 5%). Type 2 households increased from 76% to 81%. There was no change in the number of Type 3 households. When the frequency of landslides reduced, households previously following the government policy-dependent adaptation strategy shifted to the autonomous adaptation strategy. There was no change in the proportion using hybrid adaptation strategy.

With less threat of landslides, people-driven adaptation strategies can take place. With autonomous adaptation strategies, people can demonstrate self-reliance and decide where and how their houses are built. To save on cost, construction may be completed by the family members themselves or with the help of relatives, friends, and neighbors, instead of hiring carpenters and masons. House reconstruction expenses can substantially increase debts and add to the financial burden of the household, which may consequently increase vulnerability to disasters. With fewer landslides, there will also be less house repair or reconstruction work expected in the future.

Figure 7 shows the distribution of households in the study area under the three types of landslide adaptation strategies with the three different landslide frequency scenarios; most of the houses are along rivers and roads. The changes from the baseline scenario

(Scenario 1) to either Scenario 2 or 3 are not apparent in the maps, as the increase or decrease in the number of households that shifted to another landslide adaptation strategy was only 5%.

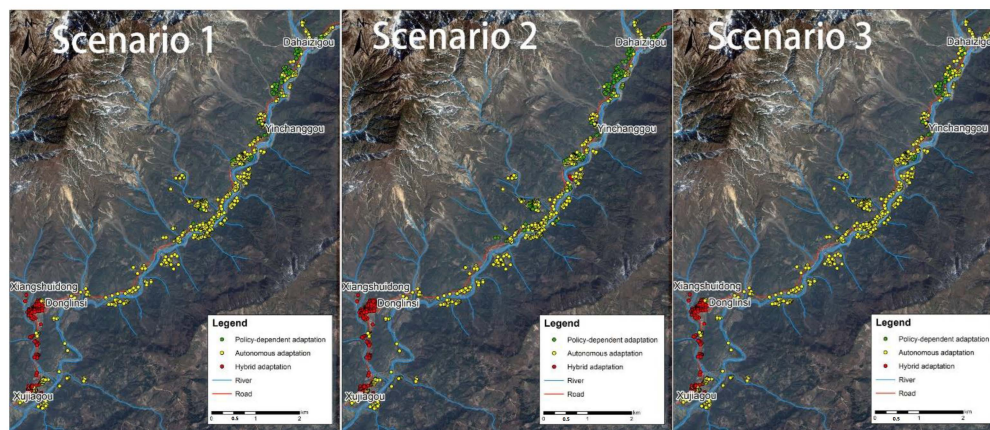


Figure 7. Results of the predicted changes in landslide adaptation strategies according to the three scenarios.

According to Alexander [47], those particularly susceptible to landslide disasters are (1) countries vulnerable to storms or torrential monsoon rains and (2) countries that are seismically active. Unfortunately, with its huge land area, China is both of these, where people in rural areas, such as the site of this study, are much more at risk due to their low or poor knowledge of landslide prevention and mitigation [40]. The role of human vulnerability in the estimation of landslide risk has consistently been underestimated as the focus has frequently been on landslide hazards [47]. Disasters and poverty are closely related. Fang et al. [48] noted that the fertile land used by farmers in their livelihood was reduced due to landslides, affecting both food security and income. Reducing disaster risks, mitigating disaster impacts, and enhancing the disaster coping capacity of people will have to involve poverty reduction [43]. Death tolls and damage to properties due to landslides are much greater in impoverished communities than in communities with substantially well-financed and technologically advanced disaster mitigation and preparedness [47]. Although the Chinese government has been trying to reduce landslide risks, more effort is needed to reach the goal. Currently, Hong Kong is considered to have the “most advanced slope safety management system in the world”, including effective policies, technical measures, and corresponding responsible government agencies [40]. The life loss rate caused by landslides in Hong Kong is 40 per million persons in a year, while the rate is 400 to 500 persons per year in mainland China [40], indicating the wide discrepancy that needs to be addressed in the coming years to reduce casualties and achieve the Sendai Framework target of substantially reducing the disaster mortality rate by 2030. In a survey conducted in 2006, the Chinese respondents had significantly lower risk perception related to landslides compared to the Japanese and Korean respondents [49]. It would be interesting to know how the landslide risk perception in China has changed since then.

