Analysis of landslide hazard area in Ludian earthquake based on Random Forests

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ABSTRACT:

With the development of machine learning theory, more and more algorithms are evaluated for seismic landslides. After the Ludian earthquake, the research team combine with the special geological structure in Ludian area and the seismic filed exploration results, selecting SLOPE(PODU); River distance(HL); Fault distance(DC); Seismic Intensity(LD) and Digital Elevation Model(DEM), the normalized difference vegetation index(NDVI) which based on remote sensing images as evaluation factors. But the relationships among these factors are fuzzy, there also exists heavy noise and high-dimensional, we introduce the random forest algorithm to tolerate these difficulties and get the evaluation result of Ludian landslide areas, in order to verify the accuracy of the result, using the ROC graphs for the result evaluation standard, AUC covers an area of 0.918, meanwhile, the random forest's generalization error rate decreases with the increase of the classification tree to the ideal 0.08 by using Out Of Bag(OOB) Estimation. Studying the final landslides inversion results, paper comes to a statistical conclusion that near 80% of the whole landslides and dilapidations are in areas with high susceptibility and moderate susceptibility, showing the forecast results are reasonable and adopted.

1. INTRODUCTION

Landslides are globally widespread phenomena, causing a significant number of human loss of life and injury, as well as extensive economic damages to private and public properties (Andrea Cimpalini, 2014). Strong earthquake often triggered a large number of landslides, the secondary disasters caused a greater loss than earthquake itself (LI Zhong-sheng, 2003), early in the 1960s, some western developed countries have begun to study earthquake landslide as the main body of the geological disaster research (Carrara A, 1983). With the development of technology, machine learning is gradually being introduced in the field of geological disaster prevention, multivariate statistical analysis (Saro Lee, 2002), artificial neural networks (Biswajeet Pradhan, 2007), fuzzy mathematics (Chung C F, 2008c) and other models have received a specific practice, although these new theories provide us more ideas and methods, but the seismic landslide evaluation is still a worldwide problem, gives us heavy disasters.

At 16:30 pm on August 3, 2014, Ludian County occurred Ms 6.5 earthquake, the epicenter was located at 27.1 °N, 103.3 °E, from the China Seismological Bureau released Ludian seismic intensity map view, the meizoseismal area intensity reached IX, on the other hand, the USGS released the PGA of Ludian earthquake, showing the meizoseismal area's PGA reached 948.5 cm/s2, this seismic explosive. By the end of August 7, 2014, Ludian earthquake caused 615 people were killed and thousands of people were injured, it brought serious economic losses (Zhang Zhen-Guo, 2014). According to the field exploration results, 637 landslide points were marked, among them, the biggest landslide in a volume of 1.68*107 m^3, in addition, the landslide blocked the NiuLanJiang River and formed a barrier lake. There are various landslide distribution along the road reducing the speed of the rescue seriously. The landslide threatening earthquake rescue personnel and the local people's life and property safety, hence, without doubt, carrying out the analysis of earthquake landslide risk in Ludian is imminent and valuable for post-disaster relief and reconstruction.

2. STUDY AREA

Ludian County, Yunnan Province, China, is located in the eastern Yunnan Seismic Belt and Xiaojiang Fault Belt, has numerous high seismic activities on this most concentrated area of Yunnan History. The county is a typical low latitude but high altitudes area, the average elevation is 1685 meters and its highest elevation reaches 4040 meters, moreover, the relative elevation is 3773 meters (FAN Jie, 2014). Ludian area has complicated topographic features, ravines horizon, WuMeng Mountain and WuLianFeng Mountain is located in there, in addition, NiuLan River throughout the county, thus, Ludian is a typical gorge region. In such a geological structure, once a large natural disaster occurs, the harm will be caused by more serious. In fact, Ludian region has repeatedly occurred some devastating earthquakes, according to the data provided by Yunnan Seismological Bureau, this area occurred more than 44 times earthquakes more than Ms 5.0, since 2003, this place had happened 3 times earthquakes more than Ms 5.0, caused significant damage. And now, it happens again. An earthquake occurred at Ludian was associated with a large number of landslides in August 3, 2014. Through the scene investigation, we found out 637 landslide points, the disaster points were mostly based on those significant characteristics: 01h, D3, p2β3 rock, complex geological structure, loose rock and soil structure, low shear strength and weathering resistance. With the arrival of the rainy season, the probability of inducing serious secondary disasters like landslide will increase sharply. Yunnan Province and Ludian landslide area in Figure 1.

