SPECIAL ISSUE

Assessment of shallow landslides from Hurricane Mitch in central America using a physically based model

**Zonghu Liao · Yang Hong · Dalia Kirschbaum ·
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Abstract Shallow landslides induced by heavy rainfall events represent one of the most disastrous hazards in mountainous regions because of their high frequency and rapid mobility. Recent advancements in the availability and accessibility of remote sensing data, including topography, land cover and precipitation products, allow landslide hazard assessment to be considered at larger spatial scales. A theoretical framework for a landslide forecasting system was prototyped in this study using several remotely sensed and surface parameters. The applied physical model SLope-Infiltration-Distributed Equilibrium (SLIDE) takes into account some simplified hypotheses on water infiltration and defines a direct relation between factor of safety and the rainfall depth on an infinite slope. This prototype model is applied to a case study in Honduras during Hurricane Mitch in 1998. Two study areas were selected where a high density of shallow landslides occurred, covering approximately 1,200 km^2. The results were quantitatively evaluated using landslide inventory data compiled by the United States Geological Survey (USGS) following Hurricane Mitch's landfall. The agreement between the SLIDE modeling results and landslide observations demonstrates good predictive skill and suggests that this framework could serve as a potential tool for the future early landslide warning systems. Results show that within the two study areas, the values of rates of successful estimation of slope failure locations reached as high as 78 and 75%, while the error indices were 35 and 49%. Despite positive model performance, the SLIDE model is limited by several assumptions including using general parameter calibration rather than in situ tests and neglecting geologic information. Advantages and limitations of this physically based model are discussed with respect to future applications of landslide assessment and prediction over large scales.

Keywords Landslide · Hurricane Mitch · Hazard prediction · Remote sensing

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Introduction

Rainfall-induced landslides pose significant threats to human lives and property worldwide (Hong et al. 2006). Overpopulation, deforestation, mining, and uncontrolled land-use for agricultural and transportation purposes, increasingly put large numbers of people at risk from landslides (Boebel et al. 2006, Sidle and Ochiai 2006).

It is important to approach landslide susceptibility, hazard, and risk assessment at the appropriate spatial scales to inform policy decisions and proper planning for mitigating risk. Landslide disaster preparedness and forecasting

systems require knowledge of the physical mechanisms influencing landsliding, information on geotechnical composition, and landslide inventory data.

Recent approaches to forecast landslide potential include empirical models that identify of rainfall intensities and duration required to trigger landslides (e.g. Dai et al. 2002, Hong and Adler 2007). These empirical models provide little theoretical basis for understanding how landslides might respond to hydrologic processes (Iverson 2000); whereas physically based landslide models consider the physical mechanisms influencing slope instability to assess landslide hazard, using a range of topographic, geologic, and hydrologic parameters (Dietrich et al. 1995; Wu and Sidle 1995; Baum et al. 2002; Iverson 2000; Lu and Godt 2008; Godt et al. 2009). These physical models generally employ high-resolution surface feature data, in situ geotechnical information, rainfall measurements at the land surface, and detailed landslide inventories. Such information is frequently unavailable at larger spatial scales due to non-uniform surface investigation and sparse landslide inventory data (Kirschbaum et al. 2011).

Recent examinations of remote sensing data sets offer an opportunity to enhance the sparse field-based landslide inventory data sets for hazard forecasting and mapping at larger spatial scales. Liao et al. (2010) developed an early landslide warning system by incorporating a physically based model to assess landslide hazard in Indonesia experimentally. In this study, a simplified physical model, SLope-Infiltration-Distributed Equilibrium (SLIDE) has been developed to identify the spatial and temporal distribution of landslides induced by heavy rainfall, employing a range of remotely sensed and in situ surface data. A primary reason for attempting to develop a forecasting model from the remote sensing data products is the potential for providing larger scale landslide maps within regions with a dearth of field-based physical data. Calculating the landslide hazard of an entire study region at once allows for the consistent analysis of rainfall's impact on the slope instability.

