Urgent landslide susceptibility assessment in the 2013 Lushan earthquake-impacted area, Sichuan Province, China

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Abstract The Lushan earthquake with magnitude M_s 7.0 (M_w 6.6, USGS) in Sichuan Province, China, triggered a large number of landslides, which seriously aggravated the earthquake's destructive consequences. This paper mainly focuses on the methodology of the urgent landslide susceptibility assessment right after the earthquake. The detailed landslide inventory (including 5,688 landslides) is prepared by means of urgent post-earthquake landslide field survey, landslide remote sensing interpretation of multi-source remote sensing images including high-resolution unmanned aerial vehicle images and historical landslide archives. Ten remarkable causative factors for landslide occurrence have been selected to conduct the landslide susceptibility assessment, including earthquake intensity, landslide density and slope gradient. An integration assessment approach is developed to facilitate the effective urgent post-earthquake landslide susceptibility assessment using three methods: factor sensitivity analysis, analytical hierarchy process and factor-weighted overlay. Such integration can effectively reduce the subjectivity and uncertainty resulting from using single method. The validation evaluation using the area under curve suggests the landslide susceptibility assessment results have satisfactory accuracy, and the suggested methodology is effective for the urgent post-earthquake landslide susceptibility assessment. The study results reveal that earthquake intensity and slope gradient are the two most important causative factors for post-earthquake landslide occurrence in the Lushan earthquake-impacted area. The dominant slope gradient and slope aspect with relatively higher landslide frequency are 45° – 50° and south-east direction, respectively. The intense earthquake impact increased the dominant slope gradient of

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landslide spatial distribution, and the thrust campaign of seismogenic fault with strike NE–SW made south-east direction as the dominant slope aspect of the landslide spatial distribution. The locations with very high and high landslide susceptibility are mainly distributed in the regions with higher earthquake intensity and adverse terrain conditions, such as Shuangshi town and Longmen town of Lushan county and Muping town of Baoxing county. The study results are expected to provide a beneficial reference for the landslide prevention and infrastructure reconstruction after the Lushan earthquake.

Keywords Lushan earthquake · Landslide susceptibility · GIS · Factor sensitivity analysis · AHP · Factor-weighted overlay

1 Introduction

On April 20, 2013, a catastrophic earthquake with magnitude M_s 7.0 (M_w 6.6, USGS) occurred in Sichuan Province, China. Its epicenter is located at 103°E and 30.3°N with a focal depth of 13 km. The focal mechanism solutions showed that this earthquake resulted from the thrust campaign of the southern section of the Longmenshan fault (Xu et al. 2013b). The earthquake has resulted in a large amount of casualties (about 193 fatalities) and economic loss.

The earthquake has triggered a large number of landslides and produced abundant loose deposits and sediments. These loose deposits and sediments are likely to be converted into landslides and debris flows under subsequent strong rainfall, which had been demonstrated in the 2008 Wenchuan earthquake, Sichuan Province, China (Zhang et al. 2014). The seriously Lushan earthquake-impacted regions have complicated terrain conditions, such as high mountains and steep slopes. The earthquake-triggered landslides blocked fragile transportation and delayed post-earthquake rescue progress. So, it is urgent to obtain the post-earthquake landslide susceptibility zoning map for guiding the post-earthquake rescue and landslide prevention.

The landslide susceptibility means the likelihood (probability) of damaging landslide occurrence with statistical sense. So far, there have been many methods for landslide susceptibility assessment and mapping at a regional scale. On the whole, these methods can be summarized into two categories: qualitative and quantitative methods. Qualitative methods mainly refer to site analysis and overlay analysis of thematic maps (for example, geomorphological and geological characteristics) based on expert experience (Anbalagan and Singh 1996; Ayalew et al. 2004). Quantitative methods mainly refer to various statistical analyses (Carrara et al. 1991; Tang et al. 2011a; Yoshimatsu and Abe 2006; Kamp et al. 2008), such as artificial neural network (ANN) (Lee and Evangelista 2006; Yilmaz 2010), support vector machine (SVM) (Yao et al. 2008; Yilmaz 2010; Xu et al. 2012), Bayesian Network (Song et al. 2012) and Logistic Regression (Dong et al. 2011; Nefeslioglu et al. 2006; Xu et al. 2013a, b). These methods have different characteristics and adaptability for various environmental conditions of different regions (Tangestani 2009; Mohammady et al. 2012; Ozdemir and Altural 2013). At the same time, GIS and RS technologies have comprehensively been used in the landslide susceptibility study (Carrara et al. 1999; Lan et al. 2002, 2004; Kouli et al. 2010; Niu et al. 2012). All landslide susceptibility assessment methods, despite methodological and operational differences, are based on the common assumption that the future landslides will be likely to occur under the

same conditions that induce past landslides (Clerici et al. 2006; Aleotti and Chowdhury 1999; Guzzetti et al. 1999).