3.3. Analysis of Prediction Results

The landslide adaptation strategies taken by 721 households living in the study area were forecasted with three scenarios shown in Table 4. There were a total of 233 households applying policy-dependent adaptation, 1624 households applying autonomous adaptation, and 306 households applying hybrid adaptation, accounting for 11%, 75%, and 14%, respectively. This showed that threequarters of the households are utilizing an autonomous adaptation strategy, which results from enhanced living standards and risk awareness to which a high quality of reconstruction and experience of disasters contribute [49,50]. Given the fact that the Chinese government was responsible for post-disaster recovery and

reconstruction in this area after the 2008 Wenchuan earthquake and its secondary disasters, policies were introduced to benefit those who live there. Therefore, these households applied policy-dependent adaptation passively when first struck by catastrophic disaster, which resulted in increasing their recovery and living quality. This elevates the capability of resisting disaster and increases the number of people choosing an autonomous adaptation strategy. It also can be a viable example for post-disaster recovery and reconstruction in other regions.

In light of the prediction results in Figure 7, the landslide adaptation strategies applied by the 721 households have distinct spatial distributions. In Scenario 1, those who adapted a hybrid strategy were concentrated in the Xujiagou area along a branch of the Jianjiang river, while the households applying a policy-dependent adaptation strategy were concentrated in the upstream area of the Jianjiang river from Yinchanggou to Dahaizigou. Because of the main traffic connection, the Yin-bai Highway (a province-level road), built along the Jianjiang river, people living on the Jianjiang riverside were more likely to adapt an autonomous strategy. Despite the fact that the Yin-bai Highway passes the upstream area of the Jianjiang river from Yinchanggou to Dahaizigou, the households there tended to depend on policies and the government due to being far away from cities that have rich work opportunities and social resources. Compared to households living in the upstream area, those who adapted a hybrid strategy lived in Xujiagou, which is along a branch of a downstream area of the Jianjiang river, resulting from inconvenient traffic conditions. In Scenario 2 and Scenario 3, the spatial distributions of adapting three strategies compared to Scenario 1 showed little change. Therefore, distance from cities and road conditions contributed to the choice of adaptation strategy, and households living in a place close to cities and with better road conditions showed preference for the autonomous adaptation strategy.

Post-disaster recovery and reconstruction play a vital role in long-term development of both regions and individuals, and the choices of the three landslide adaptation strategies can reflect the risk management ability of Longmenshan Town and the people who live there [50]. To mitigate the negative effects of disasters and enhance household capability to manage risks, there are recommendations for local governments and households. In terms of recovery, projects, such as ecological environment recovery, can be implemented to bring the potential geohazards under control, and local governments can formulate feasible plans for disaster management or emergency management. The households can prepare essential materials for emergencies and actively take part in emergency practice to enhance risk awareness. Reconstruction should consider infrastructure and housing to avoid areas with potential geohazards. Convenient traffic connections can serve the majority of people living there, and those who live in the upstream area of the Jianjiang river can move to downstream areas in a bid to move toward cities to obtain more social resources.

3.4. Limitations

This study has some limitations. The questionnaire covered five aspects of households living in the landslide area that basically reflected the adaptation strategies. However, landslides may cause huge changes in the environment that some rural households' livelihoods highly depend on. This study did not fully consider environment adaptability, as it partly overlaps with economic or physical adaptability. Moreover, the valid responses obtained could have been increased by interviewing more households. The machine learning technique GBDT is believed a feasible method, but it has restrictions when including parallel processing data due to dependencies between weak classifiers, so other methods could be utilized to enhance prediction accuracy.

4. Conclusions

It will take decades for the denudation rate in the area affected by the 2008 Wenchuan earthquake to return to the pre-earthquake rate. People in the earthquake-affected areas must adapt to a new landscape that has become prone to landslides. This exploratory study

provides a glimpse of how machine learning can be utilized to predict how adaptation strategies of households will be modified if landslide frequency changes. The households in the Yingchangou area of Longmenshan Town cope with various landslides using three main adaptation strategies, including autonomous adaptation strategies, policy-dependent adaptation strategies, and hybrid adaptation strategies. The characteristics of these strategies are widely distributed, such as policy-dependent, economy-adapted, and the information accessed. An increase in landslide frequency was expected to induce more households to adapt a government-policy-dependent landslide adaptation strategy, while a decrease in landslide frequency led to more households preferring an autonomous adaptation approach. A follow-up longitudinal study in Longmenshan Town is needed to confirm whether the predictions of the gradient boosting method employed in this study are indeed correct. A comparative study in another area may be conducted to investigate whether the extent of households shifting to another landslide adaptation approach given a change in landslide frequency that was observed in this study (around 5%) is prevalent or not. This study investigated the adaptation strategies that could be applied by households that lived in an area which suffered from disasters, such as landslides, and it can be a viable basis for decision making in post-disaster recovery and reconstruction and contribute to the prevention and mitigation of disasters. Countries located in seismic areas, including China, are more likely to be affected by earthquakes, as well as secondary disasters, such as landslides. Therefore, future studies can focus on other regions that have similar conditions to the research area and utilize diverse machine learning methods to compare adaptation strategies.

