Landslides
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Prototyping an experimental early warning system for rainfall-induced landslides in Indonesia using satellite remote sensing and geospatial datasets

Abstract An early warning system has been developed to predict rainfall-induced shallow landslides over Java Island, Indonesia. The prototyped early warning system integrates three major components: (1) a susceptibility mapping and hotspot identification component based on a land surface geospatial database (topographical information, maps of soil properties, and local landslide inventory, etc.); (2) a satellite-based precipitation monitoring system (http://trmm.gsfc.nasa.gov) and a precipitation forecasting model (i.e., Weather Research Forecast); and (3) a physically based, rainfall-induced landslide prediction model SLIDE. The system utilizes the modified physical model to calculate a factor of safety that accounts for the contribution of rainfall infiltration and partial saturation to the shear strength of the soil in topographically complex terrains. In use, the land-surface "where" information will be integrated with the "when" rainfall triggers by the landslide prediction model to predict potential slope failures as a function of time and location. In this system, geomorphologic data are primarily based on 30-m Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data, digital elevation model (DEM), and 1-km soil maps. Precipitation forcing comes from both satellite-based, real-time National Aeronautics and Space Administration (NASA) Tropical Rainfall Measuring Mission (TRMM), and Weather Research Forecasting (WRF) model forecasts. The system's prediction performance has been evaluated using a local landslide inventory, and results show that the system successfully predicted landslides in correspondence to the time of occurrence of the real landslide events. Integration of spatially distributed remote sensing precipitation products and in-situ datasets in this prototype system enables us to further develop a regional, early warning tool in the future for predicting rainfall-induced landslides in Indonesia.

Keywords Landslide · Rainfall · Warning system · Indonesia

Introduction

Rainfall-induced landslides are one of the most important disasters to occur in complex terrain areas, especially regions that routinely experience heavy rainfall. Some of these landslides occur suddenly and travel at high speeds, posing significant threats to life and property (Iverson 2000; Hong et al. 2006; Kirschbaum et al. 2009a). A disaster early warning system appears to be urgently needed for disaster preparedness and hazard management in vulnerable regions. Previously, a monitoring system has been developed to identify rainfall intensity-duration that may trigger landslides in high landslide susceptibility areas by using satellite-based global rainfall estimation system (Hong and Adler 2007; http://trmm.gsfc.nasa.gov/publications_dir/potential_landslide.html). Kirschbaum et al. 2009b evaluated this system and concluded that the current monitoring system, although showing some overall skill, must be improved if it is to be used for hazard warning or detailed studies. The objective of this study is to move one step forward from the current empirical system to a more physically based, landslide prediction modeling system for regional landslide risk assessment using data primarily from satellite remote sensing platforms or available from public domain, with the ultimate goal of capacity building and technique transfer to landslide prone but vulnerable regions.

For most shallow landslides, rainfall triggers slope failure because water reduces the shear strength and increases the shear stress in the soil layer. The physical and mechanical behavior of the soil and the mechanism of rainfall infiltration has been widely studied (e.g., Fredlund and Rahardjo 1991; Dietrich and Montgomery 1998; Sidle and Wu 1999; Iverson 2000; Baum et al. 2002; Lu and Godt 2008; Montrasio and Valentino 2008). Although these complex models may be ineffective and require simplification for modeling large areas, they provide theoretical frameworks for understanding how hydrologic processes influence landslides. In this study, using a physically based SLIDE (SLope-Infiltration-Distributed Equilibrium) model we prototyped an Early Warning System to model the rainfall-induced landslides in Karanganyar, Central Java. The SLIDE model was modified based on previous work done by Montrasio and Valentino 2008, which takes into account simplified hypotheses on the water down-flow and defines a direct correlation between the safety factor of the slope and rainfall. In order to access both the increase and decrease of water amount in the layer in one single rainfall event, SLIDE simulates net water amount staying in soil substratum differentially rather than exponentially. This prototype early warning system has been retrospectively validated using both NASA satellite-based precipitation and WRF forecasts, and results show potential to apply the system for regional landslide risk assessment.

