Landslide susceptibility assessment in Limbe (SW Cameroon): A field calibrated seed cell and information value method

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The dissected volcanic terrains around Limbe, SW Cameroon are frequently affected by small scale but destruc-
tive landslides. In this study, a raster-based data driven method involving seed cells is used to build a land-
slide susceptibility model for the Limbe area. Factors considered to be potential controls of slope failure
within this area include slope gradient, rock type, distance from roads, slope orientation, mean annual precip-
itation, soil type, land cover type, stream density and distance from stream. 63 small to very small transla-
tional and rotational landslide scars were identified through extensive field work. Landslide data is
randomly divided into a training (75%) and validation set (25%) and seed cells are generated by creating
25 m buffer zones around the head scarp of each scar. The quantitative relationship between landslide
seed cells and the above-mentioned factors is established by a data driven approach to obtain weighted factor
classes. Summing weighted factor layers, a continuous scale of susceptibility indices is obtained and reclassi-
ified into 5 susceptibility classes. Seed cells obtained from the validation data set were used to evaluate the
quality of several models involving different controlling factors. Our preferred model combines the weight
of 6 factors (i.e. slope gradient, land cover, mean annual precipitation, stream density, proximity to roads
and slope orientation). 78% of the validation seed cells are located within the high to very high susceptibility
class, which occupy 16.9% of the study area. The obtained susceptibility map is combined with the outline of
urban areas and key infrastructures to evaluate zones that are vulnerable to the impact of future slope fail-
ures. Such an approach will assist civil protection and urban planning efforts in SW Cameroon.

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1. Introduction

In the context of an exponentially growing world population, geohazards have an increasing impact on sustainable development efforts. This problem is even more acute where limited resources make less wealthy populations many times more vulnerable to given geohazards. The problem of locally devastating slope instabilities is a major issue worldwide, especially across the subtropics, and is well-known to affect or threaten the livelihoods of millions of people (Ayalew and Yamagishi, 2004; Ayonghe and Ntasin, 2008; Claessens et al., 2007; Knapen et al., 2006; Zogning et al., 2007). Landslides are frequently responsible for considerable loss of life and property. They are one of the most visible

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in situ weathering. This scenario even worsens with increased uncon-
trolled or unplanned development and changes in land use patterns
on steep, hilly terrains.

In recent years, urban populations worldwide have tripled to qua-
drupled, forcing individuals to extend their life lines to more unstable
lands thereby increasing the number of persons likely to be affected
in the event of a landslide (Moeyersons et al., 2004). The effect of
landslides in terms of mortality is more severe within low income
countries whereas economic losses are more important in the more
industrialised nations (Hansen, 1984; Smith and Petley, 2009). A bet-
ter understanding of landslide hazards, its causes and spatial distribu-
tion is therefore essential for land use and urban planning and to
mitigate its adverse impacts.

Slides, whether natural or human induced, represent a key slope
forming process (Ayalew and Yamagishi, 2004; Knapen et al., 2006)
particularly along the equator or within the sub tropics where intense or pro-
longed rainfalls are dominant. In the SW and NW Regions of Cameroon,
where 6 million people live and are in need of enhanced civil protection,
landslides have considerable social and economic consequences
(Ayonghe and Ntasin, 2008; Ayonghe et al., 2004; Che et al., 2011;
Zogning et al., 2007). In these regions, landslides result in the loss of
lives, flooding, disruption of the transportation network, degradation of agricultural land, and damage to infrastructure.

In Limbe and its neighbourhood on the SE foot slopes of Mount Cameroon (MC, Fig. 1), small but numerous and recurrent landslides have been the main cause of fatalities induced by natural hazards and destruction of local community livelihoods (Che et al., 2011). The most severe of these mass movement events, accompanied by floods, occurred on the afternoon of June 27, 2001 affecting ~3000 inhabitants and killing 23 in different neighbourhoods around Limbe (Fig. 1; Ayonghe et al., 2004; Lambi et al., 2002; Thierry et al., 2008). Total estimated economic losses from damage to houses and community infrastructure was estimated at 1.5 billion FCFA (~3 million US dollars; Ayanji, 2004). Since 2001, repeated landslides have been recorded almost every year with 6 more casualties. For this reason Limbe and its neighbourhood was chosen as the pilot area for the present study. The combination of steep slopes, heavy rainfall and unplanned land use provide favourable conditions for sliding. In most parts of the study area, landslide occurrence has increased due to human activities (Che et al., 2011; Zogning et al., 2007).

