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Preliminary studies on the dynamic prediction method of rainfall-triggered landslide

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Abstract: Rainfall-triggered landslides have posed significant threats to human lives and property each year in China. This paper proposed a meteorological-geotechnical early warning system GRAPES-LFM (GRAPES: Global and Regional Assimilation and PrEdiction System; LFM: Landslide Forecast Model), basing on the GRAPES model and the landslide predicting model TRIGRS (Transient Rainfall Infiltration and Grid-based Regional Slope-Stability Model) for predicting rainfall-triggered landslides. This integrated system is evaluated in Dehua County, Fujian Province, where typhoon Bilis triggered widespread landslides in July 2006. The GRAPES model runs in 5 km×5 km horizontal resolution, and the initial fields and lateral boundaries are provided by NCEP (National Centers for Environmental Prediction) FNL (Final) Operational Global Analysis data. Quantitative precipitation forecasting products of the GRAPES model are downscaled to 25 m×25 m horizontal resolution by bilinear interpolation to drive the TRIGRS model. Results show that the observed areas locate in the high risk areas, and the GRAPES-LFM model could capture about 74% of the historical landslides with the rainfall intense 30mm/h. Meanwhile, this paper illustrates the relationship between the factor of safety (*FS*) and different rainfall patterns. GRAPES-LFM model enables us to further develop a regional, early warning dynamic prediction tool of rainfall-induced landslides.

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Introduction

China has suffered from frequent Landslide hazards, which have caused huge casualties and property loss each year. Landslide is part of rock mass, soil mass or their compound mass slides downward along a certain sliding surface under the actions of inner and external dynamics, and it is one severe instability phenomenon of rock and soil masses (Ding et al. 2006). The factors which determine the probability of landslide may be grouped into two categories: (1) the preparatory variables which make the slope susceptible to failure, such as geology, slope, elevation, soil geotechnical properties, and long-term drainage patterns; and (2) the triggering variable which shift the slope from a marginally stable to an unstable state, such as rainfall, and earthquake (Wu and Sidle 1995).

According to the first investigation of the geological disasters in China, 90% of the landslides are directly induced by or relate to rainfall (Li et al. 2004). Previous studies have also shown that landslides are closely associated with rainfall. The rainfall-induced landslides are often regional, aggregate, abrupt and disastrous (Jia et al. 2008). A lot of research efforts have been made to identify the relationship between landslides and rainfall. The methods of predicting landslides can be divided into empirical-based model, physical-based model and statistical-based model.

Empirical models are based on the rainfall characteristics, including intensity, amount and duration of rainfall, which closely relate to slope failures. Most commonly, the empirical thresholds have been derived by the rainfall intensity-duration curve and the cumulative storm precipitation (Caine 1980; Marchi et al. 2002; Aleotti 2004; Chen et al. 2005; Chleborad et al. 2006; Guzzetti et al.2007). Most of the empirical thresholds perform reasonably well in the region where they are developed, but may not be exported to other areas, since the proposed equations may vary from one location to another. Statistical models include statistical Bayesian model, logistic regression model, neural network model, and others. These methods reduce the subjectivity of the selection of the threshold, and consider the static conditions such as slope, elevation, vegetation, lithology, hydrology and other factors (Jia et al. 2008; Ding 2006). Unfortunately, statistical models can't explain the disaster mechanism, and are not suitable for the landslides induced by the extreme rainfall. Physical-based model analyzes the mechanical condition of slopes and evaluates the stability using mathematical calculations. It is a promising approach for susceptibility analysis of shallow landslides because of its capacity to reproduce the physical processes governing landslide occurrence (Fell et al. 2008). Most recent physical models are combined with a hydrogeological model to evaluate the effect of pore water pressure which increases as a consequence of rainfall and triggers shallow landslides (Park et al. 2013). These models include SHALTAB (SHAllow Landslide STABility model) (Dietrich et al. 1993, 1995; Montgomrty et al. 1994, 1998), SINMAP (Stability Index MAPping) (Pack et al. 1998; Morrisey et al. 2001), dSLAM(Wu et al. 1995; Dhakal et al. 2003), SHETRAN (Ewen et al. 2000), SEGMENT(Extensible Geo-fluid Model of the Environment) (Ren et al. 2010, 2011) and TRIGRS (Transient Rainfall Infiltration and Grid-based Regional Slope-Stability Model) (Montgomery et al. 1994; Wilkinson et al. 2002; Iverson 2000; Baum et al. 2002).

TRIGRS model has been widely used in the world. Cong (2008) tests TRIGRS model in the typical region of Southern China, and the result shows that the model could predict the occurrence and development process of regional rainfall-triggered geological hazards dynamically. Chen (2011) uses TRIGRS model to simulate the landslides induced by a storm in Taiwan. Liao (2011) quantitatively evaluates the spatiotemporal predictability of a Matlab version of TRIGRS (MaTRIGRS) in North Carolina, and the study shows that MaTRIGRS demonstrates acceptable spatiotemporal predictive skill for landslide occurrences within a 120 m radius in space and a hurricane-event-duration in time, offering the potential to serve as a landslide warning system in areas where accurate rainfall forecasts and detailed field data are available. Kim's Study (2010) shows that TRIGRS model captured about 64.1% of landslides that were extracted from the IKONOS-2 imageries in a forested mountain region. There is a significant agreement between the TRIGRS simulated scenarios and the scar's map in the southeastern Brazil (Vieira et al. 2010). Godt's results (2008) show that the spatial prediction of shallow landslide susceptibility is improved using the transient analyses of TRIGRS model in the north of Seattle, Washington.

