A Simple Physically-Based Distributed Translational Landslide Model

Yanto, Sumiyanto, and Arwan Apriyono

Abstract

Detailed landslide susceptibility mapping (LSM) requires a skillful landslide model. Considering that translational landslide is the most type of landslides occurred in the world, a well-behaved translational model is sought. This study presents a simple physically-based distributed translational landslide model. In this model, the incident of landslide is detected from the value of factor of safety (FoS) which is computed based on Mohr–Coulomb failure criterion. In here, FoS is calculated as the ratio of shear strength and shear stress. The lower the FoS, the higher the possibility of a landslide to occur. The model input data consists of soil cohesion $\boldsymbol{c}$ (kg/cm^2), soil specific weight $\boldsymbol{\gamma}$ (g/cm^3), depth of surface of rupture (m), slope of surface of rupture $\boldsymbol{\beta}$ (degree) and friction angle $\boldsymbol{\varphi}$ (degree). Application of the model was performed in Sirampog and Kandang Serang, two subdistricts in Western Central Java that underwent the most frequent landslides in the region. Model validation was conducted by comparing the values of FoS of unsaturated and saturated soils and identifying FoS in the sites where landslide events recorded. Several goodness of fit indices to measure the model performance are accuracy (ACC), success index (SI), average index (AI) and distance to perfect classification (D2PC). Under unsaturated condition, the result shows that the number of grids having FoS less than 1 are 0% and 0.6% for Sirampog and Kandang Serang respectively, indicating no landslide occurrence. When the soil gets saturated, 17.6% and 36% of area have FoS less than 1 for Sirampog and Kandang Serang respectively. This shows that the landslide occurred in this region is rainfall-induced landslide. Overall, the model shows a good performance with ACC, SI, AI, D2PC values are 0.82, 0.58, 0.54, 0 and 0.64, 0.49, 0.49, 0 for Sirampog and Kandang Serang respectively.

Keywords

Translational landslide • Physical model • Factor of safety • Landslide susceptibility map

Introduction

Many parts of the world are susceptible to landslide (Allen and Voiland 2017). An accurate landslide susceptibility mapping (LSM) is therefore important for landslide hazard assessment and landslide mitigation planning (Brabb 1985). A number of approaches have been used for estimating LSM around the world such as Frequency Ratio (Choi et al. 2012; Silalahi et al. 2019), Landslide Numerical Risk Factor (Roy and Saha 2019), Analytical Hierarchical Process (Abedini and Tulabi 2018), Logistic Regression (Lombardo and Mai 2018) and many others. The most applied methods in developing LSM are statistical techniques, artificial neural network and machine learning algorithm (Chang et al. 2019; Dou et al. 2020; Segoni et al. 2020; Tien Bui et al. 2019). The physically-based model is useful in understanding the landslide physical mechanism through linking hydrology, geomorphology and geotechnical science with different degree of simplification. Nonetheless, physically-based LSM is very limited (Formetta et al. 2014, 2016; Segoni et al. 2020).

Physically, a landslide occurs if the slope stability disturbed. This happens as the maximum capacity of soil to bear load or stress (shear strength) is lower than the applied load or stress (shear stress) (Das 1994). The ratio of shear strength to shear stress is called factor of safety (FoS). Hence, suitable estimation of FoS in space is critical as it is

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valuable for not only an appropriate LSM but also potentially useful for the development of landslide early warning system. Accordingly, a trustful physically-based distributed landslide model is sought.

A few number of physically-based distributed model for landslide are found in literature such as GEOtop model (Formetta et al. 2014) and NewAge-JGrass hydrological model (Formetta et al. 2016). In both model, FoS is calculated from the simplification of infinite slope equation (Formetta et al. 2014). This is one of methods for modelling translational landslide, one of the most common landslide types occurred in the world (Postance et al. 2018). Translational landslide often occurs in the presence of a layer separating strong and weak soil. This layer is called surface of rupture. Therefore, trustworthy estimation of the depth of surface of rupture is critical. GEOtop and NewAge-JGrass model are dissimilar in determining this depth.

This study presents a physically-based distributed translational landslide model. The modelling framework is similar to the aforementioned model. However, we offer different approach to estimate the depth of surface of rupture. In here, we estimate this depth based on soil bearing capacity.

Model Description

The model presented here is in the first stage of development. At current form, the model is very modest. However, we show it useful in mapping landslide susceptibility zone.