Despite their frequent occurrence and dramatic impact on local communities, systematic data on this geomorphic process has only been collected recently for the Limbe region (Che et al., 2011; Thierry et al., 2008). As a result, no relevant geohazard or risk modeling has yet been developed nor have remediation strategies been explored. The relevance of this recurrent geohazard for land use and urban planning management is yet to be considered or integrated into existing schemes. National, regional and local authorities however recognize the problem as significant and are involved in efforts to enhance sustainable development or related policies.

So far, to minimise loss due to natural hazards (floods) within the study area, local authorities have identified structures located in flood-prone areas and marked them out for demolition. However, this is yet to be completed for slide prone areas because no detailed landslide susceptibility assessment has been done to map out landslide prone areas. This study therefore aims at adapting a data-driven bivariate landslide susceptibility model (for susceptibility zoning) developed in previous studies (Süzen and Doyuran, 2004; Vijith et al., 2009) that can be readily used by geoscientists in the developing world at the

![Fig. 1. Shaded relief of the study area on the SE foot slopes of Mt Cameroon with the location of major villages, road and river networks indicated. Note the presence of E–W trending asymmetric ridges of the Mabeta massif and several pyroclastic cones to the west of the study area. Insert highlights the position of the study area relative to Mt Cameroon, SW Cameroon.](image)
lowest possible cost. This model is implemented and tested in the Limbe area of SW Cameroon with the goal of identifying areas most likely to be affected by landslides in future.

2. Description of the study area

The study area lies between latitude 3° 59′ and 4° 20′ N and longitude 8°30′ and 9° 15′ E on the SE foot slopes of MC covering a total area of 361 km² (Fig. 1). It is characterised by two types of volcanic terrain: gently sloping lower slopes of MC made up of multiple lava flow and mudflow deposits with scattered scoria cones, and steep E–W trending parallel ridges and valleys dissecting weathered lava flows of the older Limbe–Mbeta massif (Che et al., 2011). Some of the low lying areas between the ridges and at the base of the cones are densely populated. The local population has increased significantly from 44,567 inhabitants in the Limbe municipality in 1987 to 84,223 in 2005 implying an average growth rate of 3.4%, and from 32,871 inhabitants in the Buea municipality in 1987 to 90,088 in 2005, i.e. a growth rate of 5.6% (Bureau Centrale des Recensements et des Etudes de Population, 2010). From these results, an average population density of 374 and 102 persons/km² was calculated for the Limbe and Buea municipalities, respectively. Consequently, people, houses, farms and villages are invading and encroaching upon steep deeply weathered and gravitationally meta-stable terrains particularly around the Limbe municipality characterised by numerous pyroclastic cones.

Hillsides are drained by numerous ephemeral streams, most of which flow only during the rainy season, and a few perennial streams (Fig. 1) the discharge of which vary dramatically with season. Observations from water wells found within the study area indicate that the regional groundwater level lies within the saprolite or at the saprolite–bedrock interfaces. Elevation within the study area varies from sea level to 1180 m above sea level. This large elevation range is associated with significant variations in the climate (temperature, rainfall) as well as variations in the vegetation and soil types. This region is characterized by thick, weathered, soils which can remain meta-stable for long time periods in the absence of destabilising factors such as rainfall, slope excavation by rivers or human activities (Che et al., 2011).

Annual rainfall in the study area is high, with yearly precipitations varying from 1500 to 6000 mm in the last 34 years for different stations within the study area (unpublished data provided by the Cameroon Development Cooperation, CDC, Meteorological Centre). The rainy season begins in March and ends in November with peak rainfall recorded from June to August and at times in September. June and July are characterised by intense and short lived rainfall usually lasting less than 5 h a day whereas August and September tend to experience less intense but more prolonged rainfalls that can last for 4 to 5 days in a row. Monthly rainfall totals frequently reach over 500 mm and sometimes up to 1000 mm in June, July and August. The mean annual temperature is ~26 °C and shows only limited variations of ~4° throughout the year. Humidity is generally above 85% (CDC meteorological centre). These characteristics correspond to the Am or tropical Monsoon climate according to the Koppen climate classification scheme (Peel et al., 2007).