This paper mainly focuses on the methodology of the urgent landslide susceptibility assessment right after the earthquake. An integration assessment approach is developed to facilitate the effective urgent post-earthquake landslide susceptibility assessment using three well-known methods: factor sensitivity analysis, analytical hierarchy process (AHP) and factor-weighted overlay. Firstly, one detailed landslide inventory was prepared, and ten remarkable causative factors were selected prudentially. Then, the factor sensitivity analysis and AHP methods were conducted to assign sensitivity coefficient of factor levels and factor weights, respectively. Finally, the factor-weighted overlay was conducted to obtain post-earthquake landslide susceptibility. The study results are expected to provide a beneficial reference for the landslide prevention and infrastructure reconstruction after the Lushan earthquake.

2 Study area and landslide inventory

2.1 Study area

The study area impacted by the Lushan earthquake is located in the southwest of Sichuan Province, China, where is the sharp transition zone from the Sichuan Basin to the Qinghai–Tibet Plateau. Figure 1 shows the overview of the study area with 21 counties and area 42,687 km², where there are many mountains and canyons, which result in steep terrain and large elevation difference. On the whole, the western regions are relatively higher with the highest elevation 7,148 m, and the eastern regions are relatively lower with the lowest elevation 379 m.

The regional geological structure is affected by several main tectonic faults: Longmenshan fault belt with strike NE, Xianshuihe fault belt with strike NW, Anninghe fault belt and Xiaojiang fault belt with strike NS. These fault belts intersect in Shimian county, Sichuan Province and form a large “Y”-shaped geological structure, which results in frequent seismic activity in history.

The rainfall is abundant, but its spatial and temporal distribution is uneven. There is relatively larger rainfall during rainy and flood seasons. The average annual precipitation is about 1,700 mm/year in Yaan city, but it is only about 800 mm/year in Kangding county. There are three larger rivers including Minjiang River, Daduhe River and Yalongjiang River, all which belong to Yangtze tributaries. The eastern regions are dominated by the purple soil of the Sichuan Basin, and the western regions are dominated by the yellow soil of plateau and canyon. Compared with the western dry-hot valley and plateau meadow, the vegetation coverage in the drainage area of Minjiang River is relatively better.

2.2 Landslide inventory

Landslide inventory is an essential first step for landslide susceptibility assessment, which can provide information for the assessment of the influence of different causative factors on landslide occurrence (Tang et al. 2011a). According to urgent post-earthquake landslide field survey conducted by the Ministry of Land and Resources of the People’s Republic of China, landslide remote sensing interpretation of unmanned aerial vehicle (UAV) images and SPOT5 images conducted by the Institute of Geographic Sciences and Natural Resources Research (IGSNRR) and the Chengdu University of Technology, and historical

Fig. 1 Overview of the Lushan earthquake-impacted area, Sichuan Province, China. Landslide inventory is divided into two parts: training set (pink circle, 80 %) and validation set (yellow triangle, 20 %)

landslide archives, one detailed landslide inventory with 5,688 landslides was prepared, which is shown in Fig. 1. The dominant earthquake-triggered landslide types are avalanches and land sliding with shallow or middle thickness in terms of urgent landslide field survey after earthquake. The coverage area and resolution of the adopted UAV images is about 11.74 km^2 and 0.5 m , respectively. The SPOT5 images with resolution 2.5 m can cover the entire study area. Figure 2 shows the partial landslide distribution derived from landslide remote sensing interpretation of UAV images. The landslide data format coming from landslide field survey, landslide remote sensing interpretation and historical landslide archives is point, polygon and point, respectively. The landslide amount coming from landslide field survey, landslide remote sensing interpretation and historical landslide archives accounts for about 21, 38 and 41 % of the entire landslide inventory, respectively.

It can be observed intuitively that the landslide spatial distribution in Fig. 1 presents the remarkable clustering characteristic in the strong earthquake-impacted area. For example, the landslide density is about $0.133 \text{ (landslide/km}^2\text{)}$ in the entire study area, and it is about $2.35 \text{ (landslide/km}^2\text{)}$ in the strong earthquake-impacted regions with earthquake intensity of 9° . However, the pre-earthquake rainfall-triggered landslides mainly distribute along active faults, gullies and rivers. So, it can be concluded that the earthquake-triggered landslides present much more spatial clustering compared with rainfall-triggered landslides.

