Probabilistic landslide risk assessment: Case study of Bujumbura

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Abstract. A spatial probabilistic landslide risk assessment and mapping model has been applied in a data scare region. The probabilistic model is based on a physical model based on Mohr coulomb failure criterion. A Monte Carlo simulation technique is applied to field collected data. The results are integrated and a probability of landslide is obtained at each cell level. The results are compared to a prepared landslide inventory. The overall accuracy of the model is 79.69%.

1 Introduction

The expansion of constructions and buildings in cities of developing countries creates new challenges in risk management of constructions and buildings and in environmental sustainable planning of peri-urban areas. Among the various potential risks, the landslide risk is a challenge for our study area. The Bujumbura peri-urban area has witnessed several hazards of different nature: floods, rock falls and landslides[1], [2]. In particular, landslides caused the loss of several lives, destruction of infrastructure, damage to land and loss of natural resources. Motivated by the increasing number of recorded incidents, Nibigira et al. (2015) inventoried past landslides in the western part of Burundi, which includes the Bujumbura region, and identified factors influencing the development of instabilities[3]. Kubwimana et al. (2018) developed a landslide susceptibility map using Analytic Hierarch Process (AHP) for the Kanyosha river watershed (Kubwimana et al., 2018)[4]. Nevertheless, the statistical approach proposed by Kubwimana et al. (2018) did not take in account the physical parameters linked with slope stability analysis. Several studies assessing and mapping landslide susceptibility have been conducted worldwide using two principal approaches: deterministic and statistical. For the developed deterministic models[5]–[9], the relevant factor is the factor of safety based on slope stability analysis. Slope stability analyses of landslides in deterministic models are usually performed using conventional limit equilibrium method based on the Mohr–Coulomb failure criterion. Statistical approaches [10]–[14] have also been used for landslide susceptibility assessment.

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Statistical approaches are more bounded to local particularities since they are always linked to a determined training dataset. The objective of this study is to develop landslide susceptibility maps using a probabilistic approach which takes in account the physical parameters of slope stability analysis and the uncertainties linked with them.

2 Methods

2.1 Study area

The study area has 31 km^2 (**Fig 1**). It covers15 administrative districts(**Fig 2**). The study area belongs to the Imbo region on his western part and belongs to the Mirwa region on his eastern part. The Imbo region is a valley adjacent to steep hills and mountains of the Mirwa region. Three major watersheds cross our study area. The altitude in our study area changes from 777 to 1386 m. The slope angle values range from 0° to 57°. The yearly average temperature is 23 °C, and the annual precipitation is 1274 mm[15].

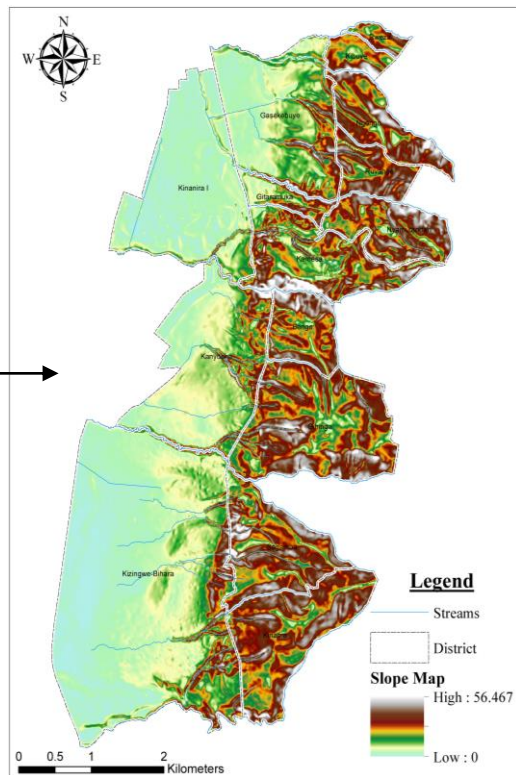**Fig 1.** Location Map of the Study area.

Fig 2. Study Area.

2.2 Landslide inventory

A landslide inventory map is required for accuracy assessment of the model results. Hence, a landslide inventory was produced using a 10 m–resolution Digital Elevation Model (DEM), literature review, aerial ortho-images, satellite imagery (Google earth Imagery) extensive field survey. In result, a detailed and reliable inventory map with a total of 89

landslides was created. The identified landslides were classified mainly as shallow translational slides according to classification proposed by Varnes[16].