3. Method of study and characterization of predisposing factors

Mitigation of landslide related hazards can only be successful when detailed information about the frequency, magnitude and character of slope failures within a particular area is known (Vijith et al., 2009). For this reason, the identification of landslide prone areas through susceptibility assessment represents a cheap and fast method in understanding this hazard and in ensuring that appropriate mitigation strategies are implemented. Landslide susceptibility assessment involves predicting where a potentially damaging landslide may occur without any reference to the time, or the intensity of associated damage (Sorriso Valvo, 2002; van Westen et al., 2006). It expresses the spatial correlation between predisposing terrain factors and the distribution of landslide scars. According to Jiménez-Perálvarez et al. (2009), landslide inventory is of prime importance in any susceptibility assessment project and determines the quality of the final results. In this study, landslide locations and associated controlling factors for each slide were determined by field work (Che et al., 2011). Maps of the identified factors were then produced for the study area and used to predict areas where future slides are likely to occur under similar environmental conditions.

Susceptibility and risk assessment with a minimum set of data, using a reproducible methodology is a major challenge to geoscientists (Glade and Crozier, 2005; Zezere, 2002). This is especially true for landslides in the study area due to the lack of historical data on landslide frequency and causal factors and, above all, deficiency in records of the exact date and time during which these landslides occur. Most proposed methods, irrespective of their operational differences, require the identification and mapping of factors conditioning slope failure, and an estimate of the relative contribution of each factor (Carrara et al., 1991, 2003; Clerici et al. 2002; Meusburger and Aiewell, 2008; Ruff and Czurda, 2008; Vijith et al., 2009). Susceptibility maps are based on the assumption that future slides will occur in similar areas and under the same conditions as past and present failures (Carrara et al., 2003; Guzzetti et al., 2005). They therefore depend strongly on the identification of landslide scars, characterisation of the properties of the failed areas prior to failure, and on the understanding of the failure mechanism for the prediction of where future slides are most likely to occur.

Susceptibility can be assessed through deterministic, heuristic or statistical approaches (Dai and Lee, 2002; Donati and Turriini, 2002; Duman et al., 2005; Ruff and Czurda, 2008; Santacana et al., 2003; Soeters and van Westen, 1996; Yalcin, 2008). Deterministic models involve site-specific characterisation of the geotechnical properties of the sliding mass and thus are capital intensive and can only be applied on a limited or restricted area. The heuristic approach, based on expert knowledge, is highly subjective and affected by limited reproducibility. The statistical approaches can either be bivariate or multivariate depending on the analysis method (Soeters and van Westen, 1996). In multivariate statistical analysis, factors are assumed to be related and are treated together while bivariate methods assume factor independence and the influence of each factor on landslides is treated independently and then summed up. The resulting susceptibility map is controlled by the theoretical bases and the assumptions made in the model (Carrara et al., 1999).

In this study we implement a data-driven bivariate landslide susceptibility model to build a susceptibility zonation map for the Limbe area. The seed cell method proposed by Süzen and Doyuran (2004) is modified and combined with the Infoval (Information value) method used by Vijith et al. (2009) using ArcGIS 9.1 software. This model is based on the following steps:

1. Systematic documentation of the location and characteristics of past landslides in the study area and converting them into seed cells;
2. Identification of key factors controlling slope stability, systematic mapping of these factors and transforming them into raster maps;
3. Calculation of zonal statistics between the seed cells and the factor maps to obtain the number of seed cells per factor class (seed cell or landslide density) which is later used to create weighted factor maps;
4. Summation of the weighted factor maps and classification of the quantitative value into 5 susceptibility classes.

This model was adopted because it is flexible, robust and has the ability to minimise expert subjectivity. Secondly, it does not require
intensive computer resources or extensive computer modelling experience.

3.1. Landslide mapping

From February 2008 to June 2010 intensive field surveys were undertaken to determine the spatial distribution of landslide scars (landslide inventory map) and field characteristics of landslides in and around the Limbe area. The inventory map was prepared at a scale of 1:50,000 based on field surveys due to the unavailability of aerial photographs. A total of 63 relatively small, shallow translation and rotational slides were observed. Typical landslide areas range from $10^1$ to $10^4$ m$^2$ and volumes are of the order of 10 to $10^4$ m$^3$. The results of the survey show that ~0.5% of the study area is affected by these landslides. Details of this survey including observed factors contributing to failure within the study area can be found in Che et al. (2011). Fig. 2a and b present the morphology of two landslides observed in the field at Moliwe and Kie villages, respectively. The landslide data set was divided into a training set (75%) used to calibrate the model and a validation set (25%) used to validate the model in ArcGIS 9.1.