Inspection of the literature reveals that physical-base models are preferred to forecast the spatial and the temporal occurrence of shallow landslides triggered by individual rainfall events in a given area (Raia et al. 2014). However, physical-process based models require high spatiotemporal rainfall data as a driving factor. Rainfall data using in the current landslide research is mainly from weather stations. The conventional observations can't show the details of spatiotemporal characteristics, and this may cause some loss of precision in the simulation. Moreover, we can't take advantage of the physical model to forecast landslides in real-time for lacking of quantitative precipitation. In recent years, a variety of rainfall data has been widely used, such as radar data and forecasting products from numerical weather model. Liao (2010) uses WRF (Weather Research Forecasting) coupled with SLIDE model (Slope-Infiltration-Distributed Equilibrium). Wei (2005) makes use of the quantitative rainfall data from MM5 (Fifth-Generation Penn State/NCAR Mesoscale Model) mesoscale numerical model to predict the landslide basing on statistical-based model.

With the rapid development of numerical weather prediction theory and model, the numerical model's precipitation products are available for the landslide early warning system. It obviously improves the prediction accuracy of rainfall-induced landslides by using numerical weather forecasting model, particularly in the areas absence of rainfall data. The resolution of the traditional landslide forecasting method is usually hundreds of kilometers, but the physical-based model with the numerical weather prediction improves the accuracy to hundreds of meters and extends the period validity.

In this paper, we prototyped a rainfall-triggered landslide disaster early warning system "GRAPES-LFM", which is coupled by a numerical weather forecasting model GRAPES and a physically based landslide prediction model TRIGRS. GRAPES model runs in 5 km×5 km horizontal resolution, and the initial fields and lateral boundaries of GRAPES are provided by Final Operational Global Analysis datasets. Quantitative precipitation forecast products of GRAPES model are downscaled to 25m×25m horizontal resolution by bilinear interpolation to drive TRIGRS model. GRAPES-LFM is applied to forecast the landslide in Dehua County during a typhoon rainfall process in 2006 in order to test the accuracy of the coupled model.

1 Study Area

Dehua County is located in the center of Fujian province, which has a subtropical mountain climate with the average annual rainfall of 1855 mm (Figure 1). There are 0.28 million people, and 70% of them live in the county center. The long-term statistical data shows that the rainfall from May to September accounts for 70% of annual accumulated rainfall or more. Because of the complex terrain, the precipitation decreases from the south to north. Furthermore, torrential rains commonly activate landslides in summer season.

According to incomplete statistics, there are 407 rainfall-induced landslides from 1980 to 2007 (Figure 2). Topographical parameters are generated from a 25m-resolution Digital Elevation Model (DEM) using ArcGIS 10.1 (Figure 2 and Figure 3). The elevations in Dehua County vary

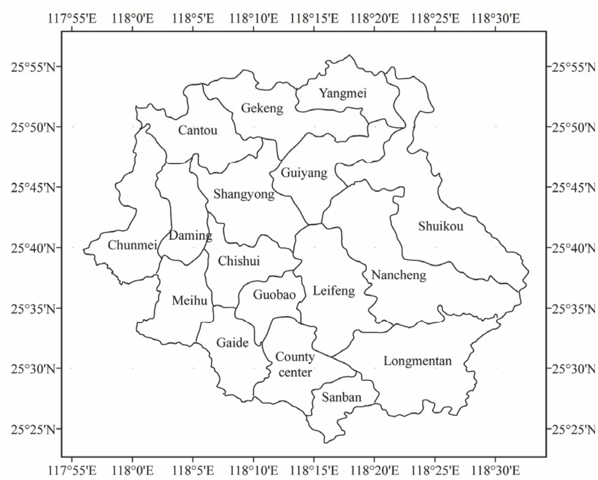

Figure 1 Location map of the study area in Fujian province, Southeast China

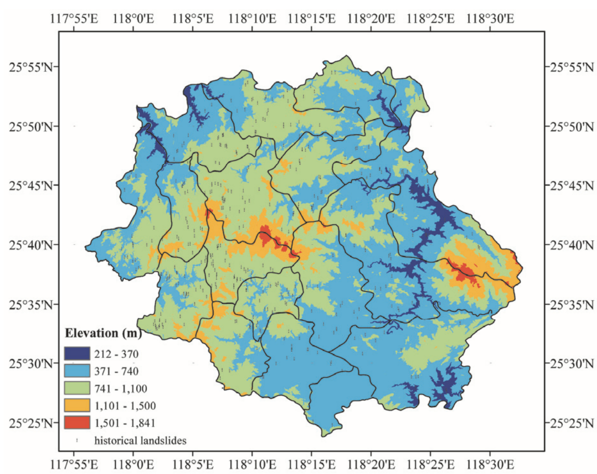

Figure 2 Distribution of elevation in Dehua County, Fujian province, Southeast China

from 212 m to 1841 m, and slope angels range from 0° to 69°. Most of the recorded landslides occurred in the areas where the elevations are less than 1100 m with the slope angles less than 40°.

The majority of the rock-soil mass in the study area is volcanic rock which accounts for 65.2%, and others are intrusions, metamorphic rock, natrocarbonatite and so on. According to the geological disaster investigation in Dehua County, the landslides account for 92.06% of the total geological disasters. Moreover, 98.17% of the landslides closely relate to the precipitation (China Geological Environmental Monitoring Institute 2010). The typhoon Bilis (Figure 4) triggered lots of landslides in 2006. There was plenty of precipitation before the typhoon Bilis landing (Figure 5), so the soil was supported to be saturated in our study.