The landslide inventory was divided into training set (including 4,550 landslides) and validation set (including 1,138 landslides) by random sampling, which accounts for 80 and 20 % of entire landslide inventory, respectively. The rule of selecting landslide training set and validation set is to ensure the uniformity of spatial distribution of two landslide set in the entire study area. The landslide training set will be integrated into the modeling process of post-earthquake landslide susceptibility assessment, and the landslide validation set will be used to validate the rationality and reliability of the modeling results.

Fig. 2 Landslide distribution in Yuquan town and Baosheng town of Lushan county derived from landslide remote sensing interpretation of unmanned aerial vehicle (UAV) images. The background map is the UAV images

The digital elevation mode (DEM) derived from topographic contour maps with scale 1:50,000 and contour interval of 10 m, which was interpolated to raster dataset with spatial resolution $20\text{ m} \times 20\text{ m}$. Then, the slope gradient, slope aspect and elevation difference can be derived from the DEM data. In addition, the other basic data include earthquake intensity maps derived from the China Earthquake Administration, geological maps, tectonic fault maps, geomorphology maps and drainage maps and so on. All above basic data, other than landslide inventory that are stored in vector format, are stored in raster format with the same spatial resolution as DEM data.

3 Post-earthquake landslide susceptibility assessment

3.1 Methodology

Figure 3 sums up the main procedures of urgent post-earthquake landslide susceptibility assessment. An integration assessment approach is developed to facilitate the effective urgent post-earthquake landslide susceptibility assessment using three well-known methods: factor sensitivity analysis, AHP and factor-weighted overlay. Such integration can produce or adjust the necessary parameters for landslide susceptibility assessment by means of the precise statistical calculation and effectively reduce the subjectivity and uncertainty resulting from using single method. Firstly, the detailed landslide inventory is prepared, and the remarkable causative factors are determined, which are the basic data for all following procedures. Then, the factor sensitivity analysis and AHP method are used to obtain the sensitivity coefficients of factor levels and the factor weights, respectively. These statistical values can reflect their corresponding contribution ratio to landslide occurrence. Finally, the factor-weighted overlay is used to obtain the post-earthquake landslide susceptibility, and the area under curve (AUC) method is adopted to evaluate the validation of assessment results.

Fig. 3 Flow-map of main procedures for urgent post-earthquake landslide susceptibility assessment

3.2 Causative factors

Post-earthquake landslide susceptibility is closely related to various causative environmental factors. Ten remarkable causative factors (Fig. 4) were selected prudentially in terms of our experience during the urgent landslide field survey after the Lushan earthquake, including earthquake intensity, landslide density, tectonic fracture density, lithology, elevation, geomorphology, slope gradient, slope aspect, drainage density, annual average precipitation, which significantly contribute to landslide occurrence. These causative factors can be divided into five categories: earthquake intensity, landslide density, geology (including tectonic fracture density and lithology), terrain and geomorphology (including elevation, slope gradient, slope aspect and geomorphology), meteorology and hydrology (including drainage density and annual average precipitation). The elevation factor is described in Fig. 1, and other causative factors are described in Fig. 5.

3.3 Factor sensitivity analysis

Factor sensitivity analysis makes use of the sensitivity coefficient (SC) to indicate the weights of factor levels, which can be classified as bivariate statistical analysis and objectively reflect the contribution ratio of various factor levels to landslide occurrence (Van Westen et al. 2006). The SC can be calculated using Eq. 1, of which the essential is the comparison of landslide distribution rule between factor levels and study area. In Eq. 1, SC_i indicates the SC of factor level i ; H_i indicates the landslide ratio of factor level i ; D indicates the landslide ratio of the entire study area; A_{in} indicates the landslide amount or

Fig. 4 Causative factors for post-earthquake landslide susceptibility assessment

Fig. 5 Causative factor maps. **a** Earthquake intensity (degree), **b** landslide density (landslide amount/km²), **c** tectonic fracture density (km/100 km²), **d** lithology levels, **e** slope gradient (degree), **f** slope aspect, **g** geomorphology, **h** drainage density (km/100 km²), **i** average annual precipitation (mm/year). The elevation factor is described in Fig. 1

area of factor level i ; A_i indicates the area of factor level i ; A_n indicates total landslide amount or area; and A indicates the total area of the entire study area.

$$SC_i = \ln(H_i/D) = \ln[(A_{in}/A_i)/(A_n/A)] \quad (1)$$

Here, the positive SC means the corresponding factor level is sensitive to landslide occurrence, and the larger the value, the higher the sensitivity. The negative SC means the corresponding factor level is not sensitive to landslide occurrence, and the smaller the value, the lower the sensitivity. When the SC is equal to zero, the sensitivity of corresponding factor level is moderate and similar with total sensitivity of the entire study area.