Landslide locations were obtained by GPS at the centre of the main scarp. As slide scars are of relatively small size, typically <25 m wide, they were recorded as point data in a Geographic Information System (GIS). Considering that the best undisturbed morphological conditions (conditions before failure) and influencing factors can be extracted from the vicinity of the landslide itself, seed cells were selected using a 25 m buffer zone around each landslide point. This buffer interval was chosen because the width and length of the landslide depletion zone rarely exceed 25 m (Che et al., 2011). Hence the buffer zone includes the entire depletion zone of each slide and its direct surrounding and thus provides the best representation of the properties of unstable areas. As the factor raster maps were produced at 20 m spatial resolution, a 25 m buffer resulted in at least 4 seed cells per landslide scar. This technique produced 222 seed cells from the training dataset and 84 seed cells from the validation data set, from which the contribution of potential predisposing factors to landslide occurrence were evaluated.

3.2. Predisposing factors

There are no universal guidelines regarding the selection of factors in landslide susceptibility mapping (Ayalew et al., 2005). One parameter may be an important controlling factor for landslide occurrence in a certain area but not in another one. The selection of causal factors therefore needs to take the nature of the study area and data availability into account. According to Ayalew et al. (2005), factors selected for landslide susceptibility assessment in a GIS-based study, must be operational, represented over the entire area, non-uniform, non-redundant and measurable. Based on the above criteria, field observations, information from inhabitants of the affected areas, and available data, a total of 10 potential predisposing factors were considered in this study, namely rock type, soil type, land cover, slope gradient, slope orientation, stream density, distance from streams, distance from roads, distance from faults and major fractures, and mean annual precipitation (MAP). These factors were identified to be operational in at least some of the observed slide sites before being considered as a contributing factor to landslide occurrence within this area (Che et al., 2011). Thematic maps were prepared for each of these factors following the methods and data described hereafter. Table 1 summarizes the factors, data sources and factor classes used in this study.

3.2.1. Rock type

The lithologic map was constructed by compiling details from field observations, topographic maps and existing geologic maps (Endeley et al., 2001; Thierry et al., 2008), as well as interpretation of Landsat and ASTER images. Fig. 3a shows the lithologic map containing 7 rock types, namely porphyritic basalt, pyroclastic deposit (scoriae fall deposits), lahar deposit, alluvial deposits, massive and vesicular porphyritic basalts, beach sand-shingle and pillow lava. Porphyritic basalts occupy about 75% of the study area, lahar deposits 17% while the other classes each cover less than 5% each of the study area. Due to the limited amount of outcrops and the various data sources used, the positions of the lithological boundaries have a limited accuracy.

3.2.2. Soil type

Soil types influence the occurrence of landslides within a particular area through their geotechnical properties. Different soil types can be derived from the weathering of the same parent rock. The resulting product depends on the degree of weathering and the drainage condition operating during the weathering process. Soils within the study area are mottled, reddish brown, yellowish brown and/or pale yellow clayey silt, silt and clays with diverse physical and chemical properties and are described in more detail elsewhere (Che et al., in preparation). Due to limited spatial coverage of the soils analysed during this research project, the soil map produced by Hasselo (1961) was digitised and used in this study (Fig. 3b). According to Hasselo’s classification, seven soil types are recognized in the study area: old volcanic soil, ash soil, lava soil, lithosol, valley clay soil, stony soil and fragipan. In this study these seven major soil groups were adopted and make up 36%, 28%, 18%, 11%, 3%, 2% and 2% of the study area, respectively. Old volcanic soils refer to soils developed on basalt lava of the first volcanic phase (assumed to have formed during the first stage of activity along the Cameroon Volcanic Line in Mio-Pliocene). They are moderately deep soils characteristic of the Mabeta massif. Ash soil, lava soil, and lithosols developed on Quaternary to Recent volcanic products. Ash soils are soils developed on reworked lava fragments deposited as lahars. Lithosols refer to shallow soils developed on hard rock such as basalt lava flows. Valley clay soils, fragipans, and stony soils are younger soils with volcanic parent material. Valley clay soils form in the valleys separating the