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References

1. Liang, G.; Zhang, X.; Ling, X.; Zhou, H.; Lin, W. Analysis of Temporal-spatial Characteristics of Geological Disasters in China from 2009 to 2019. *J. Disaster Prev. Reduct.* **2021**, *37*, 58–64. (In Chinese) [[CrossRef](#)]
2. Wang, Q.F.; Wu, J.J.; Lei, T.J.; He, B.; Wu, Z.T.; Liu, M.; Mo, X.Y.; Geng, G.P.; Li, X.H.; Zhou, H.K.; et al. Temporal-spatial characteristics of severe drought events and their impact on agriculture on a global scale. *Quatern. Int.* **2014**, *349*, 10–21. [[CrossRef](#)]
3. Xu, C.; Xu, X.; Gorum, T.; Westen, C.J.V.; Fan, X. Did the 2008 Wenchuan Earthquake Lead to a Net Volume Loss? In Proceedings of the World Landslide Forum, Beijing, China, 3 May 2014; pp. 191–196.
4. Zhang, S.; Zhang, L.M. Impact of the 2008 Wenchuan earthquake in China on subsequent long-term debris flow activities in the epicentral area. *Geomorphology* **2017**, *276*, 86–103. [[CrossRef](#)]
5. Tang, C.; Zhu, J.; Qi, X.; Ding, J. Landslides induced by the Wenchuan earthquake and the subsequent strong rainfall event: A case study in the Beichuan area of China. *Eng. Geol.* **2011**, *122*, 22–33. [[CrossRef](#)]
6. Chigira, M.; Wu, X.; Inokuchi, T.; Wang, G. Landslides induced by the 2008 Wenchuan earthquake, Sichuan, China. *Geomorphology* **2010**, *118*, 225–238. [[CrossRef](#)]
7. Gorum, T.; Fan, X.; van Westen, C.J.; Huang, R.Q.; Xu, Q.; Tang, C.; Wang, G. Distribution pattern of earthquake-induced landslides triggered by the 12 May 2008 Wenchuan earthquake. *Geomorphology* **2011**, *133*, 152–167. [[CrossRef](#)]