After determination of causative factors, the factor sensitivity analysis (Eq. 1) was used to calculate the SC of various factor levels. The landslide causative factor maps with continuous data were classified in terms of the urgent landslide field survey after earthquake and sophisticated experience. The parameters A_{in} and A_n indicate the landslide amount of factor level i and total landslide amount of landslide training set in this paper, respectively. For example, Eq. 2 shows the detailed calculation process of SC of slope gradient level of 55° – 60° . The final statistical results of factor sensitivity analysis, including various factor levels and sensitivity coefficients, are listed in Table 1, whose illustrations of distribution histogram are showed in Fig. 6.

$$SC_{\text{slope}55-60} = \ln[(173/588)/(4550/42687)] = 1.105 \quad (2)$$

3.3.1 Earthquake intensity

The abundant previous researches show a remarkable spatial exponential decay relationship between earthquake-triggered landslide frequency and earthquake intensity levels (Keefer 1984; Meunier et al. 2007; Qi et al. 2010; Dai et al. 2011). The sensitivity analysis of earthquake intensity (Fig. 6a) shows that the landslide distribution has remarkable earthquake intensity sensitivity, and the higher the earthquake intensity, the greater the sensitivity. The earthquake intensity with more than 6° can significantly increase landslide susceptibility and promote landslide occurrence.

3.3.2 Landslide density

Landslide density is a crucial reference factor, which can distinctly reveal the characteristics of landslide spatial distribution very well. Here, the landslide density (Fig. 5b), defined as the number of landslides per square kilometer, derived from the landslide training set, which suggests that the regions near epicenter have relatively higher landslide density. The sensitivity analysis of landslide density (Fig. 6b) shows that the landslide distribution has remarkable landslide density sensitivity, and the higher the landslide density, the greater the sensitivity.

3.3.3 Tectonic fracture density

Tectonic fracture density ($\text{km}/100 \text{ km}^2$) (Fig. 5c) indicates the length of faults per 100 square kilometers and is used to reflect the development degree of geological structures. The sensitivity analysis of tectonic fracture density (Fig. 6c) shows that the landslide distribution has remarkable tectonic fracture density sensitivity, and the higher the tectonic fracture density, the greater the sensitivity. When the tectonic fracture density reaches

Table 1 Factor sensitivity analysis

Factor levels and sensitivity coefficients										
EI	<5.5	5.5–6	6–6.5	6.5–7	7–7.5	7.5–8	8–8.5			
	–2.180	–0.511	0.217	0.343	0.619	1.005	1.413			
LD	0–0.01	0.01–0.05	0.05–0.1	0.1–0.15	0.15–0.2	0.2–0.25	0.25–0.5			
	–3.176	–1.567	–0.468	0.043	0.379	0.630	1.141			
TFD	0–2	2–4	4–6	6–8	8–10	10–12	12–15			
	–0.385	–0.358	–0.230	–0.207	–0.212	–0.096	0.038			
LL	1–3	3–4	4–5	5–6	6–7	7–8	8–9			
	–1.296	–0.851	–1.063	0.279	–0.402	0.679	–0.260			
ELE	0–500	500–1,000	1,000–1,500	1,500–2,000	2,000–2,500	2,500–3,000	3,000–3,500			
	–0.718	1.283	1.583	–0.027	–0.948	–1.994	–2.886			
SG	0–5	5–10	10–15	15–20	20–25	25–30	30–35			
	–2.135	–1.352	–0.765	–0.238	0.237	0.363	0.652			
SA	Flat	N	NE	E	SE	S	SW			
	–0.878	–0.081	–0.041	0.116	0.151	0.010	–0.164			
GEO	a	b	c	d	e	f	g			
	–4.680	–3.491	–1.549	–1.047	–0.546	–0.310	0.008			
DD	0–20	20–40	40–55	55–65	65–80	80–95	95–110			
	–3.596	–2.005	–0.467	0.274	0.754	0.853	0.812			
AAP	0–750	750–800	800–850	850–900	900–950	950–1,050	1,050–1,150			
	–0.088	–0.105	–0.605	–1.244	–1.164	–0.142	0.779			
Factor levels and sensitivity coefficients										
EI	8.5–9	9								
	1.431	2.010								
LD	0.5–1	1–2	2–3	3–5	>5					
	1.834	2.345	3.038	3.508	4.137					

