Landslide susceptibility evolution in an area affected by the 2015 Nepal earthquakes, derived from multitemporal landslide inventories

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Abstract: The Mw 7.8 and Mw 7.3 Nepal earthquakes in 2015 triggered >47,000 landslides and significantly enhanced landslide activity in the affected region in the following years, likely due to a drop in rock strength of the slopes there. This work analyzed the evolution of landslide susceptibility of an area close to the Zhangmu border crossing on the Araniko Highway in Nepal, which was seriously affected by the mainshock, aftershock, and monsoon rainfalls. Using eight landslide inventories we constructed to register landslides triggered by monsoon rainfalls before 2015, the mainshock, the aftershock, and the monsoon rainfalls in 2015–2019, eight susceptibility assessment models were built using the logistic regression method considering 11 control factors of landslides. The changes in the high-susceptibility zones before, during, and after the earthquakes were examined. The backward prediction abilities of the models were checked by taking landsliding and nonlandsliding data in the following years. The results show that the best susceptibility mapping results are obtained based on landslides triggered by the mainshock and the aftershock, which both have successful prediction rates >87%. The high-susceptibility regions have moved from the slope surfaces to channels since 2015, suggesting that transportation of residual debris induced by the strong ground motion resulted from erosion related to the strong post-seismic rainfall and the rivers. A series of attempts using susceptibility models to backward predict landslides in the following years demonstrate that the combination of the susceptibility results of pre-seismic and mainshock-triggered landslides, which have a higher prediction accuracy, has prediction rates >70% until 2018. This study not only will further the understanding of post-seismic landsliding effects, but also will aid in efforts toward future seismic landslide mitigation and post-seismic reconstruction.

Keywords: landslide, susceptibility evolution, backward prediction, multitemporal inventories, 2015 Nepal earthquake
1. Introduction
Seismic landslide susceptibility assessments predict the potential locations of unstable slopes according to coseismic landslides and their environmental conditions [1, 2]. Lots of relevant studies have been published, such as [3]. Most of them were based on only coseismic landslides, which are helpful for rapid and effective disaster relief after an earthquake. However, to better serve the long-term post-seismic reconstruction, it is necessary to examine the evolution of landslide susceptibility in the affected area using multitemporal inventories before and after an earthquake [4].

On April 25, 2015, a $M_w$ 7.8 earthquake (mainshock, 28.230°N, 84.731°E) rocked Gorkha, Nepal in the central Himalayan orogenic belt, affecting southern Tibet and other neighboring countries. A little more than two weeks later, on May 12, a major aftershock of $M_w$ 7.3 (27.809°N, 86.066°E) again shook this area with an epicenter east of that of the mainshock [5, 6]. These events both occurred before the rainy season (from June to September) in Nepal. More than 47,000 coseismic landslides were mapped after the earthquakes [7]. The strong shaking enhanced the landslide activity [8] and lots of large rainfall-induced landslides have been reported in Nepal since the 2015 earthquakes, such as the August 14, 2020 and September 13, 2020 landslides in Sindhupalchowk which killed 37 and 16 people, respectively [9].

Using the logistic regression method, we mapped yearly landslide susceptibilities and analyzed their changes based on eight time-series landslide inventories (from pre-seismic to the 2019 monsoon season) and six groups of common controlling factors in an area close to the Zhangmu border crossing on the Araniko Highway in Nepal. Then we checked the backward prediction performances of the logistic regression models by using landslide and nonlandslide data selected in each year. The study of successive time-series landslide susceptibility mapping will be helpful for landslide-hazard prevention and disaster reduction.