The model lies on the Mohr–Coulomb failure criterion (Hackston and Rutter 2016; Labuz and Zang 2012). Following the theory, FoS in this model is defined as the ratio of shear stress and shear strength. Shear stress is resistive force per unit area in soil due to applied shear force and shear strength is ability of soil to resist external load against failure. The model is schematically presented in Fig. 1.

According to the Mohr–Coulomb theory as shown in Fig. 1, shear strength per unit volume is calculated as follow:

$$\tau_r = c + \sigma\, tg\, \varphi \tag{1}$$

$$\sigma = \frac{Na}{L^2/\cos\beta} = \frac{\gamma L^2 H \cos\beta}{L^2/\cos\beta} \tag{2}$$

$$\tau_r = c + \gamma H \cos^2\beta\, tg\, \varphi \tag{3}$$

In here, τ_r is shear strength (kg/cm^2), Na is normal force (kg), L is grid size (m), c is soil cohesion (kg/cm^2), γ is soil specific weight (kg/cm^3), H is depth of surface of rupture measured from ground elevation (m), β is slope of surface of rupture (degree) and φ is friction angle (degree).

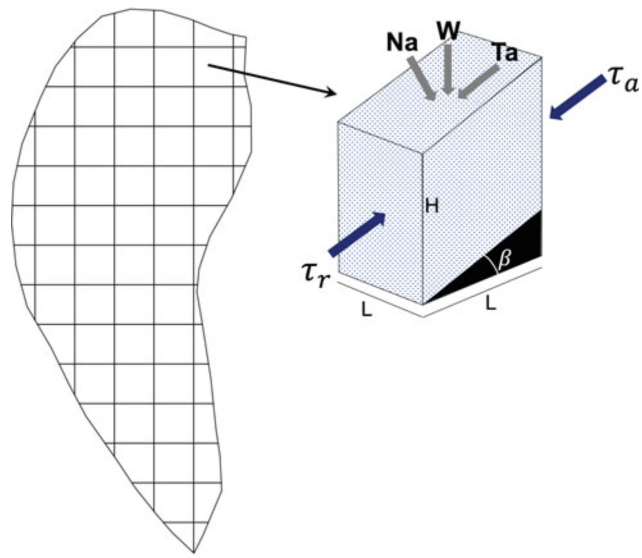

Fig. 1 Schematic representation of the model

As presented in Fig. 1, shear stress is natural force acting on the surface of rupture mainly coming from soil block above the surface. Accordingly, shear stress τ_a (kg/cm^2) is formulated as follow:

$$\tau_a = \frac{Ta}{L^2/\cos\beta} = \frac{\gamma L^2 H \sin\beta}{L^2/\cos\beta} = \gamma H \sin\beta \cos\beta \tag{4}$$

In here, Ta is shear force (kg). Based on the above-mentioned formulation, the FoS can be straightforwardly expressed as follow:

$$FoS = \frac{\tau_r}{\tau_a} = \frac{c + \gamma H \cos^2\beta\, tg\, \varphi}{\gamma H \sin\beta \cos\beta} \tag{5}$$

According to the FoS formulation, it can be inferred that landslide will occur in the areas with FoS less than 1.

Model Configuration and Input

As shown in Fig. 1, the model is run in distributed mode. Computation of FoS is performed in each grid separately. The code is written using R programming language which can be run either in R software or through Terminal or Windows Command Prompt. The input data should be written in comma separated value (csv) file format. The output from the model is a landslide susceptibility map.

For each grid, input data required to run the model are geographic location, soil cohesion, soil specific weight, depth of surface of rupture and slope of surface of rupture. The slope of surface of rupture is deemed to be the same as the slope of land surface for simplicity. The slope along with its corresponding geographic location is derived from the Digital Elevation Method (DEM) by Shuttle Radar Topography Mission (SRTM) at 30 m × 30 m resolution. In addition, soil cohesion, soil specific weight, depth of surface of rupture are obtained from soil test using in situ Cone Penetration Test (CPT) and laboratory tests.

While slope, geographic location, cohesion and specific weight can be easily and unquestionably defined from their original sources, determination of the depth of surface of rupture is quite challenging. This is because no referenced number can be used for the specific purpose. As an alternative, we set the depth of surface of rupture for the model as the depth of soil obtained from CPT where the cone tip resistance reaches up to 250 kg/m^2 which is usually used to define the hard soil layer for designing building foundation.