This article describes the approach for landslide forecasting using Hurricane Mitch as a case study within two areas in Honduras. Hurricane Mitch made landfall in late October, 1998 and dropped historic amounts of rainfall in Central America. The hurricane and related landslides killed an estimated 5,657 people, injuring another 12,272 according to the National Emergency Cabinet. Figure 1 shows the storm path and an example of the shallow landslides triggered in Honduras. This article describes the framework of the SLIDE model and remotely sensed and in situ data sets employed; it then describes the application of the model in Honduras; and finally it quantitatively evaluates the forecasting results and discusses the advantage and limitations of the model.

Methodology

Approaches for landslide forecast

Three major steps to develop a forecasting model are discussed: (1) data collection and parameter initialization; (2) model development based on infinite-slope equilibrium equations; and (3) test and evaluation of the model. The flow chart of the forecasting model is shown in Fig. 2.
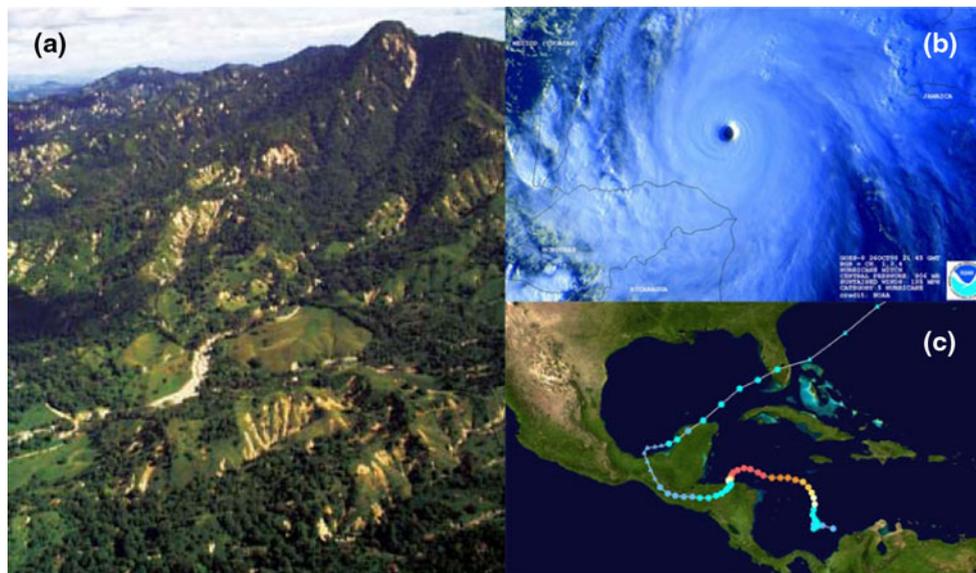
Fig. 1 **a** High concentrations of debris flows in Honduras following the Hurricane Mitch (Harp et al. 2002); **b** Aerial view and **c** path of Hurricane Mitch in the Caribbean (Credit: NOAA, October 26, 1998)
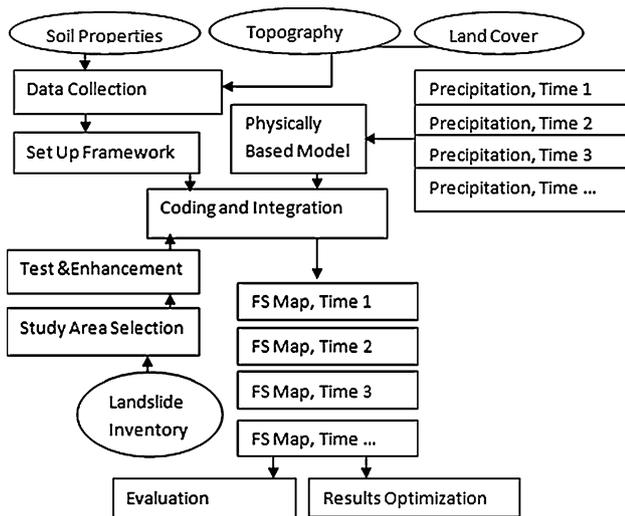
Fig. 2 Conceptual framework of a physical model for forecasting of rainfall-induced shallow landslides

Available data and parameter initialization

Landslide occurrence depends on complex interactions among a large number of factors, mainly including slope, soil properties, lithology, and land cover. With increasing frequency, remote sensing data sets have been used to develop susceptibility maps regionally and globally. Hong et al. (2007) had used some of the aforementioned remote sensing data to derive a global landslide susceptibility map. In this research, elevation, land cover, and precipitation data sets were all derived from satellites.