Table 1 continued

Factor levels and sensitivity coefficients									
TFD	15–20 0.104 9–10 –0.648 3,500–4,500 –4.880 35–40 0.963 W 0.012 h 0.323 110–130 0.269 1,150–1,250 0.910	20–25 0.212 –5.856 40–45 1.198 NW –0.085 i 0.581 130–160 –0.368 1,250–1,350 0.601	25–30 0.529 j 0.962 >160 –1.381 1,350–1,450 0.753	30–35 0.619 k 1.053 1,450–1,550 0.594	>35 0.767 l 1.148 1,550–1,650 0.408	60–65 0.563 o 1.870	65–70 0.377 m 1.311	>70 0.220 n 1.539	

EI earthquake intensity (degree), *LD* landslide density (landslide amount/km²), *TFD* tectonic fracture density (km/100 km²), *LL* Lithology levels, *ELE* elevation (m), *SG* slope gradient (degree), *SA* slope aspect, *GEO* geomorphology, *DD* drainage density (km/100 km²), *AAP* average annual precipitation (mm/year), *a* mountain with high elevation and glaciation, *b* alluvial floodplain with low elevation, *c* valley with low elevation, *d* plain with low elevation, *e* platform with low elevation, *f* river, *g* mountain with medium elevation and Karst erosion, *h* mountain with medium elevation and large fluctuation and erosion, *i* hill with low elevation and erosion, *j* mountain with high elevation and erosion, *k* mountain with low elevation and small fluctuation and erosion, *l* mountain with medium elevation and medium fluctuation and erosion, *o* valley with medium elevation, *m* plain with medium elevation, *n* platform with medium elevation. For the every causative factor, the first row presents the various factor levels, and the second row presents the sensitivity coefficients (SC) for the corresponding factor levels

Fig. 6 Sensitivity coefficient illustrations of causative factors. The *vertical axis* indicates sensitivity coefficients, and the *horizontal axis* indicates factor levels. **a** Earthquake intensity (degree), **b** landslide density (landslide amount/km²), **c** tectonic fracture density (km/100 km²), **d** lithology levels, **e** elevation (m), **f** slope gradient (degree), **g** slope aspect, **h** geomorphology, **i** drainage density (km/100 km²), **j** average annual precipitation (mm/year). The letters (a...n) of sub-figure **h** have the same meaning as that in Table 1

12–15 km/100 km², the sensitivity coefficient begins to be positive, which means that its sensitivity is greater than the total sensitivity of the entire study area, and it will promote landslide occurrence.

3.3.4 Lithology

Rock masses are the material basis for landslides, whose lithology characteristics seriously affect landslide types, size and activity modes (Gorum et al. 2011; Qi et al. 2010; Dai et al. 2011). All rock masses were divided into ten levels (Fig. 5d) in terms of their engineering mechanical properties and our experience of the urgent field survey after the Lushan earthquake. Level 1 represents the highest strength and is the most difficult to destroy, and level 10 represents the lowest strength and is the most easiest to destroy. The sensitivity analysis of lithology levels (Fig. 6d) shows that the rock masses with lithology levels 7–8 and 5–6 have higher sensitivity coefficient, which suggests the rock masses with alternating hard and soft rock are more prone to landslides.

3.3.5 Elevation

The elevation sensitivity analysis (Fig. 6e) suggests that the elevation with range 1,000–1,500 m has the highest sensitivity coefficient. Many southwest regions of the study area with higher elevation are covered by glacier and snow and are little affected by this earthquake and human activity, so there are fewer landslides and lower sensitivity.

3.3.6 Slope gradient

Slope gradient can affect the dynamic condition of landslide startup. Numerous studies about landslide distribution characteristics of the 2008 Wenchuan earthquake in China suggest that the dominant slope gradient of earthquake-triggered landslides will increase to some extent compared with rainfall-triggered landslides (Tang et al. 2011b, Huang and Li 2008). The sensitivity analysis results of slope gradient (Fig. 6f) show that the dominant slope gradient of the Lushan earthquake-triggered landslides is 45° – 50° , which should be higher than that of rainfall-triggered landslides before earthquake.

3.3.7 Slope aspect

Slope aspect can indirectly affect landslides through affecting heat and rainfall distribution, and further affecting land use and vegetation coverage. The sensitivity analysis of slope aspect (Fig. 6g) shows that the dominant slope aspect of the Lushan earthquake-triggered landslides is south-east direction, which is the same as that of the 2008 Wenchuan earthquake (Qi et al. 2010; Dai et al. 2011) and can be attributed to the thrust campaign of seismogenic fault with strike NE–SW.