Translational landslide usually takes place when the soil above surface to rupture gets saturated, partially or fully. Under saturated condition, cohesion and friction angle will variedly drop with the rate depending on the soil types, initial soil water content, etc. While soil cohesion could decrease to averagely 22%, soil friction angle could decline to about 50% (Lakmali et al. 2016; Minnesota Department of Transportation 2019). As soil parameters in this study were obtained under unsaturated condition, it is necessary to estimate their values under saturated soil using the aforementioned number.

To test the model, we run the model under unsaturated and saturated soils. It is expected that no grid will have FoS values less than 1 under unsaturated condition and some grids will possess FoS values less than 1. Hence, we can prove that the landslide occurred in this area is induced by rainfall.

Model Testing

Study Area and Data

To examine the model performance in mapping landslide susceptibility zone, we run the model on Sirampog subdistrict, Brebes, Central Java, and Kandang Serang subdistrict, Pemalang, Central Java, Indonesia as shown in Fig. 2. Sirampog and Kandang Serang have an area of 69 km^2 and 74 km^2 respectively. These places have the most frequent landslide events in the Western Central Java counting 3 events during the period of 2011–2017, (BNPB 2020).

Soil properties data to run the model were obtained from Soil Mechanic Laboratory, Civil Engineering Department, Jenderal Soedirman University. It was collected during the period of 2005–2016 with some absent data in the period of 2008–2009. The soil properties are then interpolated to the 30 m × 30 m SRTM DEM raster points. In here we used Inverse Distance Weighting (IDW) interpolation technique.

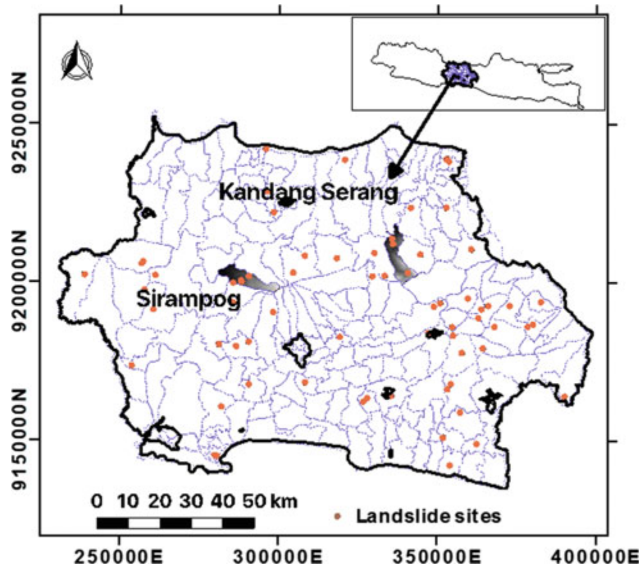

Fig. 2 Study area to test the performance of the model

Model Results

To assess the goodness of fit (GOF) of the model, we calculated several GOF indices (Formetta et al. 2016) and shown in Table 1. It can be inferred that the model performance is quite good where Sirampog produces better performance than Kandang Serang.

Table 2 also presents the FoS values from the model along with the summary of model parameter values generated from IDW interpolation for the entire Sirampog and Kandang Serang area and the values for each site where landslide occurrences recorded, i.e. Site 1, Site 2 and Site 2 for both subdistrict as presented in Figs. 3 and 4. Moreover, While the values of many model parameters are similar, soil cohesion in Sirampog and Kandang Serang shows large different. In Sirampog, the dominant soil type is organic silt, while in Kandang Serang, the dominant soil is sandy clay.

The minimum values of FoS in Sirampog and Kandang Serang are 1.27 and 0.91 respectively. The FoS values less than 1 in Kandang Serang account for 0.6% of the total area, indicating that under unsaturated condition, landslide unlikely occurs. Moreover, it can also be seen in Table 2 that the minimum FoS values of saturated soil are 0.39 and 0.27 for Sirampog and Kandang Serang respectively. The grids having FoS less than 1 under saturated condition in Sirampog and Kandang Serang are 17.6% and 36% respectively which correlated with the variability of soil cohesion in the

Table 1 Summary of GOF indices

GOF indices	Sirampog	Kendang Serang	Optimum
Accuracy (ACC)	0.82	0.64	1
Average Index (AI)	0.54	0.49	1
Success Index (SI)	0.58	0.49	1
Distance to Perfect Classification (D2PC)	0	0	0