2 Theoretical Basis of the Model

2.1 GRAPE model

The regional assimilation and prediction system of a new generation-GRAPES is developed by China Meteorological Administration (CMA). The main characteristics of the system include full compressible and hydrostatic/non-hydrostatic approximation in option, regional unified model, semi implicit-semi Lagrange decretization scheme, standardization, modularization and parallelization of the model software, etc. (Zhang et al. 2008). GRAPES model has been applied to the meteorological forecasting after ten years' development, and performs better forecasting skills (Wang et al. 2010).

2.2 TRIGRS model

TRIGRS model is a FORTRAN program for computing transient pore-pressure changes, and attendant changes in the factor of safety, due to rainfall infiltration using the method outlined by Iverson (2000). This model has been applicable to the areas where rainfall is prone to induce shallow landslides in the world, and the model's assumptions include a well-documented flow field and relatively isotropic. Further technical details of the model have been fully described in Baum et al. (2002).

The factor of safety for an infinite slope can be calculated as:

$$FS = F_f + F_w + F_c \tag{1}$$

$$F_f = \frac{\tan \emptyset}{\tan \alpha} \tag{2}$$

$$F_w = \frac{-\varphi(Z,t)\gamma_w \tan \emptyset}{\gamma_s Z \sin \alpha \cos \alpha} \tag{3}$$

$$F_c = \frac{c}{\gamma_s Z \sin \alpha \cos \alpha} \tag{4}$$

where c is soil cohesion, α is slope angle, $\emptyset$ is soil friction angle, φ is ground-water pressure head as a

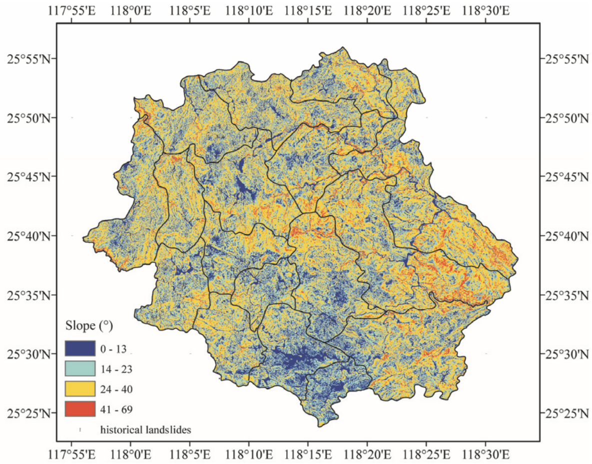

Figure 3 Distribution of slope angle in Dehua County, Fujian province, Southeast China.

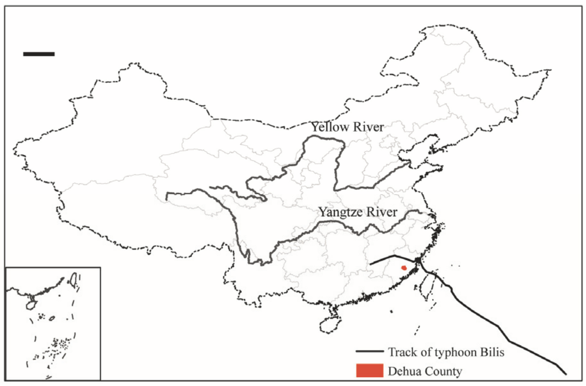

Figure 4 The track of the typhoon Bilis.

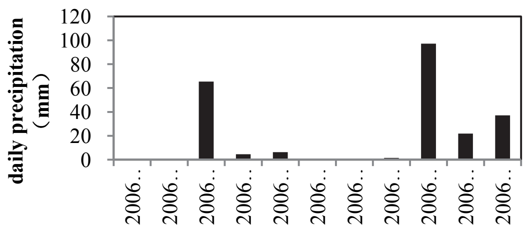

Figure 5 Daily precipitation before the typhoon Bilis landing.

function of the soil depth Z and time t, γ_w is the unit weights of water, γ_s is the soil unit weights. In addition, it is assumed that groundwater flow is parallel to the slip surface, and a slice of infinite slope mass has unit width. We support that the slope is stable when FS >=1, and the slope is unstable when FS <1.

Baum et al. (2002) generalizes Iverson's original infiltration model solution by developing the TRIGRS program for cases of variable rainfall intensity and duration. The generalized solution used in TRIGRS is given by:

$$\varphi(Z, t) = [Z-d]\beta + 2\sum_{n=1}^{N}\frac{I_{nZ}}{K_S}H(t-t_n)[D_1(t-t_n)]^{\frac{1}{2}}\sum_{m=1}^{\infty}\left\{\operatorname{ierfc}\left[\frac{(2m-1)d_{LZ}-(d_{LZ}-Z)}{2[D_1(t-t_n)]^{\frac{1}{2}}}\right]+\operatorname{ierfc}\left[\frac{(2m-1)d_{LZ}+(d_{LZ}-Z)}{2[D_1(t-t_n)]^{\frac{1}{2}}}\right]\right\} - 2\sum_{n=1}^{N}\frac{I_{nZ}}{K_S}H(t-t_{n+1})[D_1(t-t_{n+1})]^{\frac{1}{2}}\sum_{m=1}^{\infty}\left\{\operatorname{ierfc}\left[\frac{(2m-1)d_{LZ}-(d_{LZ}-Z)}{2[D_1(t-t_{n+1})]^{\frac{1}{2}}}\right]+\operatorname{ierfc}\left[\frac{(2m-1)d_{LZ}+(d_{LZ}-Z)}{2[D_1(t-t_{n+1})]^{\frac{1}{2}}}\right]\right\} \quad (5)$$