2. Study Area
Nepal is located in the southern Himalaya Mountains where the Indian plate thrusts beneath the Eurasian plate, thus Nepal hosts the most tectonically active zones. Lots of large earthquakes ($> M 7$) occurred here in history, such as the 1505 middle Himalaya $M_w$ ~8.2 earthquake, the 1803 Kumaon $M_w$ ~7.5 earthquake, the 1833 Kathmandu $M_w$ ~7.6 earthquake, the 1905 Kangra $M_w$ ~7.8 earthquake, the 1934 Nepal–Bihar $M_s$ ~8.2 earthquake, the 1950 Assam–Tibet $M_w$–8.4 earthquake, and the 2005 Kashmir $M_w$ 7.6 earthquake [10-12]. This area consists of rugged mountainous terrain with deep gorges, affected by the South Asian monsoon with abundant precipitation, especially in monsoon seasons.
This work focused on a region along the Araniko Highway, which is the important connection between China and Nepal. This region was seriously affected by the 2015 mainshock, greatest aftershocks, and monsoon rainfalls. Post-seismic catastrophic landslides have been common since the 2015 earthquake [9]. The study area is about 374 km², accounting for 3.4% of the distribution area of the seismic landslides; approximately 7600 coseismic landslides in this area were identified, making up 15% of the total seismic landslides related to the 2015 Nepal earthquake [7, 13] (Figure 1).

3. Data and Methods

3.1. Data
Combining three field investigations [8] and visual interpretation of pre- and post-earthquake remote sensing images, we mapped the landslides triggered by pre-earthquake rainfalls, the 2015 mainshock, the largest 2015 aftershock, and the 2015–2019 monsoon rainfalls in the study area (Figure 3). The source areas of each landslide were identified as regions with an elevation larger than the median elevation within each landslide boundary [14, 15]. We converted the extracted source grids and of all the landslides in each inventory into corresponding point features. Together with the centroid centers of the small landslides whose source areas cannot be automatically extracted using the abovementioned method, we marked the point features in eight inventories as corresponding landsliding samples. The same number of nonlandsliding sample points were randomly generated for points that were 10 m (the resolution of a raster cell) outside each landslide polygon. Thirty meters is the minimum distance between each nonlandsliding point. We randomly selected 70% of the each of the landsliding and nonlandsliding data/samples as the training data, and the rest were testing data. The numbers of the landsliding, nonlandsliding, training, and testing samples are shown in Table 1.

| Category        | Total Landsliding/ total nonlandsliding | Training data | Testing data |
|-----------------|----------------------------------------|---------------|--------------|
| Pre-seismic     | 12,462                                  | 17,446        | 7478         |
| 2015 Mainshock  | 58,338                                  | 81,674        | 35,002       |
| 2015 Aftershock | 16,507                                  | 23,110        | 9904         |

Figure 1. Location of the study area (a) and enlarged study area (b). The blue dash line in (a) marks the distribution area of coseismic landslides. KTM—Kathmandu; Red and Green stars are the epicenters of the April 25 mainshock and the May 12 aftershock. Red lines in (b) are the Araniko Highway (Kathmandu–Zhangmu); the coseismic landslides in (b) are from [7].
Eleven control factors, including elevation, slope angle, slope aspect, curvature, slope position, lithology, roads, drainage channels, annual average rainfalls, and perpendicular to or parallel to the strike of the seismogenic fault, were considered in mapping the landslide susceptibility in each period. These factors were divided into intervals for statistics in mapping (Table 2). Research suggested that the 2015 Nepal earthquakes resulted from ruptures of the Main Himalaya Thrust (MHT) [10]. We simplified it as a straight line with a strike of 290°, consistent with the trend of the MHT, in this study. Considering the main triggers of the landslides in different inventories, we eliminated the factors related to the seismogenic fault for rainfall-triggered landslides before the 2015 earthquake and after the 2015–2019 monsoon seasons; similarly, the rainfall factor was excluded while analyzing landslides triggered by the 2015 mainshock and the strong aftershock.