Elevation Elevation data were retrieved from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Global Digital Elevation Model (GDEM), which was developed jointly by the Ministry of Economy, Trade, and Industry (METI) of Japan and the United States NASA (https://wist.echo.nasa.gov/~wist/api/imswelcome/). Topographic properties were derived from a 30-m ASTER DEM. There have been several studies suggesting the spatial resolution of DEM is critical for landslide modeling and the current 30-m resolution can be insufficient for hydrologically driven landslide estimation (Zhang and Montgomery 1994; Claessens et al. 2005). Although only the 30-m DEM from SRTM available over large area in Honduras, the authors encourage higher resolution DEM should be used in the future study when it becomes available.

Soil Soil parameter values were determined from soil types provided by the Food and Agriculture Organization of the United Nations (FAO; http://www.fao.org/AG/agl/agll/dsmw.htm) and the Moderate Resolution Imaging Spectroradiometer (MODIS) land classification map. There are 16 soil types with referenced values provided. In this study, soil information referring to FAO map is sandy clay

and clay. Since it is limited to get field tests and obtain detailed soil information, the soil parameters were derived by adjusting through a procedure of back analysis within a certain range, respectively.

Land cover The University of Maryland's 1 km global land cover classification is produced by using data for 1992–1993 from the Advanced Very High Resolution Radiometer (AVHRR, Hansen et al. 2000). There are 12 classes in total and a certain cohesion value of vegetation will be added to soil cohesion in slope stability calculation. Schmidt et al. published the method to obtain values of root cohesion for different species of vegetation and a summary table of selected root cohesion from different sources. This method was referenced after obtaining the land cover classification validated by public vegetation information.

Precipitation The spatial distribution, duration, and intensity of precipitation play an important role in triggering landslides. The precipitation data used in this study are obtained from the NASA Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA) (Huffman et al. 2007), which provides calibrated sequential scheme for combining precipitation from multiple satellite and gauge analyses at a resolution of $0.25° \times 0.25°$ over the latitude band 50°N–50°S every 3 h. The real-time rainfall is available on the NASA TRMM web site (http://trmm.gsfc.nasa.gov).

Landslide inventory data This event-based inventory was compiled in the months following the Hurricane Mitch in November, 1998 by USGS. The hurricane triggered more than 500,000 landslides throughout the Honduras, 95% of which were debris flows with various failure plane depths including shallow landslides and deep-seated landslides, the most typical events being relatively shallow failures (Harp et al. 2002; Kirschbaum 2010). It is a supreme mass movement event of the century and cast disastrous impact over the whole country.

SLIDE model

The SLIDE model integrates the contribution of apparent cohesion to the shear strength of the soil and the soil depth
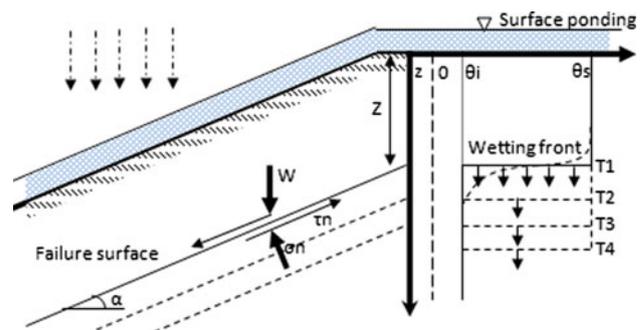
Fig. 3 Infiltration processes and infinite landslide model