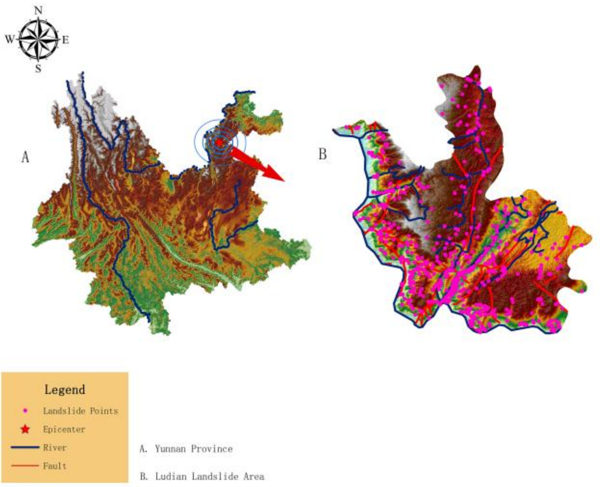


Figure 1. Yunnan Province and Ludian landslide area

3. DATA AND METHODS

3.1 Data

Landslide data used in the study from filed exploration, a total of 637 landslide points, part of landslide data as shown in Table 1. Remote sensing data from China's comprehensive national earth observation data sharing platform, these images consist of 91 images, including GF-1, KZ-1, Landsat-8, ZY-02C, ZY-3 satellites data come to 89, meanwhile, Geological map of Ludian area from the development research center of China geological survey, the local meteorological data from the national meteorological information center, the rest of the data such as drainage from Chengdu university of technology archives.

3.2 Method

Random Forests algorithm was proposed by Leo Breiman in 2011. Random Forests are an effective tool in prediction and they do not overfit. In addition, this algorithm is more robust with respect to noise and outliers and it has strong generalization ability (Breiman Leo, 2001). The algorithm use resampling method to extract multiple samples from the original sample and modelling of these samples by using decision tree (Breiman Leo, 1984), then combine the decision trees' predicted results, the final results are obtained by voting. Experimental results show that the algorithm has high prediction accuracy (FANG Kuang-nan, 2011). The mathematical expression is as follows.

$$\mathrm{H}(X) = av_k \max_{Y} \sum_{i=1}^{k} I(h_i(\mathrm{X}) = Y) \qquad (1)$$

Where $H(X)$ = the combination model
h_i = the decision-making unit
Y = the target variable
$I(\bullet)$ = the indicator function

Equation (1) indicates that the random forests algorithm is the use of voting to determine the final classification. On convergence of random forest, first define a margin function: equation (2)

$$mg(X,Y) = av_k I(h_k(X) = Y) - \max_{j \neq Y} av_k I(h_k(X) = j) \qquad (2)$$

Where $h_k(X)$ = the classification model
(X,Y) = the raw data

Margin function is used to measure the model's Reliability, The higher the function value, the greater the model reliability, then, we can deduce the generalization error formula: equation (3)

$$PE^* = P_{X,Y}(mg(X,Y) < 0) \qquad (3)$$

Breiman proved that with the increase of the decision tree classification model, $h_k(X) = h_k(X, \Theta_k)$ subject to the Strong Law of Large Number, meanwhile, he proved that as the number of the decision making unit increases, all sequences Θ_k and PE^* almost everywhere convergence on equation (4)

$$P_{X,Y}(P_\Theta(h(X,\Theta) = Y) - \max_{j \neq Y} P_\Theta(h(X,\Theta) = j) < 0) \qquad (4)$$

Equation (4) explains why this algorithm does not overfit as more trees as added. Breiman explained in his paper, bagging (Breiman Leo, 1996) is used in generating training sets (Breiman Leo, 2001) , according to theory, each training set from the original sets is not drawn with probability as $(1-\frac{1}{N})^N$, so when N is large enough, this probability will converge to $\frac{1}{e} \approx 0.368$, which means 36.8% of the data does not appear in the bootsrap samples, we call this part of data as out of bag data, using these data to estimate the model is called Out of Bag estimates (OOB estimates), Experiments show that the OOB estimates are unbiased estimator, moreover, compared with cross-validation, OOB estimates not only efficient, but also the results are very close to cross-validation. Tibshirani (Tibshirani R, 1996) and Wolpert and Macready (Wolpert D.H, 1997), proposed using out-of-bag estimates as an ingredient in estimates of generalization error (Breiman Leo, 2001).