Framework of the early warning system

Landslides are triggered by the complex interaction of multiple-factors, including dynamic triggers and ground condition variables (Hong and Adler 2007). In this study, we prototyped an Early Warning System (Fig. 1) that integrates three major components: (1) a susceptibility mapping and hotspot identification component based on a land surface geospatial database (topographical information, maps of soil properties and local landslide inventory datasets etc.); (2) a satellite-based precipitation monitoring system (http://trmm.gsfc.nasa.gov) and a precipitation forecasting model (i.e., Weather Research Forecast); and (3) a rainfall-induced landslide prediction model (i.e., SLIDE). The topographical information and soil properties will inherently determine the slope stability as a determined part of factor of safety (FS) in SLIDE model. The landslide susceptibility map also helps to identify the landslide hotspot areas. The precipitation systems will provide rainfall information as primary triggering variables in this

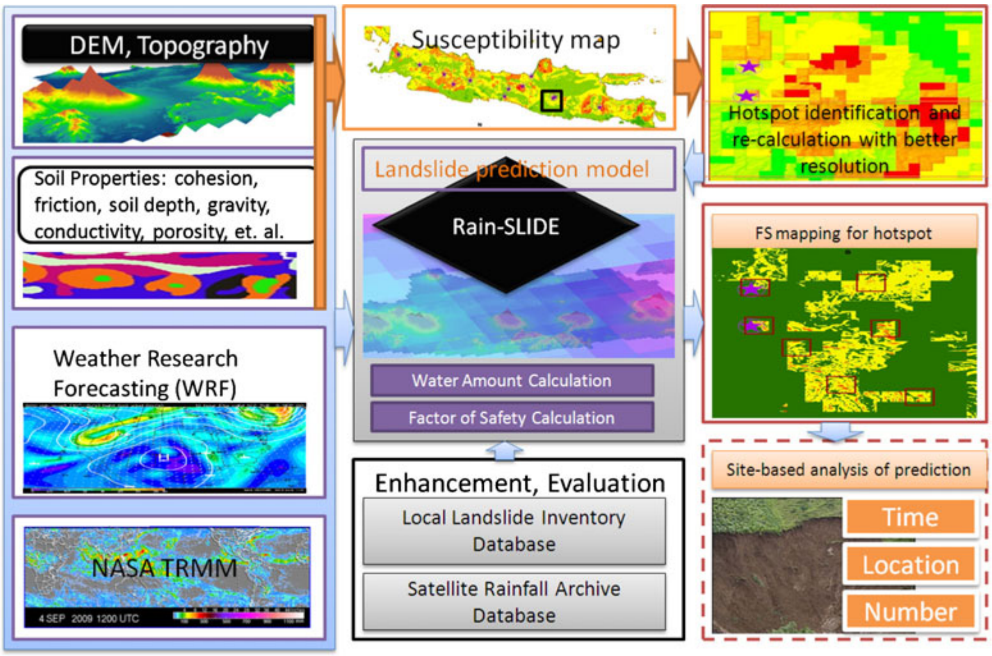


Fig. 1 Conceptual framework of the Early Warning System for rainfall-triggered landslides over Java Island, Indonesia. Note that the *dashed-line boxes* are not fully covered in this paper

study. The SLIDE will calculate triggering part of FS in time series, which will be added to determined part of FS to evaluate slope stability during rainfall events. Thus, the first-order control on the spatial distribution of landslides is the landslide susceptibility determined by the geospatial database; and the first-order control on the temporal distribution of shallow landslide occurrence is the dynamic rainfall system.

Parameters and land surface data

The landslide prediction system aims to predict landslide occurrences by calculating factor of safety values over the study region. This calculation requires many geospatial datasets as inputs. Elevation data were retrieved from the ASTER Global Digital Elevation Model, which was developed jointly by the Ministry of Economy, Trade, and Industry 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. Soil parameter values were determined by referring to the geotechnical literature according to 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 land classification map. Values and coefficients of soil have been validated by inventory and adjusted through simulation procedures. However, structure information as an important component in landslide assessment is not covered in this study due to the limitation of information resources. Factor of safety calculation of varying soil depth is recommended in this system if computational facility allows. In this paper, soil depth is assumed to be 2 m instead of varying depth to reduce the computational load. The system was run under the assumption of ground-surface-parallel slip faces. A set of input parameters and values are listed in Table 1.

Precipitation systems

The spatial distribution, duration, and intensity of precipitation play an important role in triggering landslides. A fine time resolution analysis from NASA Tropical Rainfall Measuring Mission (TRMM) is used in this study (Hong and Adler 2007). The real-time rainfall is available on the NASA TRMM web site (http://trmm.gsfc.nasa.gov). This type of precipitation product is used in the Early Warning System as dynamic triggers. On the other hand, the WRF model version 3.0.1 used in this study includes the Advanced Research WRF dynamical core (WRF-ARW; Michalakes et al. 2001; Skamarock et al. 2005), which is a non-hydrostatic, fully compressible, primitive equation model. WRF was jointly developed by the National Center for Atmospheric Research, the Air Force Weather Agency, the National Oceanic and Atmospheric Administration, and other governmental agencies and universities. The simulated 3-hourly precipitation data in the domain of 4 km spatial resolution are used in this study.