influenced by infiltration (Fig. 3). W is vertical weight of the soil layer above the failure surface, σn is normal effective force, τn is shear force and Ti is the time step of infiltration. Factor of Safety (FS) is expressed as the ratio of shear strength to shear stress to calculate slope stability. A slope is considered stable when FS > 1 and a landslide is predicted when FS nears or drops below 1. In this study of shallow landslides, an infinite-slope equation is translated as the cohesion and frictional components:

$$FS\,(Z_t, t) = \frac{c' + c_\phi(t)}{\gamma_s Z_t \sin\alpha \cos\alpha} + \frac{\tan\varphi}{\tan\alpha} \qquad (1)$$

where c' is soil cohesion, incorporating a value for root zone cohesion, γ_s is the unit weight of soil, α is slope angle, and φ is soil friction angle. $c_\phi(t)$ represents the apparent cohesion related the matric suction, which in turn, depends on the degree of saturation of the soil (Montrasio and Valentino 2008), written as:

$$c_\phi(t) = A \cdot S_r \cdot (1 - S_r)^\lambda \cdot (1 - m_t)^\partial \qquad (2)$$

where A is a parameter depending on the kind of soil and is linked to the peak shear stress at failure, λ and ∂ are numerical parameters which allow estimation of the peak of apparent cohesion related to S_r, the degree of saturation of the soil. m_t represents the dimensionless thickness of the infiltrated layer, which is a fractional parameter between 0 and 1:

$$m_t = \frac{\sum_{t=1}^{T} I_t}{n \cdot Z_t \cdot (1 - S_r)} \qquad (3)$$

in which I_t is rain intensity, n is the porosity and Z_t is the soil depth at time t, which is determined by the infiltration process:

$$Z_t = \sqrt{\frac{2 \cdot K_s \cdot H_c \cdot t}{\theta_n - \theta_0}} \qquad (4)$$

where K_s is saturated hydraulic conductivity, H_c is capillary pressure, t is time, θ_n is water content of the saturated soil, and θ_0 is initial water content of the soil.

Case study

Study area

Intense rainfall from Hurricane Mitch from October 27–31, 1998 exceeded 900 mm within some regions of Honduras and triggered in excess of 50,000 landslides throughout the country (Harp et al. 2002). Two study areas were selected to compute the FS maps, each which cover approximately 600 km² over the south coast of Honduras (Fig. 4). In the selected study areas, the highest recorded rainfall intensity was 12 mm/h, with an accumulation of close to 200 mm in