$$\operatorname{ierfc}(\eta) = \frac{1}{\sqrt{\pi}}\exp(-\eta^2) - \eta\operatorname{erfc}(\eta) \quad (6)$$

where $Z = z/\cos\alpha$, Z is the soil depth of the vertical coordinate direction, z is the soil depth of the slope-normal coordinate direction; d is the steady-state depth of the water table measured in the vertical direction; $\beta = \lambda\cos\alpha$, in which $\lambda = \cos\alpha - (I_{ZLT}/K_S)$, K_S is the saturated hydrological conductivity, LT means long term, I_{ZLT} is the steady surface flux;$I_{nZ}$is the surface flux for the nth time interval; d_{LZ} is the depth of the impermeable basal boundary; $H(t-t_n)$ is the heavy-side step function; D_1=$D_0\cos^2\alpha$, where D_0 is the saturated hydraulic diffusivity; N is the total number of intervals; $\operatorname{ierfc}(\eta)$ is the complementary error function.

TRIGRS model uses a simple method for routine of surface runoff from cells that have excess surface water to adjacent downslope cells where it can either infiltrate or flow farther downslope. The infiltration (I) at each cell as the sum of the precipitation (P), plus any runoff from upslope cells (R_u), with the limitation that infiltration cannot exceed the saturated hydraulic conductivity (K_s).

$$I = P + R_u;\ I \le K_s \quad (7)$$

At each cell where $(P + R_u)$ exceeds K_s, the excess is considered runoff (R_d) and is diverted to adjacent downslope cells.

$$R_d = P + R_u - K_s;\ R_d \ge 0 \quad (8)$$

3 Application of GRAPES-LFM model

GRAPES-LFM model is applied to forecast the landslides in Dehua County during a typhoon rainfall process in 2006. GRAPES model runs in 5 km ×5 km horizontal resolution, and the initial fields and lateral boundaries of GRAPES are provided by Final Operational Global Analysis datasets. Quantitative precipitation of GRAPES model is downscaled to 25 m×25 m horizontal resolution by bilinear interpolation to drive TRIGRS model. The time output interval of GRAPES-LFM model is 1 h, and the forecasting time is 48 h from 00:00 on July 15th to 00:00 on July 17th in 2006. GRAPES-LFM model is tested by the recorded rainfall-induced landslides.

3.1 Rainfall

The characteristics of the rainfall play important roles in triggering landslides. In Fujian province, there are twenty first weather stations, and five of them are in Dehua County. The observed daily rainfall data is generated by IDW (Inverse Distance Weighted Interpolation) method using the data from the weather stations, and the predicted daily rainfall data is provided by GRAPES-LFM model. Influenced by the typhoon Bilis, the rainfall concentrated in the southern part of Dehua County. By comparison, the spatial distribution of the predicted rainfall is similar to the observed rainfall, but the total amount of the predicted precipitation needs to be improved (Figure 6). The spatiotemporal rainfall intensity is unevenly distributed. Figure 7 shows that the maximum hourly rainfall intensity on July 15th reached 8.1 mm/h, and the rainfall intensity declined sharply on July 16th (Figure 7).

3.2 Parameterization

The TRIGRS model requires knowledge of several input parameters, some of which can be derived from 25m-resolution digital elevation model, while others have to be obtained from geotechnical field work and laboratory tests. Soil