SLIDE model

This section describes the SLIDE model, which has been modified from two previous studies, Fredlund et al. (1996) and Montrasio and Valentino (2008). Fredlund et al. (1996) and Montrasio and Valentino (2008) present a mathematical model that translated the physical phenomenon of rainfall triggering processes. This model highlights the destabilizing forces by the water down-flow and the contribution of partial saturation to the shear strength of the soil (Fig. 2). A link between the rainfall amount and the final expression of FS has been set up and translated into a simple mathematical formulation as shown in Eq. 1.

$$F_s = \frac{\cot\beta \cdot \tan\emptyset' \cdot [\Gamma + m \cdot (n_w - 1)] + C' \cdot \Omega}{\Gamma + m \cdot n_w} \tag{1}$$

Table 1 Parameters, symbols and values are used for model evaluation

Property	Symbol	Unit	Value
Slope properties			
Slope angle	β	deg	10–50
Landslide depth (water table), vertical	H	m	2
Initial Dimensionless Thickness	m_1	Unit less	0
Unit length of slope	Δs	1	1
Soil properties			
Soil composition		Unit less	Clay loam
Coefficients	A and λ	Unit less	120/25
Friction angle	$\varnothing'$	deg	28
Effective cohesion	c'	KPa	20
Cohesion coefficient	α	Unit less	1
Gravity	G_s	N/m^3	27
Porosity	n	1	0.48
Degree of saturation	S_r	%	0.6
Unit weight of water	γ_w	N/m^3	9.8
Drainage capability	K_t	m/s	3e-5
Rainfall Properties			
Rainfall intensity	I_t	mm/h	0–50
Rainfall duration	t	h	120

$$\Gamma = G_s \cdot (1 - n) + n \cdot S_r \tag{2}$$

$$n_w = n \cdot (1 - S_r) \tag{3}$$

$$\Omega = \frac{2}{\sin 2\beta \cdot H \cdot \gamma_w} \tag{4}$$

Where G_s is specific gravity, n is porosity, β is slope, H is soil layer, and γ_w is unit weight of water. The FS is defined as the ratio of resisting forces over destabilizing forces on a soil slope. FS=1 suggests that the slope is slipped, and the smaller the value the less stable the slope is. In Eq. 1 total cohesion is expressed as

$$C' = [c' + c_\varphi] \cdot \Delta s = [c' + A \cdot (1 - \lambda m^\alpha)] \cdot \Delta s \tag{5}$$

Where c' is effective cohesion, A is a parameter depending on soil type and peak shear stress at failure, λ is an intensity coefficient linked with soil type, S_r is degree of saturation, and α is a parameter representing the non-linear trend to the cohesion curve. Total cohesion includes the effective cohesion and apparent cohesion related to the matrix suction proposed by Fredlund et al. (1996). Montrasio and Valentino (2008) approximated the suction-related cohesion as a mathematical function of degree of saturation based on experimental data. Montrasio and Valentino (2008) allow writing dimensionless thickness m_t as function of rainfall intensity. This link m_t has been rewritten in a differential way to better evaluate the effects of a single rainfall. Equation 6 accounts for the precipitation discrepantly (e.g., hourly) from stratum surface and seepage throughout the substratum. The finite slope grid is conceptualized as a water balance tank that simultaneously accounts for water gain from rainfall infiltration and seepage inflow as well as the water loss due to outflow and evapotranspiration through the grid. The initial value of m could

