Comparison and Integration of Heuristic and Statistical Models of Landslide Susceptibility Mapping

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Abstract—**Heuristic and statistical models are both important models of landslide susceptibility mapping. Experts' Scoring Model (ESM) and Generalized Linear Model (GLM), typical heuristic and statistical models respectively, are adopted to carry out a case study of Shenzhen where landslides are increasingly serious. The outputs of the two models obviously differ in terms of receiver operating characteristic (ROC), susceptibility distribution, information entropy, and prediction efficiency. Two integration methods, one to change the ranks of the factors and the other to change the weights of the factors, are evaluated and the outputs of the integration models appear to be more comprehensive and reasonable than ESM and GLM. This paper will provide a guide to future studies on landslide susceptibility mapping.**

Keywords-integration; landslide susceptibility mapping; heuristic model; statistical model; GLM; ESM

I. INTRODUCTION

Landslide susceptiblility mapping is a key issue in landslide forecasting and prewarning [1-2]. In recent years, there are many research papers on landslide susceptibility mapping models, of which direct geomorphological mapping, heuristic approaches, and statistical classification models are widely appied [1-5]. Heuristic approaches employ experts' knowledge and experiences to estimate landslide occurrence probability while statistical classification models can be subdivided into two categories, bivariate and multivariate [5]. Most of the existing studies adopt only one model and study on integration of different models is rare. However, it is theoretically and practically possible to improve the landslide susceptibility mapping results via integration of heuristic model and statistical model.

Based on a case study of Shenzhen, a heuristic model, experts' scoring model (ESM), and a statistical model, generalized linear model (GLM), are adopted and the results are compared firstly. Then, the integration of the two models is studied, in which four integration models are promoted, to evaluate the integration methodology and performances of the integration methods. In this paper, ROC and AUC are employed as primary criteria to evaluate the performances of the models [6-9]. Moreover, susceptibility distribution and prediction efficiency are also adopted to further assess the models [10].

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II. STUDY AREA AND METHODS

A. Study Area and Data

Shenzhen is a fast developing city in southern China. Located in East Asian monsoon region, the mean annual precipitation is 1966 mm, and the mean annual temperature is 22.0 Celsius degrees. Landslides, mostly triggered by rainfall, have become increasingly serious and claim great life and property losses in Shenzhen. The study area, 22°41'24" N ～ 22°32'31" N, 113°54'29" E～114°05'56" E, is in the central part of Shenzhen, with an area of 342 km2 (Fig. 1). In this area, approximately 40% of this region is mountainous; the bedrock is mainly comprised of granite and diorite; superficial deposits of the Quaternary and clasolite form large part of the flat area along the drainage in the middle part of the study area; and the prevalent strike of faults is NE-NNE.

The causal factors in this study are topography, geology, hydrology, lithology, vegetation cover, and human activities [6]. Slope angle and elevation are derived as concrete topographical causal factors. Geological, hydrological, and human activity factors are represented by Euclidean distance to fault, drainage, and roads, respectively; and Normalized Difference Vegetation Index (NDVI) is adopted as land cover factor. All thsee causal factors are derived from a set of 1:10,000 geologic and topographic maps and Satellite Pour l'Observation de la Terre (SPOT) images, with a spatial resolution of 10 m. The lithological factor, obtained from geological maps, is a categorical variable. Instead of taking the lithological factor as dummy variable, this categorical variable is transformed into numerable variable in order to avoid complicated and time-consuming computing. Moreover， 226 landslide occurrence records are available in the study area, collected and provided by the Municipal Bureau of Land Resources of Shenzhen.

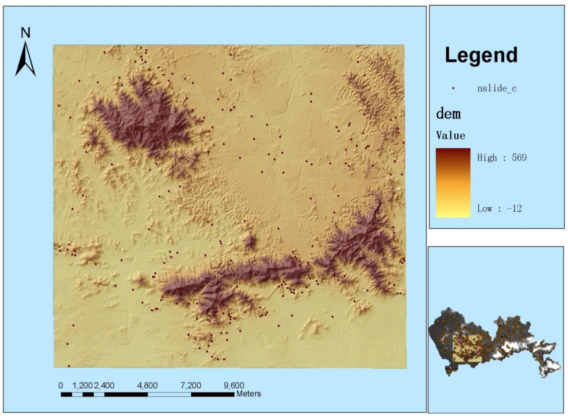

Figure 1. Study area

B. *Landslide Susceptibility Mapping Models*

a) Experts' Scoring Model (ESM)