8. Xu, G.B.; Liu, X.H.; Trouet, V.; Treydte, K.; Wu, G.J.; Chen, T.; Sun, W.Z.; An, W.L.; Wang, W.Z.; Zeng, X.M.; et al. Regional drought shifts (1710–2010) in East Central Asia and linkages with atmospheric circulation recorded in tree-ring O-18. *Clim. Dynam.* **2019**, *52*, 713–727. [[CrossRef](#)]
9. Chen, X.; Cui, P.; You, Y.; Chen, J.; Li, D. Engineering measures for debris flow hazard mitigation in the Wenchuan earthquake area. *Eng. Geol.* **2015**, *194*, 73–85. [[CrossRef](#)]
10. Huang, R.; Li, W. Post-earthquake landsliding and long-term impacts in the Wenchuan earthquake area, China. *Eng. Geol.* **2014**, *182*, 111–120. [[CrossRef](#)]
11. Li, C.; Wang, M.; Liu, K. A decadal evolution of landslides and debris flows after the Wenchuan earthquake. *Geomorphology* **2018**, *323*, 1–12. [[CrossRef](#)]
12. Song, Y.; Li, C.; Olshansky, R.; Zhang, Y.; Xiao, Y. Are we planning for sustainable disaster recovery? Evaluating recovery plans after the Wenchuan earthquake. *J. Environ. Plan. Manag.* **2017**, *60*, 2192–2216. [[CrossRef](#)]
13. Chen, N.; Li, J.; Liu, L.; Yang, C.; Liu, M. Post-earthquake denudation and its impacts on ancient civilizations in the Chengdu Longmenshan region, China. *Geomorphology* **2018**, *309*, 51–59. [[CrossRef](#)]
14. Anderson, M.G.; Holcombe, E.; Blake, J.R.; Ghesquire, F.; Holm-Nielsen, N.; Fisseha, T. Reducing landslide risk in communities: Evidence from the Eastern Caribbean. *Appl. Geogr.* **2011**, *31*, 590–599. [[CrossRef](#)]
15. Han, Y.; Fu, Y.; Hu, K.; Li, L.; Han, J.; Wang, X. Hazard insurance of secondary mountain hazards in afflicted areas by Wenchuan earthquake. *Integr. Disaster Risk Manag. (IDRiM) J.* **2013**, *3*, 196–218. [[CrossRef](#)]
16. Han, Z. *From Vulnerability to Resilience: Long-Term Livelihood Recovery in Rural China after the 2008 Wenchuan Earthquake*; University of Delaware: Newark, DE, USA, 2014.
17. Jin, L.; Chen, K.; Yu, B.; Filipski, M. Farmers' coping strategies against an aggregate shock: Evidence from the 2008 Sichuan Earthquake. In Proceedings of the conference of International Association of Agricultural Economists, Milan, Italy, 9–14 August 2015.
18. Feng, S.; Lu, J.; Nolen, P.; Wang, L. The effect of Wenchuan earthquake and government aid on rural households. In *Earthquake lessons from China Coping and Rebuilding Strategies*; Kevin Chen, Q.Z., Hsu, C., Eds.; International Food Policy Research Institute: Washington, DC, USA, 2016; pp. 11–34.
19. Peng, Y.; Zhu, X.; Zhang, F.; Huang, L.; Xue, J.; Xu, Y. Farmers' risk perception of concentrated rural settlement development after the 5.12 Sichuan Earthquake. *Habitat Int.* **2018**, *71*, 169–176. [[CrossRef](#)]
20. Andersson-Skold, Y.; Bergman, R.; Johansson, M.; Persson, E.; Nyberg, L. Landslide risk management-A brief overview and example from Sweden of current situation and climate change. *Int. J. Disaster Risk Reduct.* **2013**, *3*, 44–61. [[CrossRef](#)]
21. Korup, O.; Stolle, A. Landslide prediction from machine learning. *Geol. Today* **2014**, *30*, 26–33. [[CrossRef](#)]
22. Chen, J.L.; Huang, G.R.; Chen, W.J. Towards better flood risk management: Assessing flood risk and investigating the potential mechanism based on machine learning models. *J. Env. Manag.* **2021**, *293*, 112810. [[CrossRef](#)]
23. Zhang, Z.D.; Jung, C. GBBDT-MO: Gradient-Boosted Decision Trees for Multiple Outputs. *IEEE Trans. Neur. Net. Lear.* **2021**, *32*, 3156–3167. [[CrossRef](#)]
24. Liang, W.Z.; Sari, A.; Zhao, G.Y.; McKinnon, S.D.; Wu, H. Short-term rockburst risk prediction using ensemble learning methods. *Nat. Hazards* **2020**, *104*, 1923–1946. [[CrossRef](#)]
25. Yang, L.C.; Liang, Y.; Zhu, Q.; Chu, X.L. Machine learning for inference: Using gradient boosting decision tree to assess non-linear effects of bus rapid transit on house prices. *Ann. GIS* **2021**, *27*, 273–284. [[CrossRef](#)]
26. Pourghasemi, H.R.; Rahmati, O. Prediction of the landslide susceptibility: Which algorithm, which precision? *Catena* **2018**, *162*, 177–192. [[CrossRef](#)]
27. Shirzadi, A.; Shahabi, H.; Chapi, K.; Dieu Tien, B.; Binh Thai, P.; Shahedi, K.; Bin Ahmad, B. A comparative study between popular statistical and machine learning methods for simulating volume of landslides. *Catena* **2017**, *157*, 213–226. [[CrossRef](#)]
28. Zhou, C.; Yin, K.; Cao, Y.; Ahmed, B.; Li, Y.; Catani, F.; Pourghasemi, H.R. Landslide susceptibility modeling applying machine learning methods: A case study from Longju in the Three Gorges Reservoir area, China. *Comput. Geosci.* **2018**, *112*, 23–37. [[CrossRef](#)]
29. He, Q.; Jiang, Z.; Wang, M.; Liu, K. Landslide and Wildfire Susceptibility Assessment in Southeast Asia Using Ensemble Machine Learning Methods. *Remote Sens.* **2021**, *13*, 1572. [[CrossRef](#)]
30. Rong, G.; Alu, S.; Li, K.; Su, Y.; Zhang, J.; Zhang, Y.; Li, T. Rainfall Induced Landslide Susceptibility Mapping Based on Bayesian Optimized Random Forest and Gradient Boosting Decision Tree Models-A Case Study of Shuicheng County, China. *Water* **2020**, *12*, 3066. [[CrossRef](#)]
31. Ge, Y.G.; Song, G.H.; Guo, C.X.; Kong, Y.D. Characteristics and Causes of 8·18 Debris Flow Hazards at the Longmenshan Town, Pengzhou, Sichuan. *Shuili Xuebao* **2012**, *43*, 147–154. (In Chinese)
32. Statistical Bureau of Pengzhou. *Pengzhou Statistical Yearbook 2021*; Statistical Bureau of Pengzhou: Pengzhou, China, 2021.
33. Abu Abbas, O. Comparisons between data clustering algorithms. *Int. Arab J. Inf. Technol.* **2008**, *5*, 320–325.
34. Friedman, J.H. Greedy function approximation: A gradient boosting machine. *Ann. Stat.* **2001**, *29*, 1189–1232. [[CrossRef](#)]
35. Di, B.; Zhang, H.; Liu, Y.; Li, J.; Chen, N.; Stamatopoulos, C.A.; Luo, Y.; Zhan, Y. Assessing Susceptibility of Debris Flow in Southwest China Using Gradient Boosting Machine. *Sci. Rep.* **2019**, *9*, 12532. [[CrossRef](#)]
36. Ichikawa, D.; Saito, T.; Ujita, W.; Oyama, H. How can machine-learning methods assist in virtual screening for hyperuricemia? A healthcare machine-learning approach. *J. Biomed. Inform.* **2016**, *64*, 20–24. [[CrossRef](#)]