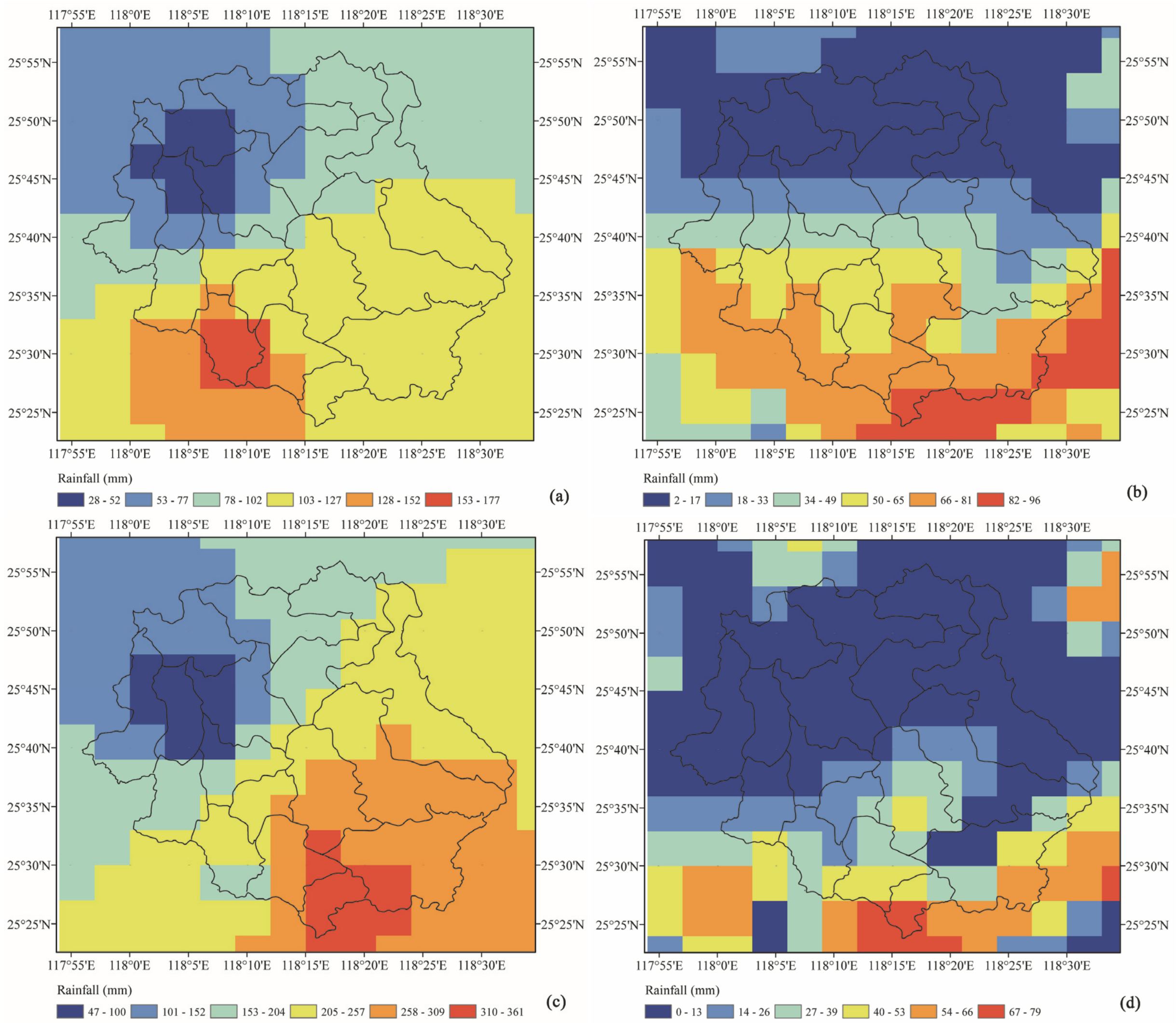

Figure 6 Observed (a) and predicted (b) daily rainfall on July 15th, 2006, and observed (c) and predicted (d) daily rainfall on July 16th, 2006.

samples were collected from six sites in Dehua County. As the results, the slope angels range from 0° to 69°, and Figure 3 depicts the spatial distribution of them in detail; the soil cohesion ranges from 12.9~40.2 kPa with mean of 24.77 kPa; the value of soil friction angels vary from 16.9°~25.4° with mean of 21.42°; the soil unit weight ranges from 11.17~14.80 kN/m^3; the saturated hydrological conductivity ranges from 4.79×10^{-7}~1.38×10^{-6} m/s. The mechanical and hydrological properties of the geological materials in the study area are summarized in Table 1.

The soil was assumed to be saturated, for there was plenty of rain before the typhoon landed. In this application, it is supposed that the hydrological diffusivity is 100 times more than the vertical hydraulic conductivity of saturated soil, and background infiltration rate is 1% of the hydraulic conductivity (Chen et al. 2011; Feng et al. 2009). The average values of soil properties are used in the model (Table 2). The map in Figure 8 shows the spatial distribution of the soil depth in Dehua County. According to the geological survey of the staff working in Fujian Monitoring Center of Geological Environment, we suppose the water table is 80% of the soil depth.

3.3 Results

The GRAPES-LFM model is applied to predict landslides triggered by the typhoon Bilis in Dehua County. The predicted accumulated rainfall from July 15th to July 16th in 2006 is between 4 to 156 mm with significant difference in spatial