Fig. 4 Two study areas in Honduras for Hurricane Mitch in 1998 (*above banner*), zooming in from the Central America (*bottom banner*)
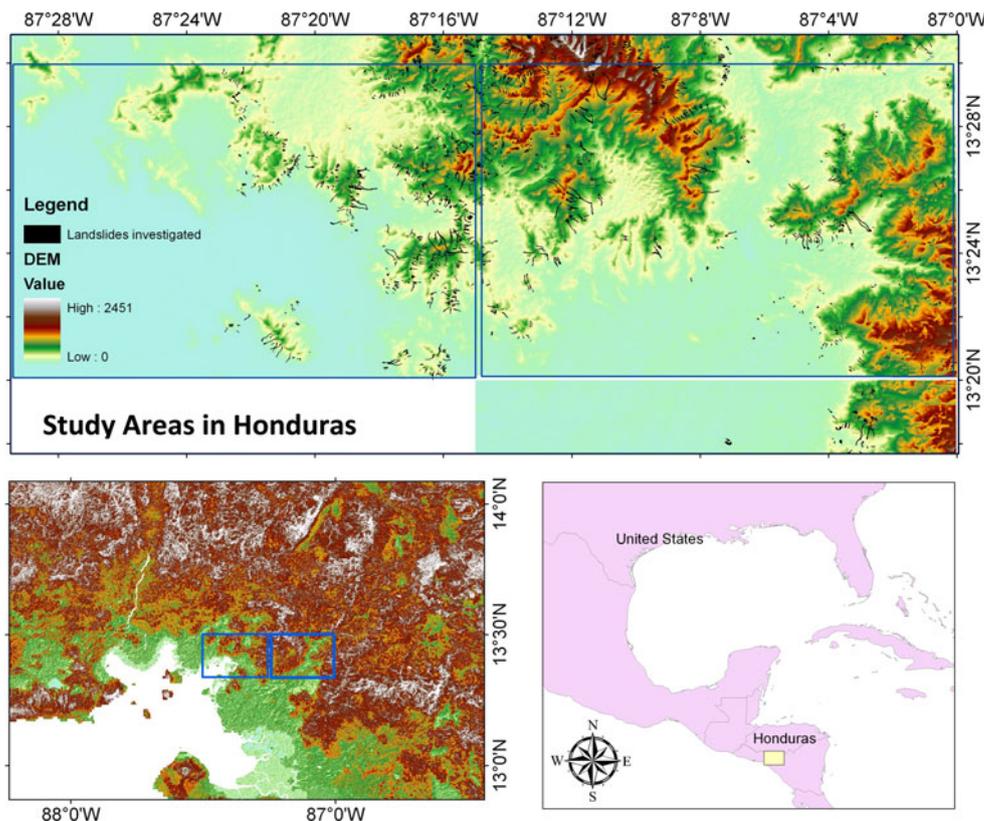
Fig. 5 Precipitation of Hurricane Mitch in 1998 for the selected study areas
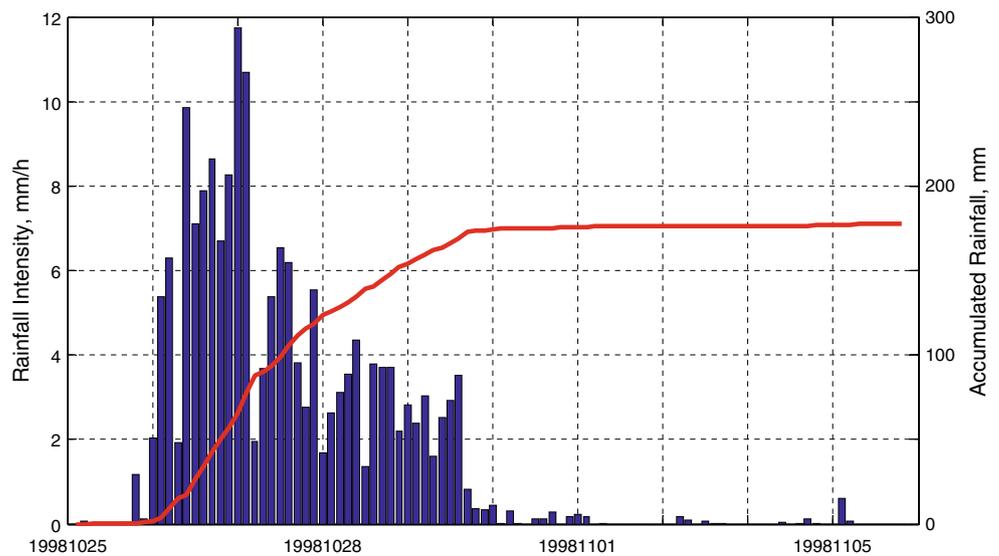
5 days (Fig. 5). This region was selected for analysis because it currently has one of the largest and most regionally extensive landslide inventory data sets compiled following Hurricane Mitch.

Parameter values for the model are summarized in Table 1. As soil values are the most difficult parameter to assess, we used the general soil information from Table 1 after adjusting through a procedure of back analysis within a certain range. Furthermore, as Honduras has a tropical climate and the study areas are covered by Latin species of pine woods, the root cohesion values added to the total cohesion are assumed to range from 3.7 to 6.4 (Schmidt et al. 2001; Waldron et al. 1983). Due to the large geographic area