In ESM, the experts' scores are recognized as the weights of the factors. A scoring table by thirty geological experts is obtained and shown in Table I.

b) Generalized Linear Model (GLM)

GLM forms a multivariate regression namely link function, between a generalized dependent variable and several independent variables [11]. The variables in GLM may be either continuous or categorical or any combination of both types [11]. In this paper, the dependant variable is binary, indicating whether there is landslide occurrence at given position. A GLM with binary link function can be expressed as:

$$\log\mathrm{it}(P) = \ln(\frac{P}{1-P}) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \quad (1)$$

where P is the output probability, β_0 is the intercept, β_i is the ith coefficient and x_i is the ith independent variable. P can be also denoted as:

$$P = \frac{\exp(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)}{1 + \exp(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)} \quad (2)$$

C. *Evaluation Methods*

a) ROC and AUC

The area under the receiver operating characteristic (ROC) curve, known as AUC or AUROC, is widely used to estimate the accuracy of presence/absence predictive models [12-15]. Given a certain probability threshold, a confusion matrix can be calculated (Table II) [16]. More evaluation indices can be derived from the confusion matrix, e.g. the true positive rate or sensitivity, defined as A/(A+C), and false positive rate, defined as B/(B+D).

TABLE I. PARAMETER OF GLM AND ESM

Factor/Variable	GLM Coefficient	ESM Coefficient	GLM Rank	ESM Rank
Slope angle	9.566	0.1634	1	2
Human activity	-7.123	0.1732	2	1
NDVI	-3.431	0.1268	3	6
Elevation	3.041	0.1488	4	4
Geology	-0.9945	0.1610	5	3
Hydrology	-0.8500	0.0780	6	7
Lithology	0.2017	0.1415	7	5
Intercept	0.2707	-	-	-

TABLE II. CONFUSION MATRIX

	Observed present	Observed absent	Total
Predicted present	A	B	A+B
Predicted absent	C	D	C+D
Total	A+C	B+D	A+B+C+D

It could be more or less subjective to determine a proper threshold. Fielding proposed AUC to overcome this problem [17]. Normally, the greater AUC, the better the result. When AUC is 0.5 or even smaller, indicating half or more than half of the samples are wrongly classified, the model could be virtually useless [16].

c) Susceptibility Distribution

The landslide susceptibility distribution should be reasonable to make the susceptibility mapping result practically efficient. The susceptibility distribution should be smooth to output larger information entropy [18]. If the distribution of probability mass function is uniform on [0, 1], the entropy value can reach the maximum [18]. The information entropy can be denoted as:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \ln p(x_i) \quad (3)$$

where $p(x_i)$ is the fitted landslide susceptibility at location *i*. Obviously, there should be no significant peaks in the susceptibility histogram because a significant peak means that many locations have the same susceptibility value and will make the susceptibility mapping practically inefficient or even useless [10].

c) Prediction Efficiency

Prediction efficiency is a useful index in evaluating prediction models [10]. It is described by the minimum proportion of the predicted landslide-prone area to the whole area when the predicted landslide-prone area covers all or a certain high percentage of known landslide occurrences [10]. The smaller the proportion, the greater the prediction efficiency.

III. COMPARISON AND INTEGRATION OF ESM AND GLM

A. *Comparison between ESM and GLM*

In the case study of Shenzhen, ESM and GLM are implemented on ArcGIS. The resulting maps are shown in Fig. 2. The corresponding AUCs are shown Table V, the susceptibility distributions and information entropies in Fig. 3 and Table VI, and the prediction efficiency in Fig. 4.

It is clear that GLM has a higher AUC value, better prediction efficiency, and more reasonable landslide susceptibility distribution than ESM. To make the comparison clearer, we choose a small region where human activity, the no. 1 factor in ESM, is less vulnerable to landslide occurrences, marked by a rectangle in Fig 2. GLM works much better in this region than ESM for GLM treats slope angle as the no. 1 factor.

In mountainous area ESM and GLM results differ most. This phenomenon is easy to explain for GLM is data-dependent and historic landslide records in mountainous are rarely collected due to inadequate observation. In such areas, ESM, a data-independent model will probably work better.

In ESM, human activity are considered as the no. 1 factor while GLM takes slope angle as the most significant factor. The reason for this is also clear. The experts do notice the relation between the human constructions and landslide occurrences in their working experiences and give high weight to human activity. But the man-made slopes are mostly retaining walls which are almost all vertical and consequently GLM takes the slope angle as the most important causal factor.