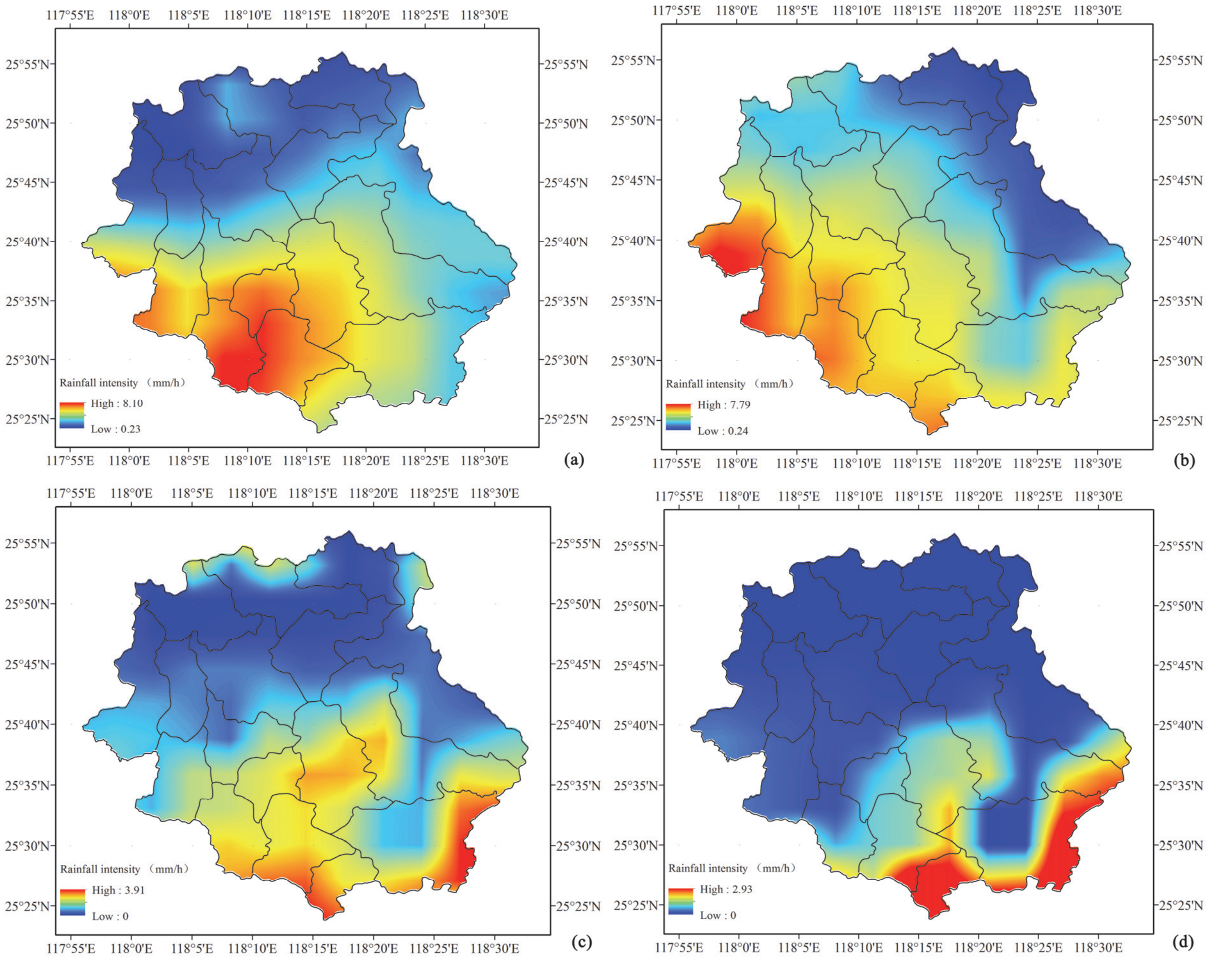

Figure 7 Predicted rainfall intensity at 05:00 (a) and at 23:00 (b) on July 15th, 2006 and predicted rainfall intensity at 04:00 (c) and at 14:00 (d) on July 16th, 2006.

distribution (Figure 9), and the rainfall mainly concentrated in the south of the study area. To test the model's performance, the geographical distribution of the factor of safety (*FS*) predicted by the GRAPES-LFM model are compared to the known distribution of rainfall-induced landslides mapped in the same area. The landslides are mapped through the fieldwork of the staff working in Fujian Monitoring Center of Geological Environment. There are 12 observed landslides which concentrated in Gaide Town and County center with the frequent human activities, and there are five observed landslide-prone areas (Figure 10). For the comparison, all grid cells with *FS*<1 are considered unstable and dangerous.

Table 1 Mechanical and hydrological properties of soils in the study area

Location	C c (kPa)	FA $\emptyset$(°)	UW γ_s (kN/m³)	SHC K_S(m/s)
Mapping	38.5	16.9	14.80	5.68×10^{-7}
Shishan	40.2	22.0	14.80	1.19×10^{-6}
Xiabi	20.2	18.1	11.27	7.74×10^{-7}
Hengtouge	12.9	21.5	12.35	1.38×10^{-6}
Qiaotingtou	19.2	24.6	11.96	5.22×10^{-7}
Pengkengcun	17.6	25.4	11.17	4.79×10^{-7}
Average	24.77	21.42	12.73	8.19×10^{-7}

Notes: C = Soil cohesion; FA = Soil friction angle; UW = Soil unit weights; SHC = Saturated hydrological conductivity.

The predicted landslides in Figure 10 are difficult to identify. Moreover, the spatial resolution of the input parameters can't reach the accuracy of 25 m. For example, the spatial resolution of the soil depth is about 250 m. For the

Table 2 Input parameters used in the application

Soil cohesion c(kPa)	24.77
Soil friction angle $\emptyset$(°)	21.42
Soil unit weights γ_s(kN/m³)	12.73
Saturated hydrological conductivity K_S (m/s)	8.19×10^{-7}
Background infiltration rate I_{ZLT} (m/s)	8.19×10^{-9}
Hydrological diffusivity D_0 (m²/s)	$8.19\times10^{*-5}$

reasons above, the risk levels of the areas are reclassified. Each assessment unit includes 400 girds (20 rows × 20 columns) with the spatial resolution of 500 m. If there are no grids in danger in the unit, the risk level is "safe areas"; if the grids in danger in each unit are less than 10%, the risk level is "dangerous areas"; if the grids in danger are more than 10% and less than 50%, the risk level is "more dangerous areas"; if the grids are more than 50%, the risk level is "most dangerous areas". Landslide risk reclassification map is shown in Figure 11. The observed landslide-prone areas are almost marked to be in danger in the predicted Landslide risk classification map. Ten in twelve landslides which have been recorded in Gaide Town and County center are predicted successfully. In fact, it is difficult to predict the accuracy location in the human settlement. The 12 recorded landslides are located in the areas affected by anthropogenic impacts, and ten in twelve landslides are predicted. In order to value the model's performance, an experiment is added as supplement. Under the rainfall of 30 mm/h, a comparison of simulating instability with the historical landslides is conducted to assess the model capability. The results show that there are 74% agreement between the predicted and the historical landslides for the entire study area (Figure 12).