Table 1 Parameters, symbols, and values are used for SLIDE application

Property	Symbol	Unit	Value
Slope angle	α	Deg	Varies
Soil depth	Z	M [L]	Varies
Soil type	1-16	Unit less	Sandy clay/ Clay
Land Cover	LC	Unit less	6, 7, 11
Coefficients	λ, ∂	Unit less	0.4, 3.4
Friction	φ	Deg	17–22
Cohesion (root included)	c'	KPa [M/LT^2]	15–24
Coefficient	A	KPa [M/LT^2]	20
Unit weight of soil	γ_s	KN/m^3[M/ L^{2}T^2]	20
Porosity	n	1	0.40–0.60
Water content	θ_0, θ_n	1	0.2, 0.6
Degree of saturation	S_r	1	0.2
Hydrologic conductivity	K_s	cm/h [L/T]	1.00–4.00
Capillary	H_c	mm [L]	50
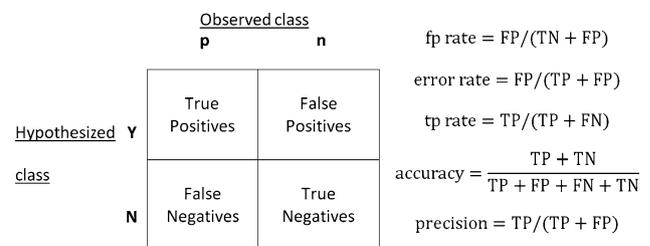
Fig. 6 Four quantitative evaluation indices from Fawcett (2006)

considered as well as the limited high-resolution data sets for this region, we make several assumptions in order to evaluate the SLIDE model in this area

- Detailed geological information was not included in this model due to the limitations of the simplified physical model and lack of homogeneous information at realistic spatial resolutions over the large study area. However, this information may be incorporated into the model when data become available.
- The layer of the soil subject to sliding is generally characterized by a certain degree of heterogeneity and can be affected by macropores in the soil caused by various living organisms (Montrasio and Valentino 2008). In this study, we consider the soil properties in the layer to be homogeneous and neglect preferential flow.
- Run-off and evapo-transpiration were neglected in the water balance. Therefore, we assume that all rainfall infiltrates into the soil, which is not physically realistic. However, the system allows only an infiltration amount approximately equal the saturated hydraulic conductivity in maximum.

All above assumptions were made to make the model easily applicable over larger areas and able to employ various remotely sensed data sets.

Results and evaluation

Using TMPA data as the rainfall input, the parameterized SLIDE model was run at 3-hourly resolution and a FS value was generated throughout the Hurricane Mitch event from Nov. 25, 1998 to Dec. 5, 1998 at every 30-m grid cell. Figure 7a and b illustrates the unstable areas computed by the SLIDE model for the two study areas over the Hurricane Mitch event. Unstable areas (FS ≤ 1) are shown in red and observed landslides are shown in black.

Firstly, the results were evaluated by comparing the unstable maps with observation by four indices from Fawcett (2006). Labels {Y, N} were used for the class forecasts produced by the physical model in 30 m grids. The labels {p, n} were used for the class of observation in the field. In the class of observation, landslide areas were

computed within a radius of 500 m radius. There are four possible outcomes when classifying a grid from the unstable map. If a computed unstable grid is inside the observed landslide area, it is counted as true positive (tp; also called hit or rates of successful estimation of slope failure locations); if it is outside the observed landslide area, it is counted as false positives (fp; also called false alarm). If a computed stable grid matches an observed landslide grid, it is counted as false negative; otherwise, it is called true negatives. Figure 6 shows the classification matrix and the equations of several indices. The true positives rate defines how well the predicted results agree with the observations. The tp rates are 78% for the Fig. 7a, and 75% for Fig. 7b. The false positives rate indicates the tradeoff between the predicted results and observations. The fp rates are 1 and 6%, respectively. The error rate is