3.2. Methods

3.2.1 Logistic regression model.

In landslide susceptibility mapping, the logistic regression model predicts the landslide occurrence probability in certain conditions by examining the regression relationship between the attributes of landsliding/non-landsliding samples (dependent variables) and the control factors (independent variables). Because of its simple operation and easy implementation, the logistic regression model is widely used in mapping landslide susceptibility [2, 16]. In this method, the regression function is expressed as:

\[
\text{logit} \ P = \alpha + \beta_1 x_1 + \cdots + \beta_m x_m \\
\]

\[
P = \frac{\exp(\alpha + \beta_1 x_1 + \cdots + \beta_m x_m)}{1 + \exp(\alpha + \beta_1 x_1 + \cdots + \beta_m x_m)}
\]

where \( P \) is the landslide occurrence probability which ranges between 0 to 1, \( \alpha \) is a constant, \( \beta_i \) is the regression coefficients, and \( x_i \) is the control factor or a subcategory of the control factor.

Table 2. Control factors of landslides

| Year | Monsoon | Rainfall (mm) |
|------|---------|--------------|
| 2015 |         |              |
| 2016 |         |              |
| 2017 |         |              |
| 2018 |         |              |
| 2019 |         |              |

| Year | Monsoon | Rainfall (mm) |
|------|---------|--------------|
| 2015 | 24,159  | 33,822       |
| 2016 | 6830    | 9562         |
| 2017 | 6724    | 9414         |
| 2018 | 3298    | 4618         |
| 2019 | 2971    | 4160         |
3.2.2 Susceptibility assessment and classification.

To examine the evolution of landslide susceptibility in the study area, we first carried out susceptibility assessments separately based on the eight landslide inventories. Taking the pre-seismic landslides as an example, we (a) obtained the logistic regression model and coefficients (here called the pre-seismic coefficients, PSC) based on the pre-seismic training samples and the corresponding control factors; (b) tested the model using pre-seismic testing samples and assessed the prediction performance of the model by comparing the predicted landsliding probability with the sliding attributions of the testing samples; and (c) if the model performed well, we then applied the coefficients to all the factors in the whole study area to get the susceptibility index. The area under the receiver operating characteristic (ROC) curve, which we abbreviate as AUC, was used to evaluate the performance of the model. AUC ranges from 0 to 1; the larger the AUC is, the better the model performs. Then we classified the susceptibility index into five categories: very high (>0.8), high (0.6–0.8), middle (0.4–0.6), low (0.2–0.4), and very low (<0.2) susceptibility classes.

We then successively validated the models, which were built according to pre-seismic, 2015 mainshock-induced, 2015 aftershock-induced, and 2015–2018 rainfall-triggered landslides, using landslides that occurred in the following years to examine their backward prediction performances. For example, we evaluated the backward prediction performance of the pre-seismic landslide susceptibility result by using landslides that occurred after the 2015 mainshock, aftershock, and 2015–2019 monsoon seasons. The ROC and AUC were again employed to compare the model’s performances.

4. Results

4.1. Landslide susceptibility evolution

The success rates of the logistics regression models built on the training samples in each period and the validated prediction rates are shown in Figure 2. All of the eight models have success rates and prediction rates greater than 80%, indicating that the models have good performance and could be used to map the susceptibilities of the study area in each period. Among them, the model obtained from the landslides triggered by the 2015 mainshock has the highest success and prediction rates, 89.1% and 89.3%, respectively; followed by the model of the landslides induced by the 2015 Mw 7.3 aftershock with success and prediction rates both around 87% (Table 3).
In comparison to pre-earthquake susceptibility distribution, the high-susceptibility regions related to the 2015 mainshock and the largest aftershock are much more concentrated; the high- and very high-susceptibility regions make up 17% of the study area (Figure 3). The distributions of the high- and very high-susceptibility areas of the landslides that occurred after the 2015, 2016, and 2017 monsoon seasons are similar; which are dispersed in patches. However, the high- and very high-susceptibility areas obtained from the 2018 and 2019 rainfall-induced landslides are confined along the drainage channels. The evolution of the high-susceptibility areas from pre-earthquake to four years after the earthquake shows a relationship with the erosion by rainfall on the loose slope material. The 2015 strong earthquakes produced a large amount of landslide mass that moved from the slope surfaces to river channels with rainfall scouring in the following years.