3.3.8 Geomorphology

There are various geomorphology types in the study area. The geomorphology sensitivity analysis (Fig. 6h) shows that the regions with valley and mountain geomorphology have higher sensitivity. However, the regions with alpine and low elevation have lower sensitivity.

3.3.9 Drainage density

The river erosion can destroy slope toe and decrease slope stability. The drainage density ($\text{km}/100 \text{ km}^2$) (Fig. 5h) indicates the length of rivers per 100 km^2 . The sensitivity analysis

Table 2 Judgement matrix and optimized factor weights of analytical hierarchy process (AHP) method

Factors	EI	LD	TFD	LI	ELE	SG	SA	GEO	DD	AAP	Weight
EI	1	2	2	2	3	1	2	2	2	3	0.1758
LD	1/2	1	1	1	2	1/2	1	1	1	2	0.0948
TFD	1/2	1	1	1	1	1/2	1	1	1	2	0.0871
LL	1/2	1	1	1	1	1/2	1	1	1	2	0.0871
ELE	1/3	1/2	1	1	1	1/3	1	1	2	1	0.0782
SG	1	2	2	2	3	1	2	2	2	3	0.1758
SA	1/2	1	1	1	1	1/2	1	1	1	1	0.0810
GEO	1/2	1	1	1	1	1/2	1	1	1	1	0.0810
DD	1/2	1	1	1	1/2	1/2	1	1	1	1	0.0772
AAP	1/3	1/2	1/2	1/2	1	1/3	1	1	1	1	0.0620

The abbreviations have the same meaning as that in Table 1

$\lambda = 10.174$, $CI = 0.0193$, $RI = 1.49$, $CR = 0.013 < 0.10$

of drainage density (Fig. 6i) shows that the drainage density with range 65–110 km/100 km² has greater sensitivity coefficient. However, the drainage density with range greater than 130 km/100 km² has lower sensitivity coefficient. This is because these northeastern regions of the study area have flat terrain and fewer landslides.

3.3.10 Precipitation

Precipitation is a very important external triggering factor for landslide occurrence (Carrara et al. 1999; Van Westen et al. 2006). In this paper, the average annual rainfall is used to characterize the precipitation factor. The precipitation sensitivity analysis (Fig. 6j) shows that when average annual rainfall is greater than 1,050 mm/year, the precipitation sensitivity coefficient begins to be positive, which means that its sensitivity is greater than total sensitivity of the entire study area, and it will significantly increase landslide susceptibility.

3.4 Factor-weighted overlay

The AHP method is a well-known multi-attribute weighting method for decision analysis, which combines qualitative and quantitative methods, and can model and quantify the complex thinking process of decision-makers. Using this method, decision-makers can divide a complex problem into a number of levels and factors and make the simple comparison and calculation among various factors. Finally, the weight of the importance degree of various factors can be obtained, which provide basis for the choice of the best available solutions (Saaty 1997). So far, the AHP method has been widely used to landslide study (Tang et al. 2011a; Yoshimatsu and Abe 2006; Kamp et al. 2008).

In our study, the AHP method was used to determine the factor weights, which indicate the importance degree of causative factors to landslide occurrence. AHP method applies a one-level weighting system developed by collecting expert opinions (Kamp et al. 2008), in this case, our experience during the urgent field survey after the Lushan earthquake. The results of the judgment matrix and optimized factor weights are listed in Table 2. The random consistency ratio ($CR = 0.013$) of judgment matrix is less than 0.1, which suggests

the optimized factor weights are reasonable and reliable. All factor weights were normalized, and their sum is equal to 1. The results suggest that earthquake intensity and slope gradient are the two most important causative factors for landslide susceptibility after the Lushan earthquake, and the following is landslide density that can reflect the spatial distribution characteristics of existing landslides. The average annual precipitation has the least contribution for landslide susceptibility. Compared with pre-seismic landslides, the earthquake intensity is an additional and special causative factor for post-earthquake landslide susceptibility, because it has changed the spatial distribution characteristics of traditional rainfall-triggered landslides.