NO.	Name	Scale ($1*10^4 m^3$)	Longitude	Latitude	NO.	Name	Scale ($1*10^4 m^3$)	Longitude	Latitude
1	JingKou Landslide	0.75	103° 29′ 59″	27°09′ 13″	8	HuiLongwan landslide	30.00	103° 25′ 07″	27°06′ 56″
2	XiaoBa Landslide	3.00	103° 15′ 10″	27°14′ 27″	9	LongJia Landslide	122.50	103° 36′ 03″	27°07′ 10″
3	TaoJiaPin Landslide	3.50	103° 33′ 00″	27°01′ 50″	10	XiaoJiaPing Landslide	102.00	103° 23′ 23″	27°05′ 07″
4	XiaHongdin Landslide	6.00	103° 35′ 50″	27°02′ 53″	11	HuLuQiao Landslide	172.60	103° 23′ 22″	27° 06′ 58″
5	MiaoZai Landslide	12.20	103° 16′ 25″	27°12′ 27″	12	LaoBei Landslide	500.00	103° 14′ 11″	27° 13′ 37″
6	ShaZiTian Landslide	14.00	103° 15′ 23″	27°08′ 56″	13	GanYanjiao Landslide	1680.00	103° 22′ 52″	27° 03′ 59″
7	PanZai Landslide	24.00	103° 36′ 13″	27°00′ 41″					

Table 1. Part of landslide field exploration data

In fact, in terms of the data we use is nonlinear, on the other hand, the relationships among these factors are fuzzy, Breiman wrote in Random Forests: the random forests algorithm does not overfit because of the Strong Law of Large Number (Breiman Leo, 2001). In other words, the random forest obvious advantages in processing large quantity, while this algorithm can easily adapt to this nonlinear effects, in addition, it is more about robust with respect to noise and outliers, that is the reason why we choose random forests.

4. RESULTS AND CONCLUSION

We use the Random Forests algorithm to build Ludian earthquake landslide risk analysis model, experiments were performed using the related computer program. As mentioned previously, selecting SLOPE (PODU); River distance (HL); Fault distance (DC), Seismic Intensity (LD) and Digital Elevation Model (DEM), the normalized difference vegetation index (NDVI) which based on remote sensing images as evaluation factors. These factors have different effects on the final results, through the concrete algorithm, we obtain figure 2.

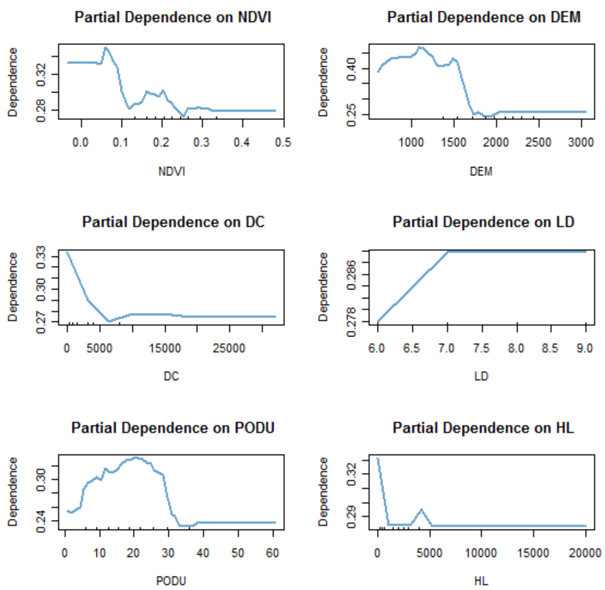
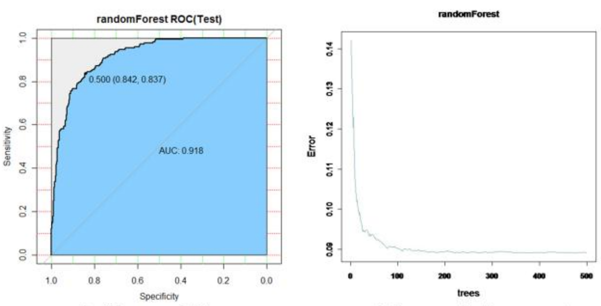