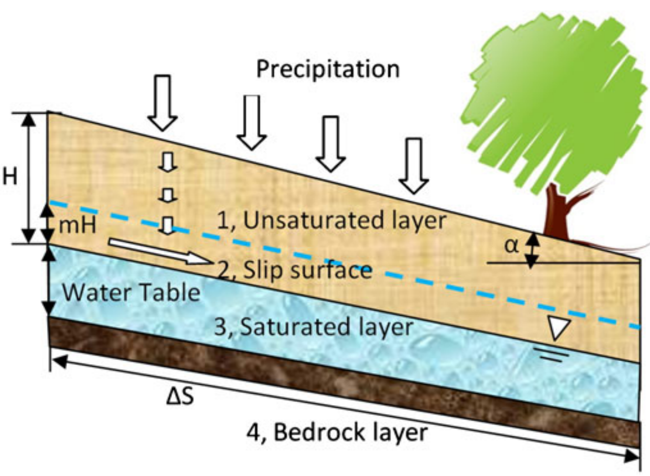


Fig. 2 Schematic illustrating the SLIDE model of the infinite slope

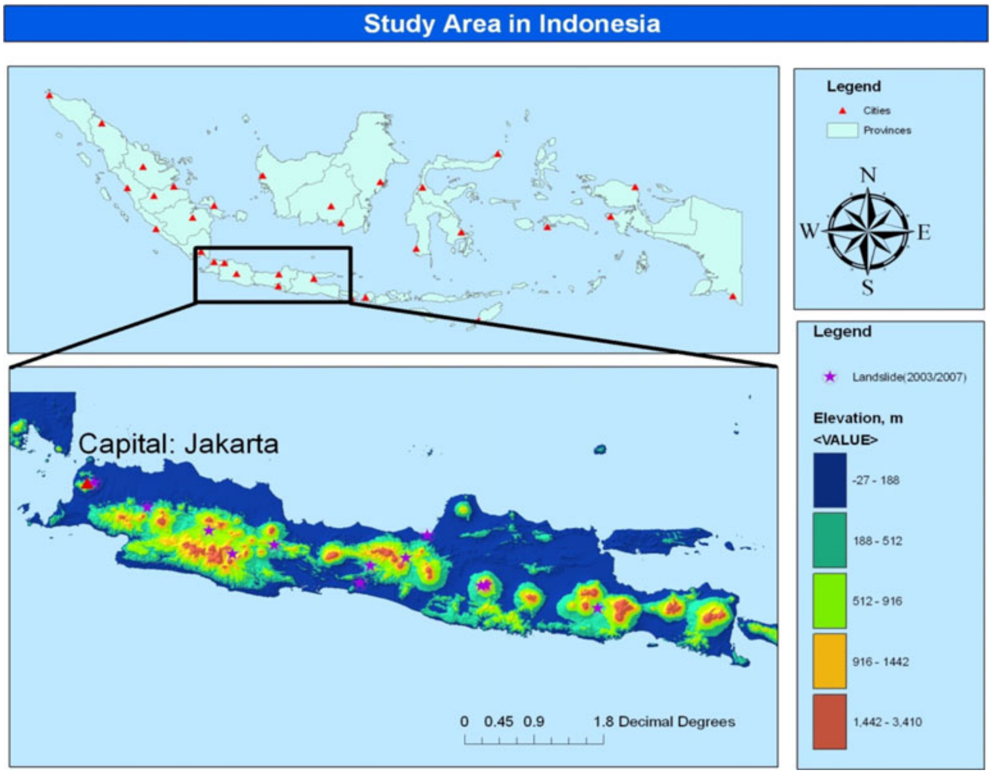


Fig. 3 The study area and the landslide inventory (2003, 2007) in Java Island, Indonesia

