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Regional Integrated Meteorological Forecasting and Warning Model for Geological Hazards Based on Logistic Regression

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Abstract: Information model is adopted to integrate factors of various geosciences to estimate the susceptibility of geological hazards. Further combining the dynamic rainfall observations, Logistic regression is used for modeling the probabilities of geological hazard occurrences, upon which hierarchical warnings for rainfall-induced geological hazards are produced. The forecasting and warning model takes numerical precipitation forecasts on grid points as its dynamic input, forecasts the probabilities of geological hazard occurrences on the same grid, and translates the results into likelihoods in the form of a 5-level hierarchy. Validation of the model with observational data for the year 2004 shows that 80% of the geological hazards of the year have been identified as "likely enough to release warning messages". The model can satisfy the requirements of an operational warning system, thus is an effective way to improve the meteorological warnings for geological hazards.

Key words: geological hazard; information model; Logistic regression; rainfall; spatial analysis

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0 Introduction

Geological hazards such as landslide, debris flow and landslip are affected by various geographical, geological and environmental factors. In addition to them, rainfall is always a dominant triggering factor. Debris flow is a kind of solid-liquid mixed two-phase fluid saturated with sands, blocks and boulders directly triggered by rainfall, which can happen as laminar flow or turbulence flow. Landslide and landslip are usually indirectly triggered by rainfall in a way that rainfall infiltrates to cause rapid mass movement along the slope. According to a general survey covering all counties (cities) in China carried out by the Ministry of Land and Resources, rainfall accounts for not only all the debris flows, but 90% landslides and 81% landslips as well[1].

During the recent decade, the statistical forecasting technology for rainfall-induced geological hazards had been widely studied and substantial progresses had been made. Statistical forecasting models can be roughly categorized into two classes: precipitation threshold model and occurrence probability model. ① Most of the existing precipitation threshold models are based only on the characteristics of rainfall that triggers landslides, debris flows, etc[2-12]; Song *et al* also tried introducing factors of geosciences into their model[13]. The main shortcoming of such kind of model is the lack of rigorous theoretical

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foundation of statistics. Model factors and their weights are usually arbitrarily determined, so that it is difficult to test the model performance statistically. ② Occurrence probability model applies Logistic regression to link the occurrence probabilities to contributing factors of geological hazards based on high- resolution data of geosciences in Geographic Information System (GIS). Most of such models did not introduce the triggering factors of rainfall, thus cannot forecast the occurrences of geological hazards dynamically, but just serve as assessment tools for hazard susceptibility[14-16]. Dai and Lee tried introducing 24-hour precipitation as a predictor for Logistic regression, thus provided the model with primary dynamic forecasting ability[17]. However, their hazard-triggering precipitations were simply represented by nearby rain gauge records, which could not faithfully reflect the rainfall conditions at the very sites where hazards occurred. Occurrence probability model has rigorous theoretical foundation of statistics, but, owing to the great differences between the triggering rainfall process and other contributing factors concerning their physical properties, spatial-temporal scales and measurements, how to effectively integrate the precipitations and the factors of geosciences to construct a dynamic probability forecasting model for occurrences of rainfall-induced geological hazards still remains unsolved.

In recent years, remote sensing technology had provided abundant observational data which are almost continuous in space; meanwhile GIS had been able to effectively integrate observational data with various physical properties and spatial-temporal scales, to represent the spatial patterns of attributes concerning rainfall-induced geological hazards. On the other hand, numerical weather forecasting technology had been able to provide precipitation forecasts for future 1-7 d in raster data format, with high spatial resolution of 0.5-5 km. These technological developments have provided objective facilities to construct occurrence probability model for rainfall-induced geological hazards with dynamic forecasting ability. Based upon the forementioned research works, the work reported here makes full use of progresses in geosciences and meteorology, adopts Logistic regression to construct Regional Integrated Meteorological Forecasting and Warning Model for Geological Hazards (abbreviated to RIMFWMGH) with dynamic forecasting ability. In the development of such a model, particular efforts had been made to address the following two existing issues:

① Spatial analysis of hazard-triggering precipitation. Precise retrieve of the historical triggering rainfall at the very site where a hazard had occurred is a crucial point in the model development. Former works simply use nearby rain gauge records to represent, by which triggering precipitations are often underestimated. An effective spatial analysis technique, the thin-plate smoothing splines method, is adopted in this work to retrieve historical hazard-triggering precipitations as precise as possible.