Figure 2. Each factor’s effects on the final results

The research team choose ROC graphs to evaluate the reliability of the model prediction results. Receiver operating characteristics (ROC) graphs are useful for organizing classifiers and visualizing their performance, and in recent years have been used increasingly in machine learning and data mining research (Tom F, 2006). When the area under the ROC curve (AUC) close to 0.5, predicted no meaning; when AUC is smaller than 0.7, the forecast accuracy is lower; when the AUC ranged between 0.7 and 0.8, the accuracy of prediction is acceptable; between 0.8 to 0.9, the forecasting accuracy is higher; when AUC is greater than 0.9, the accuracy of prediction is very high (Hosmer D W, 2000). The experimental ROC graphs and the generalization error as shown in figure 3.



A. ROC curve and AUC area B. The generalization error rate

Figure 3. ROC graphs and the generalization error

You can clearly see from the left image, AUC area reached 0.918, greater than 0.90, while the right panel shows the generalization error rate, with the increase of trees, the generalization error down to 0.05, it is an ideal result, these two results prove that the experimental result is accurate and effective.

We divide the results to four levels according to 0-0.25, 0.25-0.50, 0.50-0.75, and 0.75-1.00 classification standard: Lowest susceptibility zone (green); Low susceptibility zone (light green); Moderate susceptibility zone (yellow); High susceptibility zone (red). The landslide susceptibility map is illustrated as in figure 4.

Overall the result shows that the high risk zone of red is relatively concentrated, reflected as zonal distribution, showing a certain convergence. Can believes examine the effect of disaster risk assessment model should take into account two aspects: first, the risk of a large number of disaster areas appear as much as possible ; second , the risk of a large regional area as small as possible (can T, 2005). According to our statistical result, 270 points of 617 fall on high risk area, the ratio is 43.76%, while the zone of yellow has 205 points, a ratio of 33.23%, which means that a total of 76.99% of all points fall higher (high) susceptibility zones, combined with Can's theory, the landslide susceptibility result is accurate.

Therefore, this result is also available for the relevant departments for reference, at the same time, we suggest: the people and rescue personnel should leave the red area as soon as possible; disaster mitigation department should start suspicious landslide investigation as early as possible.

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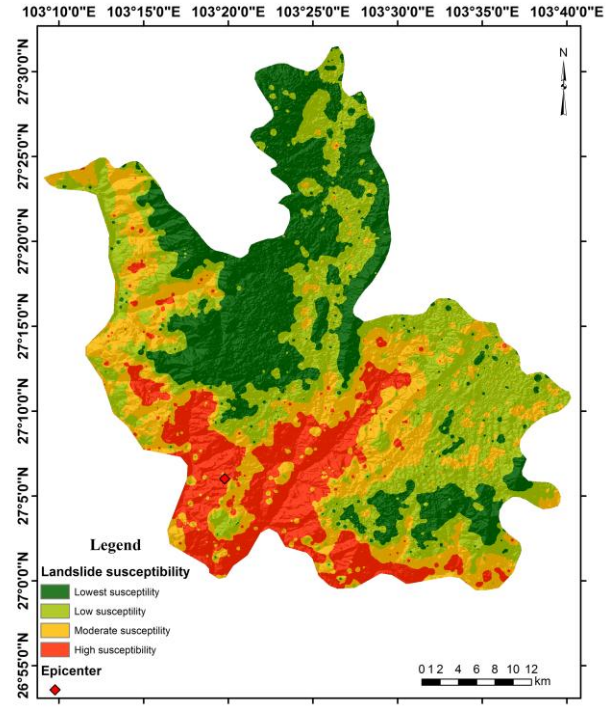

Figure 4. Landslide susceptibility map of Ludian earthquake area

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