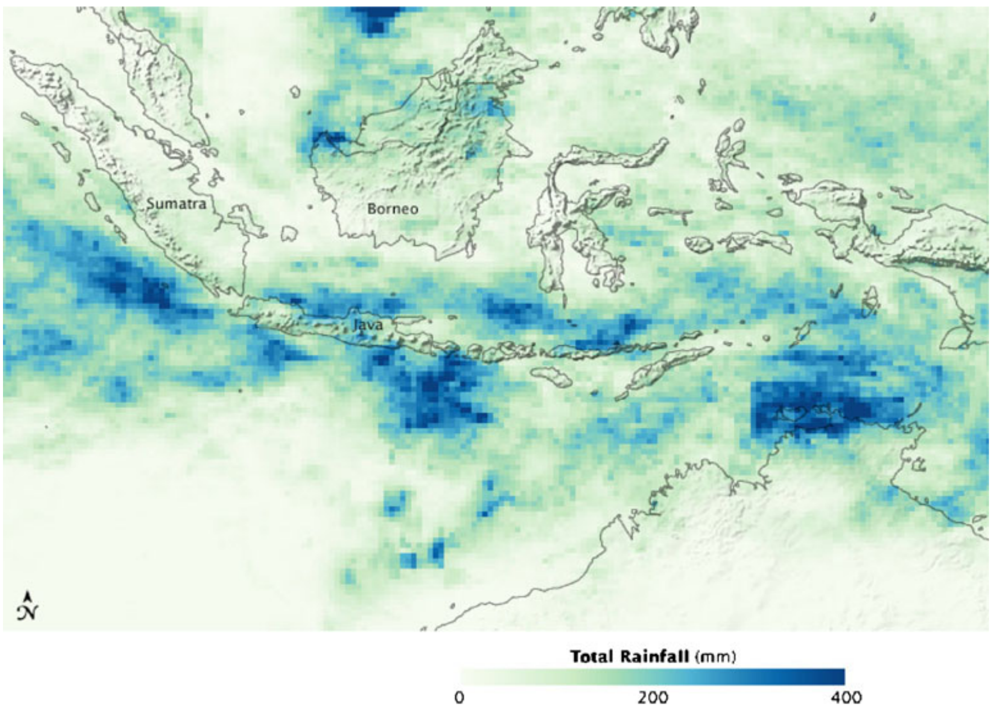


Fig. 4 Image of rainfall accumulation by NASA TRMM-based Multi-satellite Precipitation Analysis over Java Island in late December, 2007, posted by Earth Observatory, NASA on January 8, 2008 (http://earthobservatory.nasa.gov/IOTD/view.php?id=8376)

be determined by an in-situ test of the groundwater table and then m_t could be derived by calculation of water balance at each time-step based on Eq. 6.

$$\begin{cases} m_1 = 0 \\ O_t = K_t \cdot \sin\beta \cdot m_t \cdot H \cdot \cos\beta \cdot \Delta t \\ \Delta m_t = \frac{(I_t - O_t)}{n \cdot H \cdot (1 - S_r)} \\ m_{t+1} = m_t + \Delta m_t \end{cases} \tag{6}$$

Where t is time, Δt is time interval, m_1 is initial value of m, and m_t is calculated at each time-step. O_t represents the water outlet of a finite portion of a slope of finite length L. I_t is rainfall intensity, and K_t is the significance of a global drainage capability due to both the intrinsic soil permeability and the presence of numerous preferential down-flow ways.

Application

Study area

Indonesia suffers from typhoons, typhoon-triggered floods, and landslides during rainy seasons every year (Wardani and Kodoatie 2008). During the period 1981–2007, the annual landslide frequency reached an average of 49 events per year (Christanto et al. 2008). According to a landslide inventory database