2.3 Physical model

Several deterministic model have been applied in landslide hazard mapping[6], [7], [9]. Lu and Godt (2008) proposed a generalized framework for the stability of infinite slopes under steady unsaturated seepage conditions[17]. As all the deterministic models, the purpose is to determine a safety factor reflecting the stability of a considered slope. The proposed framework by Lu and Godt relies on the existing understanding of unsaturated-zone hydrology and considers for the first time, the contribution of suction stress in the stress analysis. The safety factor is defined by the relationship:

$$FS = \tan\varphi' / \tan\beta + 2c' / \gamma H \sin2\beta - [\sigma^s (\tan\beta + \cot\beta) \tan\varphi'] / \gamma H \qquad (1)$$

Where φ' is the friction angle; β is the slope angle; c' is the soil cohesion; γ is the unit weight of moist soil; H is the height of the soil column above the bedrock and σ^s is the suction stress defined by:

$$\sigma^s = \ln [(1+q/k_s) \, e^{-\gamma_w\alpha z} - q/k_s] / \alpha \quad u_a - u_w \leq 0 \qquad (2)$$

$$\sigma^s = \{\ln [(1+q/k_s) \, e^{-\gamma_w\alpha z} - q/k_s] / \alpha\} / \{1+ \{-\ln [(1+q/k_s) \, e^{-\gamma_w\alpha z} - q/k_s]^n\}^{(n-1)/n}\} \quad u_a - u_w > 0 \; (3)$$

where k_s is the field hydraulic conductivity; q is the steady infiltration; γ_w is the unit weight of water; α and n are the empirical fitting parameters of unsaturated soils properties and the matric suction $u_a - u_w$ is defined by:

$$u_a - u_w = -\ln [(1+q/k_s) \, e^{-\gamma_w\alpha z} - q/k_s] / \alpha \qquad (4)$$

The proposed slope stability takes in account soil suction. However, in the framework of our research the infiltration rate is considered equal to soil hydraulic conductivity. In this particular case the safety factor takes the form:

$$FS = \tan\varphi' / \tan\beta + 2c' / \gamma H \sin2\beta \qquad (5)$$

A field survey and an extended laboratory work were conducted for the 15 administrative districts. Two hundred and twenty-five samples were collected and analyzed in laboratory. At each district level, a mean average value and a standard deviation for the concerned variables were determined from laboratory analysis(Table 1).

Table 1. Values of input variables

District	Friction Angle, degrees		Cohesion, kPa		Soil Bulk Density, kN/m^3	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
Ngongo	34.860	1.040	22.680	4.461	14.351	0.103
Sagamba	35.447	1.851	27.453	11.845	13.834	0.595
Kinama	34.867	2.307	19.507	9.187	12.714	0.234
Benge	37.680	3.301	31.600	10.315	14.478	0.237

Gihinga	35.453	1.524	40.887	10.139	14.270	0.287
Ruyange	34.840	2.573	29.460	13.312	13.051	0.294
Nyamutenderi	39.020	1.236	14.000	4.879	12.946	0.268
Kibuye	26.180	6.257	38.140	6.465	13.271	0.272
Rweza	25.280	1.849	36.680	17.513	14.258	0.218
Kizingwe-Bihara	31.453	5.861	39.720	21.587	13.604	0.353
Kanyosha	38.200	4.975	26.120	19.162	14.140	0.231
Kamesa	35.100	1.666	22.600	12.665	12.946	0.225
Kinanira I	37.200	5.703	17.260	10.789	15.050	0.229
Gitaramuka	30.540	6.390	48.320	22.543	12.770	0.320
Gasekebuye	33.640	3.568	44.380	12.806	14.511	0.093

The definition of the depth of soils is difficult to conduct on a regional scale. In this study a soil depth model, using a simplified approach often used in largescale regional analyses, is applied[18]. The considered model correlates soil depth to the local slope and has the form:

$$H_i = H_{max} \left[1 - (\tan\beta_i - \tan\beta_{min}) \, (1 - H_{min} / H_{max}) / (\tan\beta_{max} - \tan\beta_{min})\right] \qquad (6)$$

where H_i is the computed soil depth, H_{max} and H_{min} are respectively, the maximum and the minimum soil depth measured in the area, β_i is the local slope angle value and β_{max} and β_{min} are respectively maximum and minimum slope angle value measured in the area.