Fig. 7 Instability maps of landslides produced by SLIDE for the study areas **a** and **b**
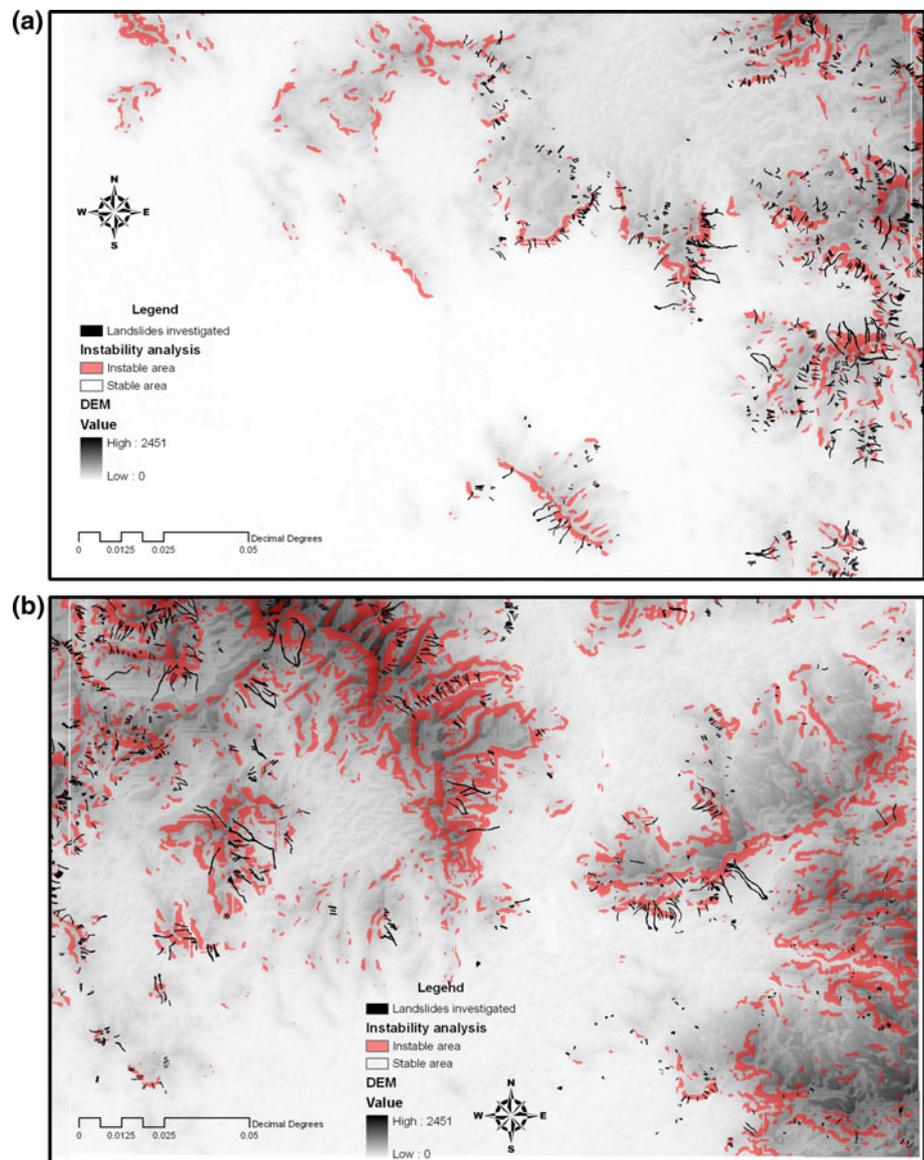
Table 2 Evaluation statistics for instability maps of landslides produced by SLIDE

Indices	True positive rate (%)	False positive rate (%)	Accuracy (%)	Precision (%)	Error rate (%)
Study area (a)	78	1	98	65	35
Study area (b)	75	6	92	51	49
Perfect Values	100	0	100	100	0

defined as the portion of the computed unstable grids that did not contain observed landslides (Sorbino et al. 2010). The SLIDE model provides a value of error rate of 35% in Fig. 7a while error rate is 49% in Fig. 7b. Accuracy represents the level of agreement between the forecast and the observations of landslides. The accuracy values are 98% for the study area a and 92% for the study area b. The precision means positive predictive value. The precisions for two areas are 65% in Fig. 7a and 51% in Fig. 7b. All the statistics values are listed in Table 2.

The model forecasts show good agreement with the mapped inventory over the two study areas. However, the model over predicts the landslide areas, particularly in the west part of Fig. 7a. In Fig. 7b, the predicted landslide areas by the model are much larger than observed areas. In general, the model forecast result in larger hazard zones than what is observed, resulting in an overestimation of hazard areas. This is consistent with other studies performed at regional scales (Nadim et al. 2006).