Finally, the factor-weighted overlay method (Eq. 3) was used to conduct the urgent post-earthquake landslide susceptibility assessment, which adopts weighted average of various factor indexes. In Eq. 3, LSI indicates the landslide susceptibility index that represents the relative landslide susceptibility degree; W_i indicates the factor weights; and SC_i indicates the sensitivity coefficient of factor levels. All causative factors were overlaid using sensitivity coefficient (Table 1) and factor weights (Table 2) to obtain landslide susceptibility index, which was accomplished using the classical overlay operation in ARCGIS in terms of Eq. 4.

$$LSI = \sum_{i=1}^n W_i \times SC_i (i = 1, 2, 3, \dots, n) \quad (3)$$

$$LSI = 0.1758EI + 0.0948HD + 0.0871TFD + 0.0871LI + 0.0782ELE \\ + 0.1758SG + 0.081SA + 0.081GEO + 0.0772DD + 0.062AAP \quad (4)$$

4 Results

The post-earthquake landslide susceptibility can be divided into five levels in terms of LSI through natural breakpoints in ARCGIS: very high landslide susceptibility, high landslide susceptibility, moderate landslide susceptibility, slightly low landslide susceptibility and low landslide susceptibility. Figures 7 and 8 show the entire and local landslide susceptibility zoning maps in the Lushan earthquake-impacted area, respectively.

The landslide validation set was used to evaluate the validation of landslide susceptibility assessment results. The landslide susceptibility indexes were arranged using descending order (from high landslide susceptibility to low landslide susceptibility) and categorized into 100 equal classes. Then, the corresponding cumulative percentage of landslide occurrence and coverage area of 100 equal classes were used to create success rate curve (Fig. 9). AUC indicates the area between the horizontal axis and the curve, which can be used to evaluate the performance of models, and its value ranges between 0.5 and 1 (Song et al. 2012). The higher the percentage of the area below the curve, the better is the prediction (Kamp et al. 2008). The AUC in Fig. 9 suggests the accuracy of landslide susceptibility assessment is approximately 82 % in our study area, which is acceptable for the landslide susceptibility prediction.

5 Analysis and discussion

The statistical results of landslide susceptibility zoning map are listed in Table 3, and their illustration is shown in Fig. 10. It can be found that about 64 % of post-earthquake

Fig. 7 Landslide susceptibility zoning map in the Lushan earthquake-impacted area. The landslide susceptibility includes five levels: very high landslide susceptibility, high landslide susceptibility, moderate landslide susceptibility, slightly landslide susceptibility and low landslide susceptibility

landslides are mainly distributed in the regions with very high and high landslide susceptibility, and only about 7 % of post-earthquake landslides are mainly distributed in the regions with slightly low and low landslide susceptibility. The cumulative percentage curves in Fig. 10 present that the increase rate of post-earthquake landslide cumulative percentage is higher compared with area cumulative percentage of study area, which further demonstrates the rationality of landslide susceptibility assessment results.

5.1 Very high landslide susceptibility

The regions with very high landslide susceptibility account for about 0.23 % of the entire study area, but the percentage of post-earthquake landslides is about 27 %. These regions are mainly distributed in the regions with earthquake intensity of 8–9°, such as Shuangshi town and Longmen town of Lushan county and Muping town of Baoxing county, where there are much adverse environmental conditions for landslide stability including great elevation difference, high slopes, deep valleys, developed faults, weak rock masses, etc. The main rock masses are pyroclastic rock, sandstone, carbonate and amphibolite. The dominant geomorphology type is mountain with medium elevation and large fluctuation. There are abundant loose deposits and sediments resulted from the intense effect of the

Fig. 8 Local landslide susceptibility zoning map in the Lushan earthquake-impacted area. The location is indicated by the red frame in Fig. 7

Fig. 9 Success rate curve. The cumulative percentage is in terms of the descending order of landslide susceptibility indexes (from high landslide susceptibility to low landslide susceptibility). Area under curve (AUC) suggests the accuracy of landslide susceptibility assessment is approximately 82 % in our study area

Table 3 Statistical results of landslide susceptibility zoning map

Landslide susceptibility	Study area			Post-earthquake landslides		
	Area (km ²)	Percentage (%)	Cumulative percentage (%)	Count	Percentage (%)	Cumulative percentage (%)
Very high	100.00	0.23	0.23	322	26.99	26.99
High	826.71	1.94	2.17	440	36.88	63.87
Moderate	6,174.92	14.47	16.64	343	28.75	92.62
Slightly low	17,595.53	41.22	57.86	86	7.21	99.83
Low	17,990.15	42.14	100	2	0.17	100
Total	42,687.31	100		1,193	100	

Fig. 10 Illustration of statistical results of landslide susceptibility zoning map **Fig. 11** Two typical landslide scenes from urgent post-earthquake landslide field survey. **a, b** is located in the marker A and B in Fig. 8, respectively

earthquake, which are very beneficial to landslide occurrence under subsequent strong rainfall. A large amount of landslides have occurred and seriously destroyed or threatened human lives and basic infrastructure. For example, Figs. 11 and 12 present several typical landslide scenes from urgent post-earthquake landslide field survey and remote sensing interpretation of UAV images, respectively.