2.4 Monte Carlo simulations

In regional slope stability assessment, probabilistic methods are applied. These methods provide an accurate estimation of slope stability at a regional scale without the amount of laboratory and field work required in physical models. There are several methods such as the point estimate method [19] , first order second moment [20], [21] or Monte Carlo simulation [22] which are usually combined with a slope stability model to provide a probability of landslide instead of a safety factor. In this work a Monte Carlo simulation is applied. Soeters and Westen (1996) had given a detailed description about the application of Monte Carlo simulation method in slope stability assessment [23]. The approach includes the following steps:

1. Generate a sample of random variables using the probability distribution of φ', c' and γ using Monte Carlo simulation method.
2. For each grid cell, compute the safety factor using the generated samples of random variables. Repeat the procedure N times. In most studies, N has a value between 50 and 2000. In our cases N has the value of 500. After N computations, probabilistic distribution curve of the slope safety factor can be obtained. By integrating the slope failure safety factor distribution curve, slope failure probability for the grid can be finally obtained.
3. Repeat the above procedure for the entire grid and create a landslide probability map.

3 Results

The landslide susceptibility map obtained spatially approximates landslide inventory map prepared which validates the results obtained with our model. Landslide susceptibility map

obtained using Monte Carlo simulations shows that 17.86% of the study area is under high probability of landslide(**Fig. 3**).
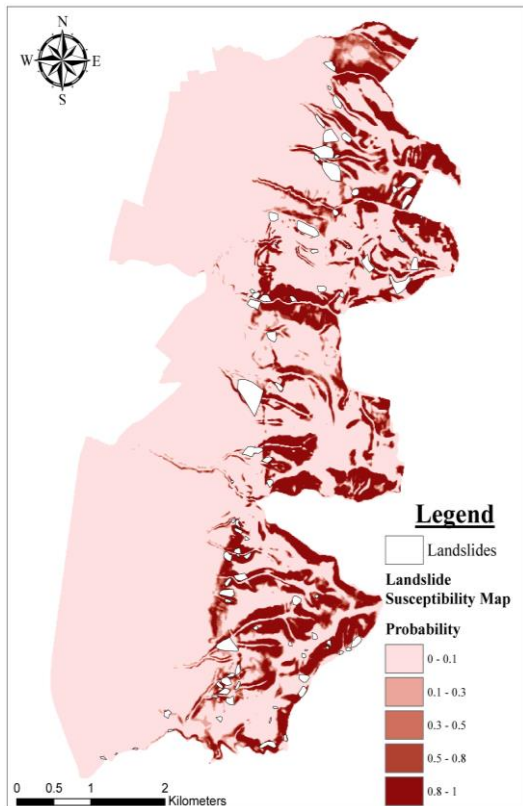

The model correctly detected the areas with low probability of landslide more accurately compared to areas with high probability of landslide. Respectively, 88.23% of true negative rate to 38.64% of true positive rate. However, the model has an overall accuracy of 79.69% hence an error rate of only 20.31%(Table 2). Around 52.11% of areas with high landslide probability have a mean friction angle of 35 degrees. This shows that there is no linear relationship between probability of landslide and the friction angle in this region. In contrast, cohesion shows direct relationship to landslide probability since 41.33% of the areas with high probability of landslide have a mean cohesion value of 19kPa corresponding to the lowest values of cohesion in the region. The landslide susceptibility map produced spatially approximates the slope angle map. This is due to the high contribution of the slope angle the probability of landslide.

Fig. 3. Landslide susceptibility map.

Table 2. Confusion Matrix

Observed		Predicted		
		landslide		Percentage Correct
		no landslide	landslide	
landslide	no landslide	31592	4214	88.23
	landslide	4571	2879	38.64
	Overall Percentage			79.69

3 Conclusion

This research presents a complete framework for a GIS-based landslide hazard assessment and mapping in a data scarce region. The information provided forms the basis for various stakeholders in decision-making especially for risk management and environmental planning. The method proposed combines the physical parameters of slope stability and the probabilistic estimation of slope failure. The accuracy of the model was assessed using a prepared landslide inventory. The model proposed has an overall accuracy of 79.69%. The results presented here showed the importance of soil cohesion in this particular region. Further study to validate and compare the model with other models need to be conducted.

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