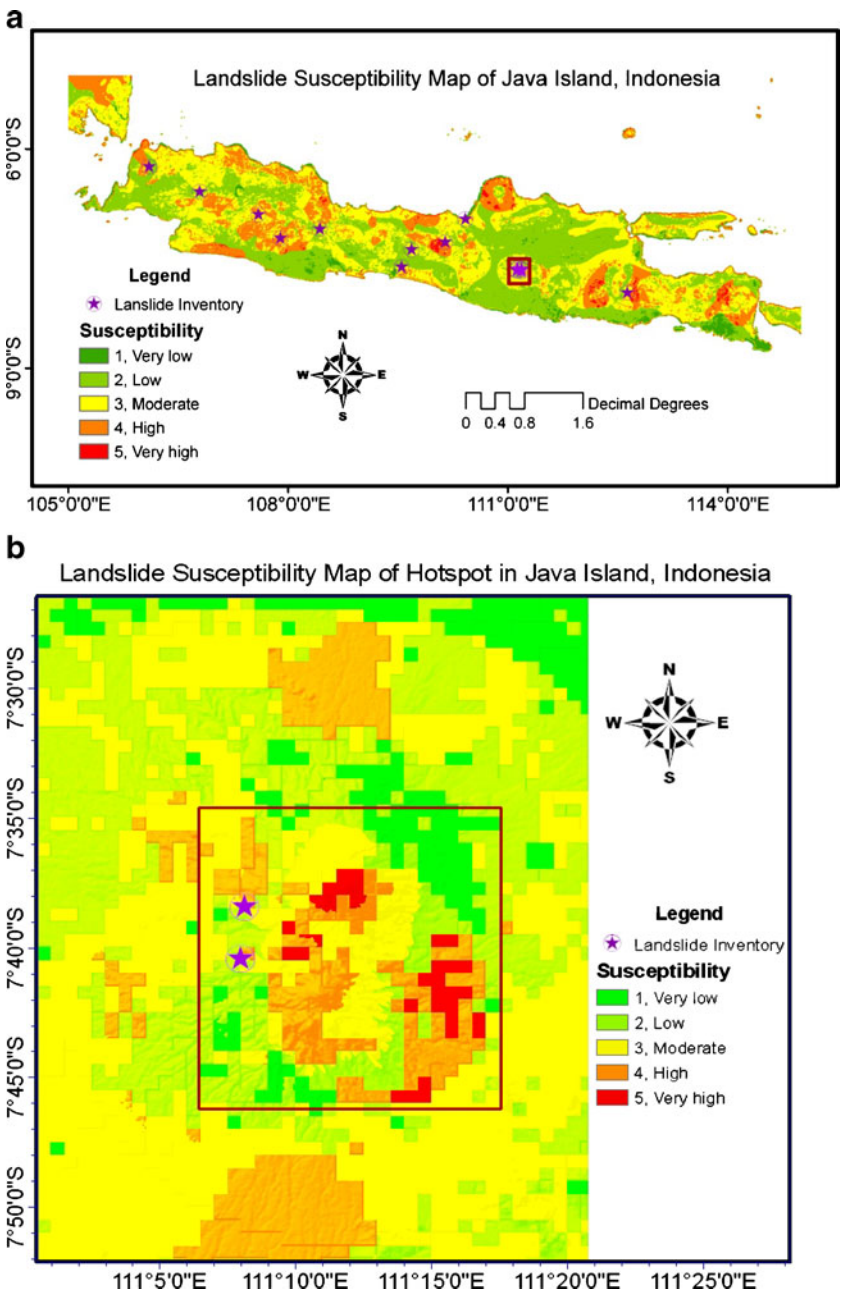


Fig. 5 **a** Susceptibility map by 1-km spatial resolution of Java Island, Indonesia. Note that the *red square lines* indicate the hotspot study area in this paper; **b** susceptibility map of the hotspot by a 30-m ASTER DEM in central Java Island. Note that the *red square lines* indicate the FS calculation zones

(Kirschbaum et al. 2009a, b), in Indonesia 402 people were killed by 17 landslides in 2003 and 243 people were killed by 13 landslides in 2007. Among these landslides, 12 rainfall-induced landslides occurred in Java Island, shown as Fig. 3. On December 26, 2007, two major landslides triggered by a typhoon rainstorm killed at least 65 people in Karanganyar, Central Java (indicated in Fig. 5) and several other landslides occurred and claimed more lives according to the local media reports. We implemented the Early Warning System prototype to model landslides triggered by the typhoon event in Karanganyar, Java.

Rainfall

Heavy rain during the rainy season caused landslides in Central Java Island in late December, 2007. Figure 4 shows the accumulated NASA TRMM rainfall during the period from December 24, 2007 to January 2, 2008. Although the highest rainfall totals were over the ocean, the central parts of Java received close to 250 mm of rainfall. Storms delivering above-average rainfall can create dangerous scenarios for regional flooding and landsliding in Karanganyar, Central Java. Besides the satellite rainfall data, we also used the WRF model to forecast the typhoon rainfall at 4-km spatial resolution.

Results

In this paper, a weighted hazard rating methodology for mapping Indonesia is applied. This approach integrated remote sensing and geographic information system (GIS) techniques. First, all the land surface database, geospatial data sets and important terrain factors contributing to landslides derived are collected in GIS. Then a weighted linear combination function is performed to compute the susceptibility map (Hong and Adler 2007). The susceptibility map of Java is classified into five categories: 1—very low, 2—low, 3—moderate, 4—high, and 5—very high susceptibility. Figure 5a demonstrates the hotspots of the high landslide susceptibility over Java Island. These results are in compliance with the two-year inventory data (Kirschbaum et al. 2009a). Particularly, central Java shown in Fig. 5b is selected as our study area and susceptibility is re-calculation by a 30-m DEM. The very high and high susceptibility categories account for 1.76% and 13.61% of land areas in the hotspot. Both landslides induced by rainfall on December 26, in Karanganyar, Central Java are indicated as a category of 4 in the susceptibility map.

FS values were calculated over the area with categories above 4 (including 4) in the hotspot susceptibility map. A FS map at the peak of the rainfall event is shown as Fig. 6. Five categories based on FS value are used, as the lower value indicates higher potential for landslides to occur. Values above 3 are accounted as inherently safe in this case. Results shows that during the peak of the typhoon rainfall, FS values below 1.2 account for 25.06% of land areas which rank susceptibility categories of high and very high. For FS values below 1, seven areas shown as red squares in Fig. 6 are predicted to have landslides. According to reports of local news, two out of the seven square areas had large landslides that killed more than 65 people. The other five predictions are not validated due to lack of landslide information in remote and non-residence areas.