Table 2 Summary of model parameter values

Model Parameter/Result	Sirampog				Kendang Serang			
	Range	Site 1	Site 2	Site 3	Range	Site 1	Site 2	Site 3
c (kg/cm^2)	0.08–6.15	0.49	0.51	0.57	0.06–0.31	0.30	0.29	0.31
γ (g/cm^3)	1.55–1.71	1.56	1.56	1.56	1.54–1.57	1.55	1.55	1.56
H (m)	2.77–11.53	7.17	7.15	7.08	2.57–7.63	7.31	7.22	7.41
β (°)	0–56.17	9.17	28.30	16.82	0–87	4.19	9.71	26.62
φ (°)	30.05–40.46	30.82	30.90	30.86	28.95–36.88	29.34	29.60	29.72
Unsaturated FoS	1.27–Inf	6.50	2.23	3.84	0.92–Inf	11.30	4.92	1.81
Saturated FoS	0.39–Inf	2.33	0.76	1.32	0.27–Inf	4.37	1.89	0.68

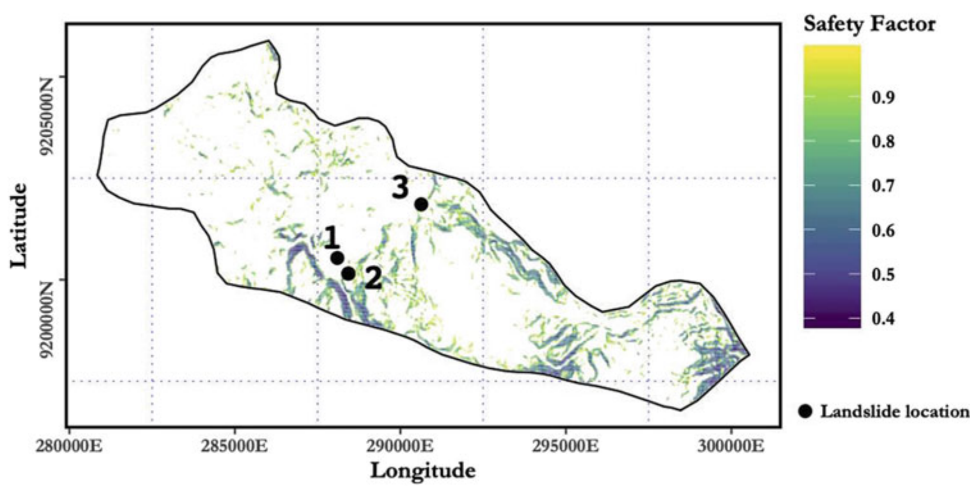

Fig. 3 Landslide susceptibility map of Sirampog along with landslide sites

two places. Accordingly, it can be inferred that the landslide events are rainfall-induced landslide.

Sirampog Subdistrict

The LSM of Sirampog overlaid with the sites of recorded landslide is presented in Fig. 3. As shown in Fig. 3, the landslide susceptible zones are more distributed to the eastward, while in the westward there exists less susceptible areas. The map is consistent with the spatial arrangement of elevation and land surface slope (not shown due to page limitation) where elevation and slope increase eastward. Moreover, the spatial pattern of LSM is corresponding to the spatial configuration of β.

The value of FoS in Site 1, Site 2 and Site 3 is 2.33, 0.76 and 1.32 respectively showing that only 1 out of 3 sites is correctly modelled. It can be observed that these values are strongly correlated with the values of β. The β values in Site 1 and Site 3 are 9.17 and 16.82° respectively, which can be considered too low to generate a landslide. In addition, it can also be noticed that value of c decreases from 0.57 to