4.2. Backward prediction and validation of susceptibility models
The susceptibility assessment model derived from the 2015 mainshock-triggered landslides shows good prediction abilities for the landslides triggered by the 2015 aftershock and the 2015–2017 rainfalls with backward prediction rates of 82.2%, 76.5%, 76.6%, and 74.1%, respectively (Table 3). The pre-seismic susceptibility result predicts more than 74% of the landslides induced by the 2015 mainshock and 2015–2017 rainfalls. Moreover, the preseismic model has better performance by predicting the 2015 and 2016 landslides. Additionally, the susceptibility model related to the 2015
rainfall-induced landslides has higher prediction rates for the 2016 and 2017 landslides. Specifically, the susceptibility models that are built on rainfall-induced landslides are better at predicting the landslide distribution triggered by subsequent rainfalls, while the model derived from the earthquake-triggered landslides facilitates seismic landslide susceptibility predictions.

To explore the combined effect of high-frequency rainfalls and occasional earthquakes, we overlaid the pre-seismic and 2015 mainshock-triggered landslide susceptibility by assigning a 50% influence to each. The combined susceptibility map was then applied to predict the landslides related to the 2015 mainshock, 2015 largest aftershock, and 2015–2019 monsoon rainfalls. The prediction rates are close to or larger than 70%, which proves that the integrated model could provide useful information for high-susceptibility area identification after a major earthquake. The combined susceptibility map and prediction ROC curves are shown in Figure 4.

Table 3. Backward prediction rates of susceptibility models derived from landslides in different periods.

| Susceptibility model | Predicted group | Pre-seismic | 2015 mainshock | 2015 aftershock | 2015 monsoon | 2016 monsoon | 2017 monsoon | 2018 monsoon | 2019 monsoon |
|---------------------|----------------|------------|---------------|----------------|-------------|-------------|-------------|-------------|-------------|
| Pre-seismic         |                | 80.9%      | 73.1%         | 63.9%          | 75.3%       | 75.5%       | 74%         | 65.7%       | 68.2%       |
| 2015 mainshock      |                | -          | 89.3%         | 82.2%          | 76.5%       | 76.6%       | 74.1%       | 70.9%       | 67%         |
| 2015                |                | -          | -             | 87.5%          | 69.4%       | 73.2%       | 70.7%       | 66.7%       | 67.5%       |

Figure 3. Multitemporal inventories and derived susceptibility maps for the preseismic, 2015 coseismic, 2015 aftershock-induced, and 2015–2019 monsoon rainfall-triggered landslides.
aftershock

| Year | Monsoon | Susceptibility | Pre-seismic and 2015 mainshock combined |
|------|---------|----------------|----------------------------------------|
| 2015 | -       | 84.1%          | 86.2%                                  |
| 2016 | -       | 84.8%          | 87.5%                                  |
| 2017 | -       | 84.9%          | 88.2%                                  |
| 2018 | -       | 83.2%          | 89.3%                                  |
| 2019 | -       | 83.2%          | 86.5%                                  |

The bold numbers are the prediction rates for the testing samples of the susceptibility models. The pre-seismic and 2015 mainshock combined model combines the susceptibility maps with weights of 0.5 each.

5. Conclusions

The susceptibility assessments were carried out based on eight landslide inventories related to pre-earthquake, 2015 mainshock, 2015 largest aftershock, and 2015–2019 monsoon rainfalls. The susceptibility models resulting from landslides in each period show that the 2015 mainshock and aftershock models perform well, with success and prediction rates greater than 87%. The distribution changes of high-susceptibility areas indicate that the 2015 strong earthquakes produced lots of landslide mass and their residue is continually moving from slope surfaces to river channels with the scouring of subsequent rainfalls and river erosion that reduced the rock strength of slopes.

To examine the backward prediction performance of the models, we tested the prediction ability of the susceptibility models using landslides that occurred in the years after the 2015 Nepal earthquake sequence. The pre-seismic model and the 2015 mainshock model are the best. Then we combined these two susceptibility maps with weights of 0.5 to predict the subsequent aftershock- and rainfall-induced landslides and predicted more than 70% of them, which provides a new approach for landslide susceptibility zoning in the following years after an earthquake.

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