Fig. 12 Two typical landslide scenes from post-earthquake remote sensing interpretation of unmanned aerial vehicle (UAV) images. **a**, **b** is located in the marker *C* and *D* in Fig. 8, respectively

5.2 High landslide susceptibility

The regions with high landslide susceptibility account for about 1.9 % of the entire study area, but the percentage of post-earthquake landslides is about 39 %. These regions are mainly distributed in the regions with earthquake intensity of 7–9°, where there are also some adverse environmental conditions for landslide stability including great elevation difference, developed faults, etc. The main rock masses are mudstone, sandstone and siltstone in south regions, and the main rock masses are phyllite, slate and limestone in north regions. The dominant geomorphology types are mountains with medium–low elevation and small fluctuation, and valley with low elevation. The loose deposits and sediments are relatively abundant and provide necessary material resources for future landslide occurrence.

5.3 Moderate landslide susceptibility

The regions with moderate landslide susceptibility account for about 15 % of the entire study area, but the percentage of post-earthquake landslides is about 29 %. These regions are mainly distributed in the regions with earthquake intensity of 7–8°, where the main rock masses are sandstone, siltstone and mudstone. The dominant geomorphology types are mountains with medium–low elevation and medium–small fluctuation. The earthquake effect is medium, and the frequency and intensity of post-earthquake landslides are slightly greater than that before earthquake.

5.4 Slightly low landslide susceptibility

The regions with slightly low landslide susceptibility account for about 41 % of the entire study area. These regions are mainly distributed in the regions with earthquake intensity of 6–7°. The earthquake effect is relatively low, and the frequency and intensity of post-earthquake landslides are approximately the same as that before earthquake.

5.5 Low landslide susceptibility

The regions with low landslide susceptibility account for about 42 % of the study area. These regions are mainly distributed in the regions with earthquake intensity less than or equal to 6°. The earthquake effect is basically negligible.

6 Conclusions

After 2013 Lushan earthquake, an urgent project was initiated to obtain landslide susceptibility zoning map within the shortest time for guiding the post-earthquake rescue. This paper mainly focuses on the methodology of the urgent landslide susceptibility assessment right after the earthquake. Firstly, one detailed landslide inventory (including 5,688 landslides) was prepared by means of urgent post-earthquake landslide field survey, landslide remote sensing interpretation of multi-source remote sensing images and historical landslide archives. Ten remarkable causative factors for landslide occurrence were selected prudentially, including earthquake intensity, landslide density and slope gradient. Then, an integration assessment approach is developed to facilitate the effective urgent post-earthquake landslide susceptibility assessment using three well-known methods: factor sensitivity analysis, AHP and factor-weighted overlay. Such integration can produce or adjust the necessary parameters for landslide susceptibility assessment by means of the precise statistical calculation and effectively reduce the subjectivity and uncertainty resulting from using single method. The validation evaluation suggests that they are capable of acquiring the excellent results of urgent post-earthquake landslide susceptibility.

The earthquake intensity and slope gradient are the two most important causative factors for post-earthquake landslide occurrence in the Lushan earthquake-impacted area. There is a distinct positive correlation between earthquake intensity and post-earthquake landslide frequency. The dominant slope gradient and slope aspect with relatively higher landslide frequency is 45°–50° and south-east direction, respectively. The intense earthquake impact increased the dominant slope gradient of landslide spatial distribution, and the thrust campaign of seismogenic fault with strike NE–SW made south-east direction as the dominant slope aspect of the landslide spatial distribution. The earthquake-triggered landslides present much more spatial clustering in the strong earthquake-impacted regions compared with rainfall-triggered landslides before earthquake.

On the whole, the landslide susceptibility shows descending trend with the increasing distance from epicenter. The locations with very high and high landslide susceptibility are mainly distributed in the regions with higher earthquake intensity and adverse terrain conditions, which account for about 2.2 % of the entire study area, such as Shuangshi town and Longmen town of Lushan county and Muping town of Baoting county. However, the locations with slightly low and low landslide susceptibility are mainly distributed in the regions with lower earthquake intensity and flat terrain, which account for about 83 % of the entire study area. The developed integration assessment approach is expected to be used in the urgent landslide susceptibility assessment after future earthquakes, and the study results are expected to provide a beneficial reference for the landslide prevention and infrastructure reconstruction after the Lushan earthquake.

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