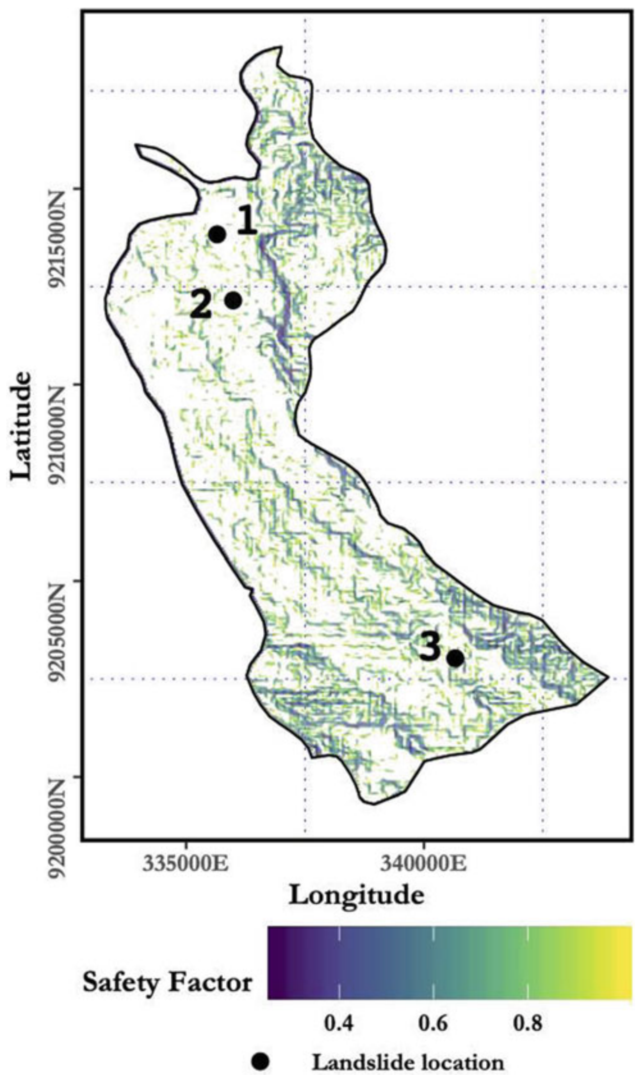

Fig. 4 Landslide susceptibility map of Kandang Serang along with landslide sites

0.51 kg/cm^2 as the β increases from 16.82 to 28.30°. This conforms the inference presented previously.

Based on the above analysis, it can be roughly deduced that the model is sensitive to the values of β, the slope of surface of rupture. This is in accordance with other studies showing the sensitivity of landslide model to digital terrain model (Pawluszek et al. 2018; Segoni et al. 2020). Moreover, it brings a new challenge on the model parameterization, particularly estimation of β.

Kandang Serang Subdistrict

The LSM of Kandang Serang along with the sites of landslide events is displayed in Fig. 4. As can be seen in Fig. 4, the spread of landslide susceptible zones is quite uniform. Moreover, about 36% of Kandang Serang's area is susceptible to landslide, higher than Sirampog which is about 17.6%. This resembles the fraction of slope more than 30°. In Kandang Serang, about 11% areas have slope of more than 30°, larger than in Sirampog, which is 8%. Again, this corroborates the previous hypothesis.

In this area, there are 491 grids possessing FoS less than 1 under unsaturated condition. Theoretically, these places should be full of landslide events record, but it is not. One reason should be addressed is the model assumption to equalize slope of surface of rupture with land surface slope, which is unlikely factual for high slope values. For example, it is dubious to have soil block can rest on the surface of rupture with slope of more than 45° unless it has high soil cohesion, which is not the case of hilly topography. Another possibility is that a place with slope of more than 45° is a massive rock formation which is not subject to Mohr–Coulomb failure criterion.

To verify the above analysis, we extracted the values of β in the places where FoS less than 1 under unsaturated condition. We found that the values of β in these grids range from 49.8 to 68.6°. This finding conforms our premise.

The values of FoS in Site 1, Site 2 and Site 3 are 4.37, 1.89 and 0.68 which correspond to the values of β. The higher the β, the lower the FoS, signifying the sensitivity of the model to the value of β.

Future Model Development

Model parameterization is prerequisite for developing a skilled model (Guimaraes et al. 2003; Knowling et al. 2019; Kuriakose et al. 2009). In line with the result of model testing and to extend the use of the model, model parameterization will be directed to the estimation of β involving geological setting, valuation of c under different soil moisture to reflect the influence of rainfall on the variability of c and the connection of the model with hydrological model, such as VIC. The later enables the model to be run in a simulation mode such that it can be employed for landslide early warning.

Conclusion and Remark

A physically-based distributed translational landslide model at its very basic form is presented in this paper. Its application on two different regions shows that the model produces a good performance. However, some paucities are found and some hypothesize proposed. Nevertheless, the model is thought to be useful and it can be potentially extended for the development of a landslide early warning system.

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