② Representation and integration of factors of geosciences. Under the conditions of rich remote sensing data and various factors of geosciences, another crucial point in the model development is to analyze the statistical correlations between occurrence probability of geological hazard and factors with various attributes, and then represent these correlations farthest in proper forms. Only through proper representations of the correlations between factors of geosciences and geological hazard, can rainfall and factors of geosciences be effectively integrated in the model, which enables the model to faithfully reflect the statistical correlations between occurrence probability of geological hazard and factors, and to make realistic forecast for occurrence probability of geological hazard. In this work, Information Model is adopted to integrate factors of geosciences that have significant driving effects on geological hazard occurrence, to provide a synthetic representation of hazard susceptibility distribution as the background of the occurrence of rainfall-induced geological hazard.

The above issues addressed, Logistic regression is used to combine the dynamic rainfall condition with the static hazard susceptibility distribution, to model the occurrence probability of rainfall-induced geological hazard. This solution addresses by a great extent the problem of effective combination of dynamic rainfall condition and static hazard susceptibility distribution. The RIMFWMGH is finally constructed.

1 Regional Integrated Meteorological Forecast and Warning Model for Geological Hazards

1.1 Model Design

RIMFWMGH is the core of the operational system of meteorological forecast and warning for geological hazards at the Central Meteorological Observatory. With the 24-hour numerical precipitation forecasts and historical observations inputted, the system makes hierar-

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chical forecasts for geological hazards on grid points covering the whole country. The numerical forecasts and daily observations are updated everyday, which are the dynamic inputs of the system. Geological, geographical and environmental factors concerning the geological hazards are the relatively static background. Accordingly, the model predictors consist of two parts, representing the dynamic rainfall input and the static background. Logistic regression is applied to integrate the two parts of predictors to model the occurrence probability of rainfall-induced geological hazard.

The development of RIMFWMGH is a two-stage procedure. Stage 1: using Logistic regression to build the hazard occurrence probability model with respect to historical hazards. The historical daily precipitations at hazard sites retrieved through spatial analysis of rain gauge records serve as dynamic rainfall input of the model. Since currently the warning system operates only for rainy season (from May to September), historical hazard and rainfall records during rainy seasons are taken only. Factors of geosciences sampled at hazard sites are integrated by Information Model to serve as the relatively static background of hazard occurrence. Stage 2: sampling factors of geosciences at grid points, then integrating them by Information Model to serve as the relatively static background of the forecasting area. Historical precipitations at grid points are retrieved through spatial analysis, together with numerical precipitation forecasts at same points to constitute the dynamic input of the model. The occurrence probability model for geological hazards with inputs from grid points constitutes the RIMFWMGH, which forecasts the occurrence probabilities of rainfall-induced geological hazards at grid points in the forecasting area, and by translating them releases the hierarchical warning messages.

Figure 1 shows the framework of RIMFWMGH.

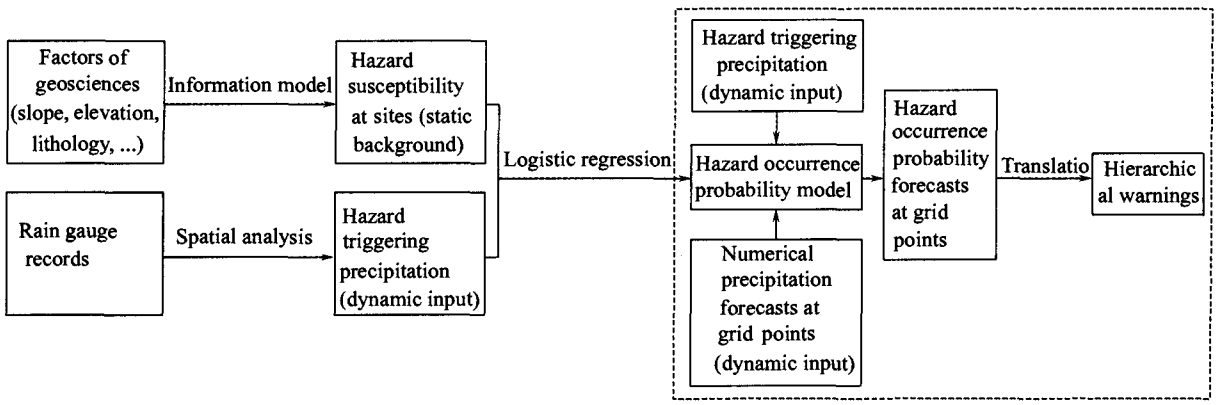


Fig.1 Framework of RIMFWMGH

1.2 Choices of Model Predictors

① Rainfall predictors

Both the short-term heavy rainfall and the continuous rainfall for several days can trigger geological hazards of different types. Short-term heavy rainfall can be represented by 24-hour precipitation of the day. For the continuous rainfall lasted for several days, because of runoff and evaporation, total precipitation infiltrating the rock mass is less than the sum of successively observed daily rainfall amounts, therefore the effect of the previous days' rainfall on the hazard occurrence is evaluated by the previous working precipitation instead[8], which is formulated as follow:

$$R_w = \sum_{i=1}^{n} (k^{i-1} R_i) \qquad (1)$$

where R_w is the previous working precipitation, R_i is the previous ith day's precipitation, k is the damping coefficient which is set to 0.8 and n is the total number of days which is set to 14. Since the great variation of the climate over China, hazard-triggering precipitation varies in space accordingly. Therefore, either the daily precipitation or the working precipitation is actually expressed in the relative form in the model, which is the ratio of daily or working precipitation to the long-term averaged annual precipitation.

In addition, in case that neither the 24-hour precipitation of the day nor the previous working precipitation is heavy, the continuity of the previous rainfall can also contribute to the triggering of hazards. Thus the number of wet days during the previous 14 days is taken as a triggering factor into account in the model.

② Information Model for geological hazard susceptibility assessment

Information Model is applied to take various geo-

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logical and environmental factors into account, to work out hazard susceptibility assessments on hazard sites as the relatively static part of RIMFWMGH. Information Model has been widely used in geological hazard susceptibility assessment[18-20]. It takes the forecasting area as a whole to evaluate the effect of a factor in a certain state on the hazard occurrence at a spatial unit. The forecasting area in this work is the mainland China with spatial unit set to 1 km^2. Let S be the total number of units in the forecasting area, S_{i,A_i} be the number of units where the state of the ith factor is A_i, N be the number of units where geological hazards occurred, N_{i,A_i} be the number of units with hazards occurred where the state of the ith factor is A_i. For each unit where the state of the ith factor is A_i, the contribution of the factor to the hazard susceptibility at the unit, or the Information of the factor, is

$$I_{i,A_j} = \ln\left(\frac{N_{i,A_i}/N}{S_{i,A_i}/S}\right), \quad i = 1,2,\cdots,n \tag{2}$$

The sum of all the contributions of factors to the hazard susceptibility at the unit, or the total Information of the unit, is

$$I = \sum_{i=1}^{n} I_{i,A_i} \tag{3}$$

The larger the total information I is, the higher the hazard susceptibility for the unit.

For each unit in the forecasting area, information of each factor and the total information at unit are calculated respectively. The total information at a hazard site is defined by the total information at the unit where the site locates. Consequently, the total information of all the hazard sites is obtained and is used as the static part of the model representing the effects of geological and environmental factors on hazard occurrences.

1.3 Logistic Regression

Logistic regression is adopted to construct the occurrence probability model for geological hazards[21]. In terms of the geological hazard forecasting, the dependent variable to regress is the probability p_i for the ith case of hazard occurrence that is defined on [0, 1], whereas the predictors are the geological and environmental factors that are usually defined on $(-\infty,+\infty)$. In order to build the regression, a link function is introduced to map [0, 1] onto $(-\infty,+\infty)$. Specifically,

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \sum_{j=1}^{m}(\beta_j x_{i,j}) \qquad i = 1,\cdots,n \tag{4}$$

Equation (4) is called Logistic regression, where $\beta_j (j = 0,\cdots,m)$ are model parameters, $x_{i,j} (j = 1,\cdots,m)$ are m predictors corresponding to the ith case of hazard occurrence and $\mu_i (i = 1,\cdots,n)$ is the response to predictors valued for the ith case. Model parameters can be estimated by the maximum likelihood method.

1.4 Translation of Forecasts and the Release of Warnings

When forecasting on a grid point based on the above hazard occurrence probability model, with the total information representing the hazard susceptibility, previous 14 days' rainfall observational data and 24-hour rainfall forecast on that point inputted, the model can forecast the hazard occurrence probability on the same point. With respect to the population of rainfall events, the frequency of triggered hazards is very small anyway. In addition of the incompleteness of the data, the forecasted probability of hazard occurrence is extremely small quantitatively, thus can not be used directly for warning purpose. Despite all this, if the observed hazard occurrences are regarded as a sample of the population, it can be assumed that the model still reflects the essential relationship between the hazard occurrence and various triggering factors in the form of probability. Therefore, the forecasted probability should be used in an indirect way, i.e. through translation for warning purpose. According to the criteria for warning operations at the Central Meteorological Observatory, warnings for rainfall-induced geological hazards are released in a 5-level hierarch ranging from the most unlikely occurrence to the most likely occurrence[12]. Warnings at level 3 and above will be published through mass media. Accordingly, all the fitted probabilities of hazard occurrences are graded by quantiles 0, 0.25, 0.45, 0.65, 0.85 and 1 as from level 1 to level 5. Level 3 and above can cover most of the historical hazard occurrences. In warning operation, the warning level for the forecasted probability is determined by at which interval the quantile of the forecasted probability locates.