The ranks of NVDI in ESM and GLM differ most among all factors, 6th in ESM and 3rd in GLS. It is common sense that vegetation is helpful for the conservation of soil and water and accordingly prevents the landslide occurrences. But areas with high NDVI values in the study area are mainly covered by arbor which is weak in conservation of soil and water due to its relatively sparse distribution.

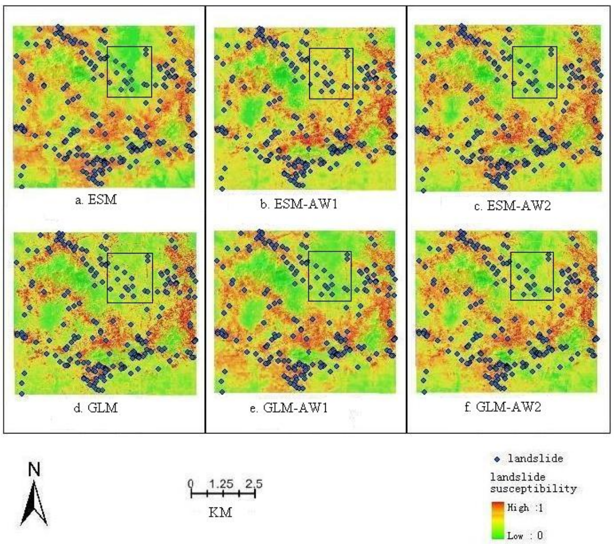

Figure 2. Susceptibility maps

B. *Integration of ESM and GLM*

a) Adjust Factor Weights Based on the Factor Ranks in ESM

The ranks of factors in ESM are based on the working experience of the experts and subject to the inadequate observation in certain areas. The factor weights in GLM are data-dependent but also quantitatively meaningful. The GLM-based combination model, GLM-AW1, is designed to switch the weight of one factor in GLM with another weight value in GLM in its corresponding rank in ESM to utilize the experiences of experts. For example, NDVI, originally with a weight of -3.431 and 3rd rank in GLM, is adjust to have a weight of -0.85 for it rank in ESM is 6th. The adjusted factor weights are in GLM-AW1 shown in Table III.

Another ESM-based integration model, ESM-AW1, is also designed. In ESM-AW1, the weight of one factor in ESM is substituted by the weight in GLM in the same rank as its original one in ESM. After the substitution, all new weights in ESM are normalized again. Take NDVI for example again, with a weight of 0.1268 and 6th rank in original ESM, its weight becomes 0.0337, the normalized value of 6th weight in GLM, 0.078, and still the 6th in ESM. The adjusted factor weights in ESM-AW1 are shown in Table III.

TABLE III. FACTOR WEIGHTS IN ESM-AW1 AND GLM-AW1

Factor/Variable	GLM-AW1 Coefficient	ESM-AW1 Coefficient	Rank
Slope angle	7.123	0.2826	2
Human activity	-9.566	0.3795	1
NDVI	-0.8500	0.0337	6
Elevation	3.041	0.1206	4
Geology	-3.431	0.1361	3
Hydrology	-0.2017	0.0080	7
Lithology	0.9945	0.0395	5
Intercept	0.2707	-	-

b) Apply Average Weights of ESM and GLM

Two more integration models are designed to apply the average weights of ESM and GLM. ESM-AW2 is ESM-based and the GLM-AW2 is GLM-based. The weights in original GLS are normalized before the average weights are calculated. To keep the model feasible, the average weights in ESM-AW2 are in fact the absolute values. The adjusted factor weights of ESM-AW2 and the GLM-AW2 are listed in Table IV.

All the four integration models are also implemented on ArcGIS. The resulting maps are shown in Fig. 2, the corresponding AUCs in Table V, the susceptibility distributions and information entropies in Fig. 3 and Table VI, and the prediction efficiency in Fig. 4.

Among all the six models, the AUC of GLM is still the greatest and the AUC of ESM is the smallest. All the four integration models have AUC values between those of GLM and ESM, not as good as GLM but better than ESM, which indicated the ESM-based integration models do improve the original ESM. ESM-AW2, with the second best AUC value, 0.761, improves the original ESM greatly.

Considering the landslide susceptibility distribution and information entropy, GLM-AW1 performs the best. It has the smoothest landslide susceptibility distribution and greatest information entropy among all six models. This clearly demonstrates that the integration model can improve the original ones considerably in terms of landslide susceptibility distribution and information entropy. It can also clearly seen in Fig. 4 that GLM has the greatest prediction efficiency and the ESM has the smallest one among all six models. Both of the two ESM-based integration models improve the original ESM in term of prediction efficiency.