Discussion

This study tests the model performance for a specific event in order to test the forecast capabilities of the forecast system. Quantitative evaluation of the landslide Hurricane Mitch case study indicates that the model demonstrates good predictive skill when compared to the landslide inventory over the two study areas. The *tp* rates for the two study areas are 78 and 75%, respectively, while the *fp* rates are as low as 1 and 6%. The low *fp* rates come from the accurate prediction of stable areas by the physical model. The high *tp* rates and low *fp* rates demonstrate the potential to employ a physically based model for the forecast of landslide disasters using remote sensing and geospatial data sets over larger regions; particularly in regions where comprehensive field data and fine-scale precipitation observations and forecasts are available. The remotely sensed data products used in the SLIDE model describe the most important factors influencing the slope movement, which serves to simplify the model calculations and decrease the computational load.

However, over-prediction is clearly indicated by the error rates which are 35 and 49%, though it is possibly due to a number of model assumptions and the limitation of

physical models. Furthermore, there are several limitations of simplifying the physically based relationships and employing remotely sensed, rather than in situ data products. These shortcomings can limit model accuracy and should be improved for future applications, these include:

(1) Uniform geological structures of slopes are assumed as parameterization, which could lead to potential errors of modeling results. Neglecting various geological features within the model calculations greatly limits the forecast ability of the physical models. In the future application of the other study area, information of geological structures from high risk prone area could better enhance the hazard assessments.

(2) It decreases the accuracy of modeling results by applying same soil values to the regional-scale modeling. A same type of soil from different places reveals various physical and mechanical properties in a certain range, regardless of the vegetation roots and the rainfall infiltration. In this study, the same soil under different stratigraphic conditions was set to be homogeneous by inputting a same set of physical and mechanical values. This hypothesized procedure would reduce the spatial variances. A study of the empirical soil properties would improve this problem.

(3) Higher spatiotemporal resolution of satellite rainfall, DEMs, and accurately validated remote sensing soil information are expected to better account for landslide-prone regions. In situ tests of hotspot areas would provide better soil values for input and improve the performance of model forecast. The higher spatial resolution of DEM would be used to derive better topographical features of slope, resulting in reducing the over-prediction of failure locations by the model. However, the remote sensing could not get soil-depth information to date, thus effects of topographic convergence in soil–bedrock interface geometry and bedrock fracture flow, which have been shown to be important for simulating slope failure initiation (Ebel et al. 2008), were not accounted for in this study.

(4) Over-prediction and error rates of landslides are difficult to reduce due to the geomorphologic variations, and different triggering mechanisms. Furthermore, landslide-prone areas can also largely be affected by anthropogenic impacts such as improper

building and roads, which have not been incorporated within the physically based model approach. As only an extreme event is presented, the areas identified as "unstable" and computed by error indices could still be unstable and triggered in future events.

While there are several limiting factors affecting the accuracy of model forecasting, the SLIDE model shows potential as a landslides forecasting tool over larger regions. The model may be suitable to be incorporated into future real-time early landslide warning system when high quality data sets are available.

Conclusions

A physically based landslide forecast model SLIDE has been presented for assessment of shallow landslides triggered during Hurricane Mitch in Honduras in 1998. A number of remotely sensed data sets have been applied in the model to analyze landslide hazard over a study area of approximately 1,200 km^2. The major remotely sensed data sets used to set the landslides forecasting system includes an ASTER DEM for deriving geospatial features, the University of Maryland's land cover classification for adjusting soil cohesions, and the NASA TRMM precipitation for driving the hydrologic response of the system. Empirical geotechnical parameters were referenced to estimate the FAO soil values used in the forecast. The results highlight a rate of successful estimation of slope failure locations of 78% and an error index of 35%. Similar acceptable results were obtained for the other study area, with a rate of successful estimation of slope failure locations of 75% and an error index of 49%. The evaluation of the results reveals that error indices were probably due to the unavoidable over-predictions. In the work presented here, the SLIDE model shows promise for integration into regional-scale early-warning systems for landslides triggered by extreme precipitation events.

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