37. Zhang, C.; Liu, C.; Zhang, X.; Alpanidis, G. An up-to-date comparison of state-of-the-art classification algorithms. *Expert Syst. Appl.* **2017**, *82*, 128–150. [[CrossRef](#)]
38. Natekin, A.; Knoll, A. Gradient boosting machines, a tutorial. *Front. Neurobot.* **2013**, *7*, 21. [[CrossRef](#)]
39. Van der Maaten, L.; Hinton, G. Visualizing high-dimensional data using t-SNE. *J. Mach. Learn. Res.* **2008**, *9*, 2579–2605.
40. Huang, R.; Li, W. Formation, distribution and risk control of landslides in China. *J. Rock Mech. Geotech. Eng.* **2011**, *3*, 97–116. [[CrossRef](#)]
41. Johnson, C.; Lizarralde, G. Post-disaster housing and reconstruction. In *International Encyclopedia of Housing and Home*; Smith, S., Ed.; Elsevier: San Diego, CA, USA, 2012; pp. 340–346.
42. Park, A.; Wang, S. Benefiting From Disaster? Public and Private Responses to the Wenchuan Earthquake. *World Dev.* **2017**, *94*, 38–50. [[CrossRef](#)]
43. Dunford, M.; Li, L. Earthquake reconstruction in Wenchuan: Assessing the state overall plan and addressing the ‘forgotten phase’. *Appl. Geogr.* **2011**, *31*, 998–1009. [[CrossRef](#)]
44. Gariano, S.L.; Guzzetti, F. Landslides in a changing climate. *Earth Sci. Rev.* **2016**, *162*, 227–252. [[CrossRef](#)]
45. Massazza, A.; Brewin, C.; Joffe, H. The nature of ‘natural disasters’: Survivors’ explanations of earthquake damage. *Int. J. Disaster Risk Sci.* **2019**, *10*, 293–305. [[CrossRef](#)]
46. Liu, H.; Zhang, D.; Wei, Q.; Guo, Z. Comparison study on two post-earthquake rehabilitation and reconstruction modes in China. *Int. J. Disaster Risk Reduct.* **2017**, *23*, 109–118. [[CrossRef](#)]
47. Alexander, D. Vulnerability to landslides. In *Landslide Hazard and Risk*; Glade, T., Anderson, M., Crozier, M.J., Eds.; Wiley: Chichester, UK, 2005; pp. 175–198.
48. Fang, Y.-P.; Zhu, F.-B.; Qiu, X.-P.; Zhao, S. Effects of natural disasters on livelihood resilience of rural residents in Sichuan. *Habitat Int.* **2018**, *76*, 19–28. [[CrossRef](#)]
49. Zhai, G.; Suzuki, T. Risk perception in Northeast Asia. *Environ. Monit. Assess.* **2009**, *157*, 151–167. [[CrossRef](#)]
50. Di, B.F.; Li, J.R.; Dandoulaki, M.; Cruz, A.M.; Zhang, R.X.; Niu, Z.P. Household recovery strategies in Longmen Mountain area, Sichuan, China, following the 2008 Wenchuan earthquake disaster. *Nat. Hazards* **2020**, *104*, 123–137. [[CrossRef](#)]