2 Data Preprocessing and Model Fitting Results

2.1 Data Sources and Preprocessing

The data set used in fitting RIMFWMGH consists of historical hazard data, precipitation data, geological data, geographical data and environmental data.

① Historical hazard data

The historical hazard data are provided by the Geological Environmental Monitoring Center of China span-

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ning the period from 1980 to 2003. In addition, hazard data for the year 2004 either collected by the Central Meteorological Observatory or from other local land resource departments, are used for model validation. Rainfall-induced landslide, debris flow and landslip events are equally treated as historical hazard events. Owing to the incompleteness of hazard data, it is assumed in this work that the period before a hazard event in the year is the developmental phase of the event, and that the concurrent 24-hour precipitation is the triggering precipitation of the event. Rainfall events before the hazard occurrence at the same site in the year are taken as samples without hazards triggered.

② Precipitation data

Daily precipitation data from weather stations all over the country spanning the period from 1990 to 2004 are the 24-hour cumulative precipitations observed at 20 o'clock each day, and are provided by the National Meteorological Center, China Meteorological Administration. Spatial analysis is applied to these data for modeling.

To develop the model, various properties of the hazard-triggering rainfall are required. The available rainfall observations are ground station based; the locations and distribution of these stations are fixed. The spatial resolution of the weather station network is relatively low; the recorded precipitation can represent local characteristics only. However, hazard occurrence shows spatial randomness. If the hazard-triggering precipitation is simply represented by record at a nearby station, its local characteristics cannot be faithfully represented. In order to retrieve the triggering precipitation and previous precipitations of a historical hazard event and rebuild relevant rainfall properties, more delicate spatial analysis method is needed. Currently the thin plate smoothing splines method, which has been extensively used in meteorology, has excellent local properties[22,23]. This method not only makes use of positions of stations, but also can take other factors affecting the spatial pattern of rainfall such as elevation, terrain, etc. into account, thus is possible to retrieve local heavy precipitation higher than nearby station records. Consequently, the interpolation accuracy is greatly improved. In the meantime, this method can be carried out automatically without manual intervention, thus can satisfy the automatic operation requirement of a warning system.

③ Geological, geographical and environmental data

Geological, geographical and environmental data are essential to understand and forecast the occurrence of a geological hazard. The attributes that show most significant effects on the hazard susceptibility include geology, geomorphology, vegetation, land use, etc. Remote-sensed and surveyed data for these attributes used in this study are provided in raster format by the National Meteorological Center, China Meteorological Administration. See Table 1 for summary information of these data.

Table 1 Summary information of remote-sensed and surveyed data for model fitting

Data	Attributes
Slope gradient[a] /(°)	0-90
Elevation[b] /m	0-8841
Height difference[c] /m	0-2510
Engineering geological classification of rock mass[d]	1: magmatic rocks; 2: rocks; 3: carbonate rocks; 4: metamorphic rocks; 5: soil masses.
Fault density[e] / km·(100km^{-2})	0-200, 200-400, 400-600, 600-800, 800-1000, >1000.
Seismic intensity[f]	1-9
Land use[g]	1: farmland; 2: forest; 3: grassland; 4: water area; 5: town; 6: unexploited land.

Image resolutions for a-c: 1:250 000; for d, f: 1:4 000 000; for e: 1:500 000; for g: 1:100 000.

2.2 Analysis of the Conditions for Geological Hazard Occurrence and the Choice of Factors

The choice of factors of geosciences should be based on the analysis of inner relationships between the factors of geosciences and geological hazard occurrences from the physical mechanism point of view using principles of geology, mechanics, etc, according to the geological, geographical and environmental properties of the forecasting area. The model predictors are chosen accordingly. This part of work will be reported in another paper[24]. According to the analysis result, elevation, slope gradient, height difference, fault density, seismic intensity, engineering geological classification of rock mass and land use are chosen as factors to calculate the total Information, which is taken as the background part of the forecasting model. Plain, desert and water areas where rainfall-induced geological hazards have extremely little or none possibility to occur and areas where data are unavailable have been excluded in advance. The result shows that the total Information in mainland China area ranges from −13.29 to 6.31.