FS values are calculated for one landslide induced by rainstorms on December 26, in Karanganyar, Central Java using the proposed Early Warning System. The landslide has been simulated with TRMM and WRF data. A landslide warning would be issued when the FS value reaches below the critical value of 1, expressed in Eq. 1. Figure 7a denotes a predicted slope failure at the 23rd time-step (shown by the yellow arrow) in the TRMM rainfall series, where the FS value is below the critical value indicated by the dash line. FS values decrease after rainfall reaches its peak value of approximately 50 mm/3 h. The total rainfall keeps accumulating until it reaches above 150 mm. Although the prediction time shows a 3-h delay, it is still in agreement with the date of the event occurrence reported in local news on December 26, 2007. In addition to the TRMM rainfall, the model has been run by WRF precipitation to investigate how well the model would perform in the Early Warning System. Figure 7b shows the WRF rainfall series with much lower intensity compared with TRMM for the same event over the Landslide Site B (the Headscarps shown in Fig. 8). The WRF rainfall gives a storm event accumulation of rainfall 150 mm, which agrees with the TRMM values. In the WRF driven simulation, FS values show the same trend in time with the lowest value of 0.99 indicating a landslide.

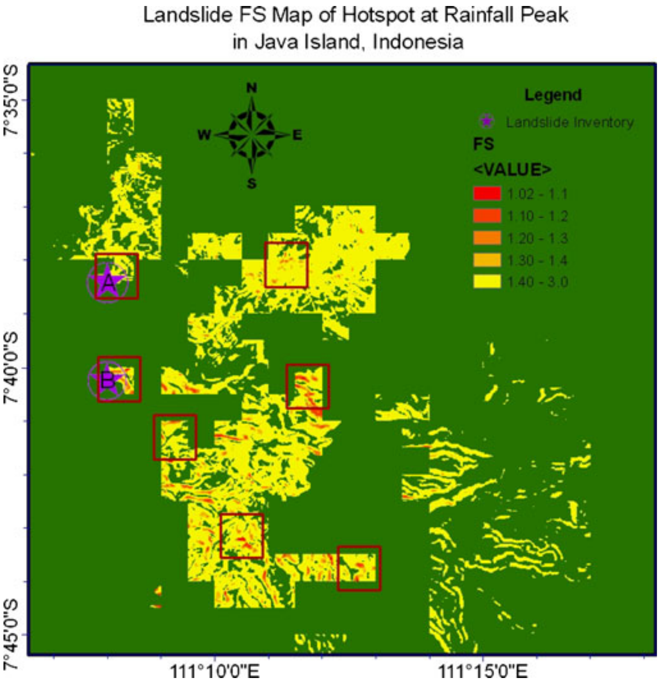
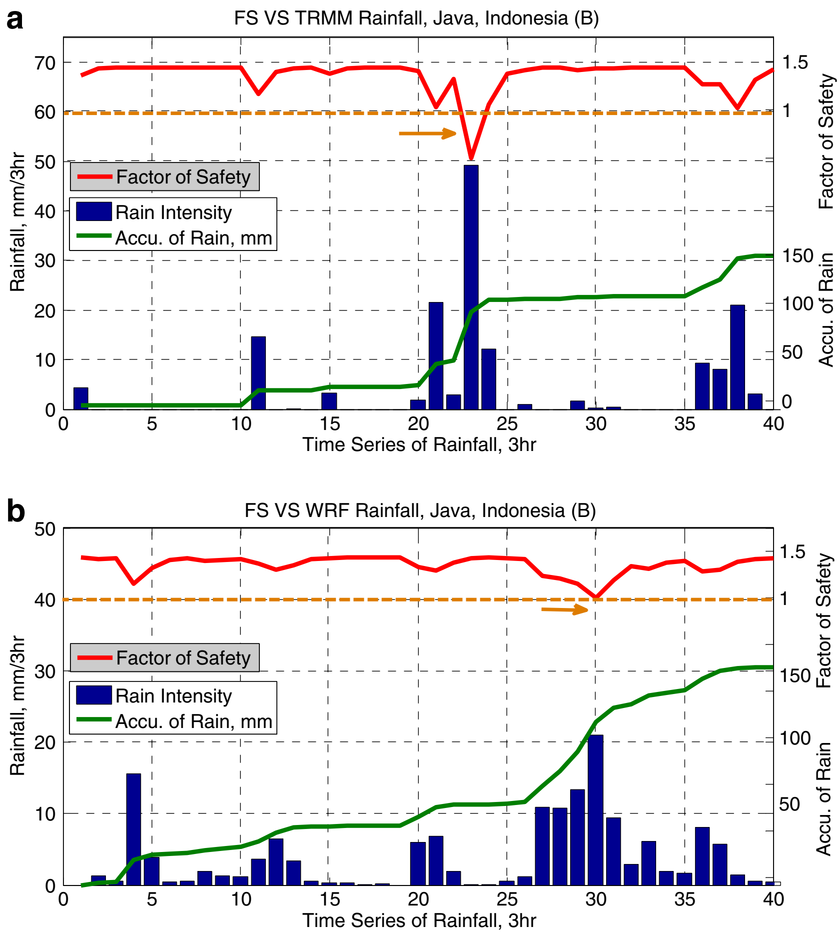