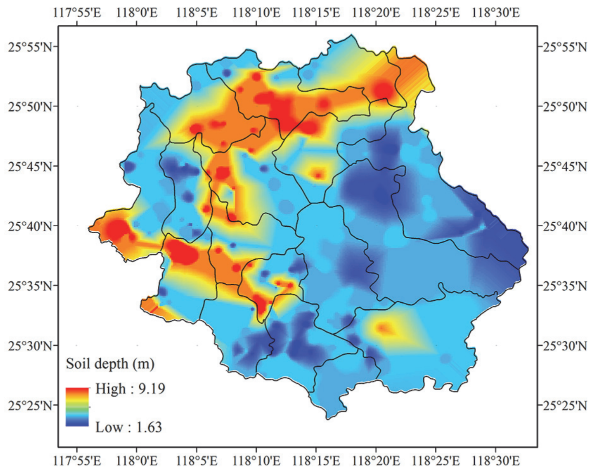

Figure 8 Distribution of the soil depth in Dehua County.

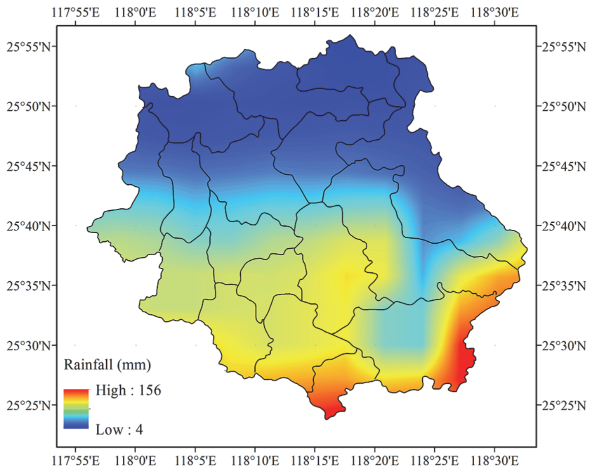

Figure 9 Predicted accumulated rainfall from July 15th to July 16th.

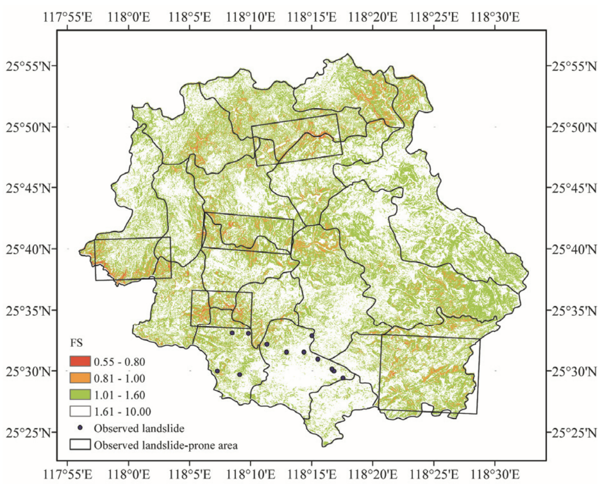

Figure 10 Distribution of the factor of safety in Dehua County.

3.4 Model sensitivity to rainfall pattern

For the physical-based model, sufficient and accurate information has to be obtained to construct an accurate landslide risk map. But the data is often imperfections. For example, the

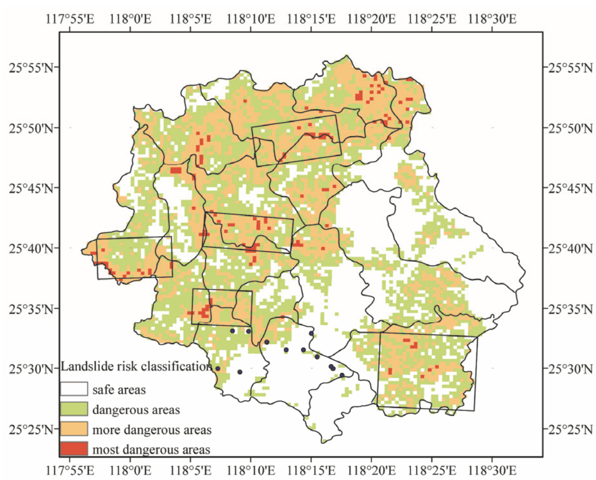

Figure 11 Landslide risk classification map.

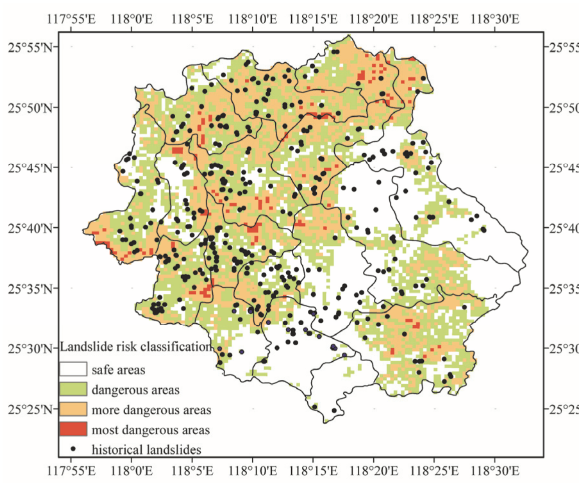

Figure 12 Landslide risk classification map under the rainfall of 30 mm/h.