TABLE IV. FACTOR WEIGHTS IN ESM-AW2 AND GLM-AW2

Factor/Variable	GLM-AW2 Coefficient	ESM-AW2 Coefficient	Rank
Slope angle	0.2715	0.2715	1
Human activity	-0.2279	0.2279	2
NDVI	-0.1315	0.1315	4
Elevation	0.1347	0.1347	3
Geology	-0.1002	0.1002	5
Hydrology	-0.0559	0.0559	7
Lithology	0.0747	0.0747	6
Intercept	0.2707	-	-

TABLE V. AUCS

Method	AUC value
ESM	0.7173
ESM-AW1	0.7429
ESM-AW2	0.7610
GLM	0.7734
GLM-AW1	0.7494
GLM-AW2	0.7485

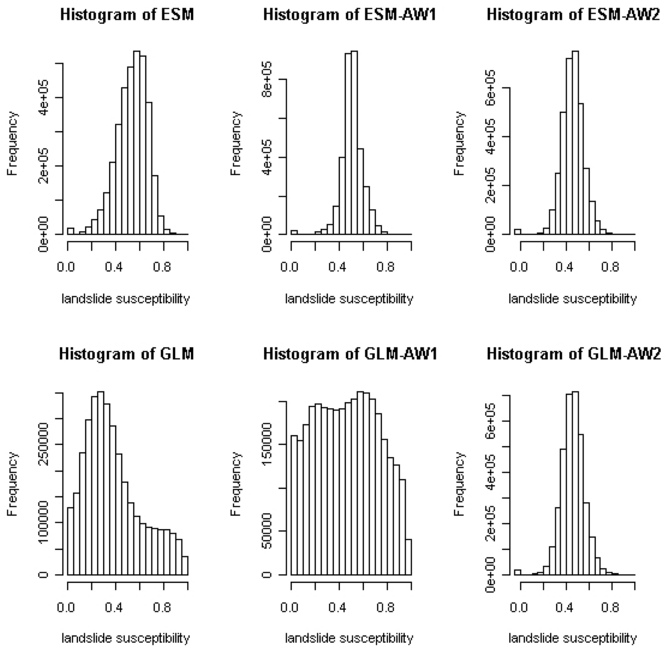

Figure 3. Landslide susceptibility histograms

TABLE VI. INFORMATION ENTROPIES

Model	Information Entropy
ESM	3718240.27
ESM-AW1	2961132.48
ESM-AW2	1178565.13
GLM	6478087.26
GLM-AW1	7728495.75
GLM-AW2	1175869.23

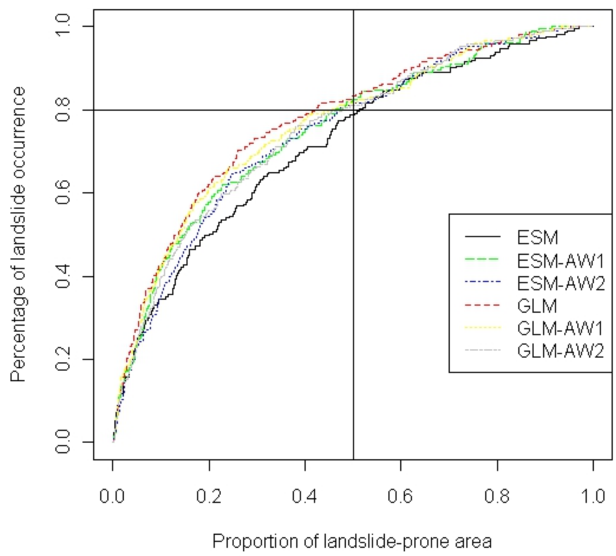

Figure 4. Prediction efficiencies

IV. CONCLUSIONS

Comparison and integration of ESM and GLM, typical heuristic and statistical susceptibility mapping models respectively, are carried out in a case study of Shenzhen in this paper, taken AUC, susceptibility distribution, and prediction efficiency as major evaluation criteria. Four integration models by different integration methods are promoted and evaluated along with the original two models. The two original models are different and GLM appears to be obviously better. All the four integration models perform better than ESM in one or more aspects. ESM-AW2, an ESM-based integration model, improves the AUC of ESM greatly and GLM-AW2, a GLM-based integration model, has the greatest information entropy among all evaluated models. It can be concluded that it is possible and feasible to improve the landslide susceptibility mapping models through integration of them, though the integration method should be further studied.

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