Fig. 6 Factor of safety (*FS*) map by a 30-meter ASTER DEM showing the locations of two observed landslides and seven predictions at the peak time of the rainfall series. Note that the *red square lines* indicate the landslide predictions by the Early Warning System, and A and B indicate observed landslides reported by local news, then investigated by members of the University of Gadjah Mada and the International Consortium on Landslides

Conclusion and discussion

Water content in the soil column during a rainfall event is an important factor in determining slope stability. SLIDE, a physical model linking water content in the soil column and rainfall series has been integrated into an early warning system and applied to Java Island, Indonesia. The system objectives aim to predict regional landslides by mapping FS over a defined region using a set 30-m DEMs to set up a physical framework. NASA TRMM

Fig. 7 **a** FS VS TRMM rainfall in the landslide B; **b** FS VS WRF rainfall in the landslide B



precipitation system and WRF rainfall prediction system have been used as rainfall inputs through the simulation process.

In the Early Warning System, the SLIDE obeys differential equations, which, in turn govern slope failure motions. The growth of parameter m could occur quickly in response to intensive rainfall and reverse values as rainfall dissipates. Results show that the SLIDE model successfully predicted the occurrence of the two landslides on the dates of the real events. The prediction time from the modeling results shows only a 3-h delay on December 26, 2007.

Fig. 8 Headscarp of landslide (B) which occurred at Tengklik Sub-Village, Tawangmangu, Karanganyar Regency, Java, Indonesia. The University of Gadjah Mada and the International Consortium on Landslides investigated this landslide and installed three sets extensometers, a pore pressure and a rain gauge for continual monitoring and early warning for further retrogressing landslides in this village

While the system has the potential to become a next generation tool for early warning of landslides, it also neglects factors that can be important. For examples, soil strength corresponding to the interaction of different soil layers, geological structures information that might accelerate the slope failure, and circular failure surface with more complex mechanical effects are neglected. The evaluation can be further improved if additional landslide observation information was available (e.g., the time of failure for each landslide and the area and volume). Several limitations in simulating landslide occurrence accurately by the Early Warning System are: (1) Factor of Safety values dipping below 1 do not always generate landslide conditions but rather provide a threshold case where a landslide could occur, (2) This system has only been validated with a small amount of events, in order to gain a better and more comprehensive understanding of the model performance accuracy, additional landslide inventories and events need to be tested, (3) resolution and the absence of necessary surface inputs, namely accurate and detailed soil information and in situ measurements of water infiltration, etc., limit the system performance accuracy. The assumptions made on the subsurface processes require very good soil data. Without such information, the results and warning may be less meaningful or should be approached with some uncertainty value.

Despite the limitations currently affecting the Early Warning System, the simulation results suggest that the prototype system demonstrates skill in predicting rainfall-induced landslides by considering the most important dynamic triggering factor (i.e., rainfall in this study) in finite slope grids quantitatively. Utilizing satellite remote sensing data in landslide studies enables researchers to develop an operational early warning system at regional scales, not just at site-based locations. Using higher-resolution remote sensing data along with more detailed in-situ data to simulate real landslide conditions, we anticipate the development of future warning systems to be enhanced through continuous community-wide collaborations by collaboration among modelers, geotechnical engineers, and weather forecasters. For example, as shown in Fig. 8 the University of Gadjah Mada and the International Consortium on Landslides investigated this landslide and installed three sets extensometers, a pore pressure and a rain gauge in this village. We will work together to enhance the existing prototype system for operationally monitoring and early warning for landslides risks in Java Island.

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