Table 3 Input parameters for model sensitivity analysis

SD z(m)	WT d(m)	SC c (kPa)	SFA ϕ(°)	SUW γ_s (kN/m³)
6	3	24.77	21.42	12.73
SAα(°)	BIR I_{ZLT} (m/s)	HD D_0 (m²/s)	RA(mm)	
30	0.01*K_S	100*K_S	300	

Notes: SD = Soil depth; WT = Water table; SC = Soil cohesion; SFN = Soil friction angle; SUW = Soil unit weights; SA = Slope angle; BIR = Background infiltration rate; HD = Hydrological diffusivity; RA = Rainfall amount.

spatial resolution of the predicted rainfall is several kilometers. Previous research works mainly focus on the uncertainty of the strength and hydrology parameters, so we don't know how different rainfall patterns affect the *FS* in the TRIGRS model. In the following sensitivity analysis, the effect of variability in the rainfall patterns is examined. The other parameters used the typical values are shown in Table 3. For the typical parameters and the hydraulic conductivity of 8.19×10^{-5} m/s, the time to failure under the constant rainfall intensity is about 38 h. If the rainfall intensity changed, the time to failure changes too. Along with the increase of the hydraulic conductivity, the time to failure shortens dramatically. The results show the time of the slope to failure is different with the same total amount of the rainfall, when the hourly rain intensity is different, so the rainfall patterns have significant effects on the time to failure (Figure 13).The experiment confirms the importance of the accuracy of the rainfall data in predicting shallow landslides.

4 Conclusions and Discussion

Drawing on recent advances in numerical weather prediction model, this paper proposes a

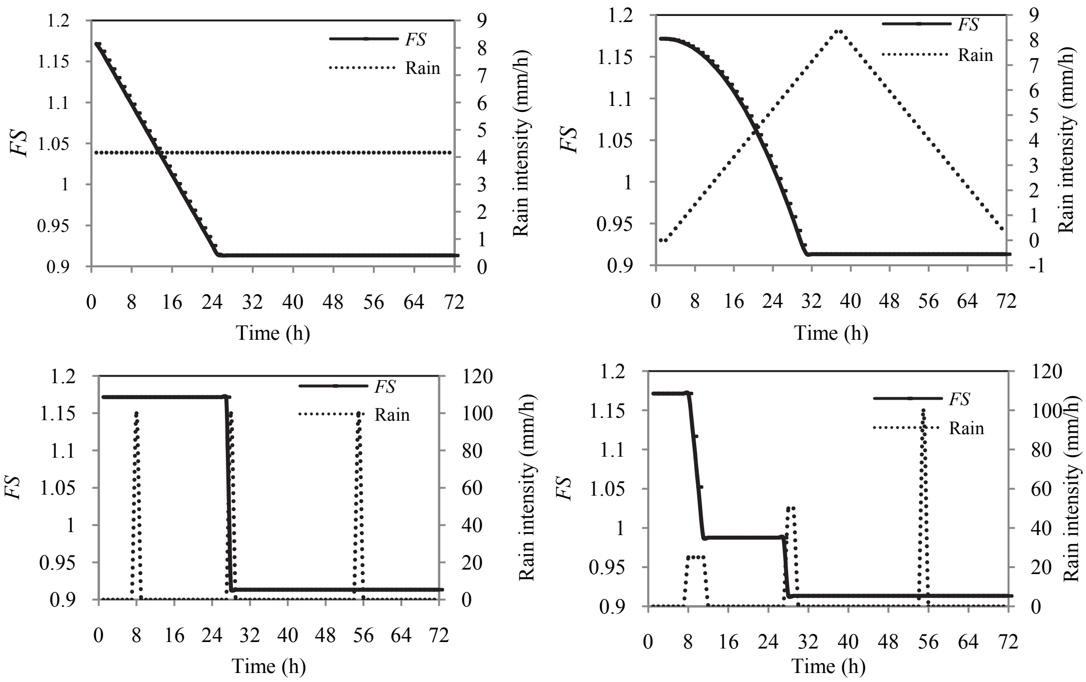

Figure 13 Relationship between factor of safety (*FS*) and rainfall intensity (K_S=8.19×10^{-5} m/s).

conceptual framework for a real-time landslide prediction model GRAPES-LFM, which considers both the induced effect of the rainfall and the mechanism of the landslide. The model objectives aim to predict regional landslides by mapping *FS* over a defined region using a set 25-m DEMs to set up a physical framework. The effectiveness of this model is applied to several rainfall-triggered landslides induced by the typhoon Bilis in 2006 and the historical landslides under a rainfall scenario. GRAPES-LFM model extends the warning lead time of landslide forecasts. Results show that the GRAPES-LFM model successfully helps to identify the landslide hotspot areas.

There are several limitations of simplifying the physically based relationships. These shortcomings can limit model accuracy and should be improved for future applications: (1) Isotropic, homogeneous materials are assumed, which limit the forecast ability; (2) The higher spatiotemporal resolution of the input data is better as the model's input parameters. If we get more precise slope angels, soil characteristics and rainfall data, maybe the over-prediction of failure could be reduced; (3)The model only simulates the natural landslide process, but the areas affected by anthropogenic impacts is hardly presented.

Despite the limitations currently, the simulation results still suggest that GRAPES-LFM model demonstrates skill in predicting rainfall-triggered landslides considering the dynamic inducing factors. This type of real-time prediction system for disasters can provide policy planners with overview information to assess the spatial distribution of potential landslides. Gathering more observed landslide data and detailed input parameters, we will still work to test and enhance the GRAPES-LFM model.

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