2.3 Model Fitting Results and Validation

Taking precipitation and hazard records on wet days for rainy seasons during the period from 1990 to 2003 as observational data, combining the factors of geosciences at the hazard sites, Logistic regression is used to model hazard occurrence probabilities at hazard sites. Predic-

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tors are selected as precipitation of the day, previous 14 days' working precipitation, number of wet days during the previous 14 days and total Information. The fitting results are listed in Table 2.

Table 2 Fitting results of RIMFWMGH

Model predictors	Fitted values of parameters	Standard errors
Constant	-10.088 515	0.088 031
Precipitation of the day	6.561 416	0.105 088
Previous working precipitation	2.228 535	0.147 125
Previous number of wet days	0.300 200	0.006 149
Total Information	0.022 872	0.003 212

The ANOVA shows that all the above predictors are significant at the level 0.001. For the standard errors of the fitted parameters it can be seen that the highest one is taken for the total information, which is only 1/7 of the fitted value. All this indicates that these factors are significantly correlated with the hazard occurrence probability and thus are proper predictors of the model.

Validation of the model by the data for the year 2004 shows that above 80% of the hazard events have been given warnings at level 3 or above, which are "likely enough to release warning messages". The model performance is fairly satisfactory. However, there are also 35% of forecasted probabilities at warning level 3 and above are overestimated. The reason for this is that the predictors are usually continuous at large scale, which is difficult to match the spatial scale of hazard occurrence. It is difficult to reduce the error rate of this type simply by improving the model itself. In addition to improve the spatial resolution of data, a practical solution is to compare the forecasts with local conditions. Areas that are unlikely to have geological hazard occurred will be eliminated in order to make the forecasts more realistic.

3 Conclusion and Discussions

This work combined the dynamic rainfall conditions with the static hazard susceptibility distribution to model the occurrence probability of rainfall-induced geological hazard based on Logistic regression. Predictors are selected as precipitation of the day, previous 14 days' working precipitation, number of wet days during the previous 14 days, and total Information representing the hazard susceptibility. Statistical test and data validation all indicate that the RIMFWMGH has great ability to forecast the occurrence probability of rainfall-induced geological hazard and is suitable for meteorological warning operations. Some discussions for knowing problems and future improvements of the model are as follows:

① The retrieving of historical precipitations at hazard sites is one of the difficulties that must be overcome in developing RIMFWMGH, and is a part that still needs improving in the future. Thin plate smoothing splines are used in this work for spatial analysis of historical triggering precipitations at hazard sites. This method can take factors affecting the spatial pattern of rainfall such as elevation into account and thus greatly improve the interpolation accuracy. It also satisfies the requirement of the automatic operation of forecast and warning system. However, spatial analysis depends on mathematical techniques, which cannot provide more information of rainfall. In recent years, with the development of weather radar network in China, more and more weather radars have been in operation, the radar precipitation estimation technology has also been greatly improved. Radar precipitation estimation will replace the spatial analysis methods gradually, thus address the problem of retrieving the historical triggering precipitation thoroughly.

② Information model is a simple and effective method for hazard susceptibility assessment; total Information can be used as a model predictor. The current problems affecting the model performance are that the spatial resolutions of remote-sensed data are not in agreement with the spatial scale of hazards so that the data cannot reflect the actual conditions of hazard sites, and that the interpretation and classification of remote-sensed data are not perfect. To further improve the resolution, interpretation and classification of remote-sensed data is crucial for a better performance of information model.

③ The forecasted probability of hazard occurrence should be translated rather than directly used for hazard warning purpose. The warning levels could be specified by quantiles of the fitted probabilities of hazard occurrences. With more and more hazard records available, the warning level specification should also be adjusted accordingly.

④ Since the predictors of RIMFWMGH usually have large-scale spatial continuity, the model has the problem of "good intent false alarm". Validation by data for 2004 shows that 35% of forecasted probabilities at warning level 3 and above are overestimated, i.e. there

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are actually no hazards happened. It is difficult to reduce the error rate of this type simply by improving the model itself. A practical solution is to compare the forecasts with local conditions. Areas that are unlikely to have geological hazard occurred should be eliminated in order to make the forecasts more realistic. In addition, improving the performance of regional weather model and the resolution of numerical precipitation forecast will help reduce the error rate and improve the precision of geological hazard forecast.

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