![a](image1.png) ![b](image2.png)

Fig. 2. Field view of two landslides within the study area. a. June 29–30, 2009 slide at Moliwe; b. August 6, 2009 slide at Kie (Ngeme).
ridges of the Mabeta massif. Stony soils are less than 60 cm thick, characterised by undulating broken surfaces and correspond to gravelly and stony soils developed on "young lava flows". The distribution of the soil groups are presented in Fig. 3b. The accuracy of the soil map produced by Hasselo (1961) is not constrained but is expected to be similar to the one of the lithological map.

3.2.3. Land cover
Landslides are natural occurring phenomena and will occur whether people are there or not. However, human land use practice may accelerate the occurrence or play a significant role in the occurrence of landslides. A land cover map (Fig. 3c) was produced by supervised classification of a 30 m spatial resolution orthorectified
Landsat ETM+ image of the Mount Cameroon region, acquired on December 10, 2000. This classification was based on observed variations in spectra and texture of objects on the Landsat ETM+ image and was calibrated using field observations. Because of significant cloud cover, results of the classification were edited and simplified by manual digitisation. Four main land cover types were considered, namely mixed forest/farmland, plantations, built-up areas, and mangrove forest. These classes make up ~58, 36, 6, and 1% of the study area, respectively. Based on validation from field observations, the land cover map has an accuracy of the order of the Landsat image spatial resolution (~30 m).

3.2.4. Slope gradient and slope orientation
It has been observed that slope failure is more common on steep slopes than on gentle slopes. However above a certain threshold the frequency of landslides decreases as very high slope gradients will not support the accumulation of soil. Thematic maps of slope gradient (Fig. 3d) and slope orientation were generated as 20 m grids from a Digital Elevation Model (DEM). The DEM was obtained by interpolating 20 m contours lines digitised from a georeferenced 1:50,000 topographic map of the study area using the "Topo to raster" interpolation function of ArcGIS 9.1. Slope gradient ranges from 0 to 43° and were regrouped into 8 classes of 5° intervals, all the pixels above 35° being grouped in one single class. Tests were made to assess the influence of the class ranges on the derived factor class weight, but an equal interval was found to be the most rational choice.

Slope orientation, which represents the direction of maximum slope was categorised into 8 classes of 45° intervals, i.e. into N, NE, E, SE, S, SW, W and NW facing slopes.

3.2.5. Proximity to streams and stream density
The proximity to streams is considered as a potential controlling factor as streams undercutting a slope base have been recognized to be the cause of several landslides in the region (Che et al., 2011). Proximity to streams is implemented by applying the Euclidean distance function in ArcGIS along the streams and rivers digitised from the topographic map. The distance is then reclassified into 7 classes of 50 m interval, with all pixels further than 300 m from drainage lines grouped into a single class as it is assumed that the influence of the stream would be negligible beyond such a distance. Based on topographic map digitisation, checked against drainage network derivation from the DEM, the mapped river courses are assumed to be accurate to a few tens of meters.

To approximate the regional distribution of groundwater conditions, a drainage density map (Fig. 3e), which defines the number of line elements of fixed length in a fixed area (Süzen and Doyuran, 2004), was obtained by a non interpolative mean using the density function in ArcGIS. The stream drainage density map was computed with a search radius of 600 m and classified into 7 classes of equal interval of density values.
3.2.6. Proximity to roads

Proximity to roads is also considered as a potentially important factor because road construction is usually accompanied by excavation in some areas and the addition of material to the slope in other areas. This might result in changes in the slope line or may be accompanied by the creation of artificial slopes or road cuts that might be affected by landslide activities (Che et al., 2011). The role of this factor on the occurrence of landslides is evaluated by applying multiple buffers (50 m increments) around roads digitised from the topographic map and corrected by tracking new roads with a Garmin GPS 60CSX receiver (Fig. 3c). The 50 m buffer was chosen as a trade-off between the 20 m resolution of the factor map and the accuracy of the road mapping from the initial topographic map. The accuracy of the road mapping from the topographic map has been checked with GPS tracking and has been found to have accuracy of ~20 m. Areas located at a distance greater than 200 m from a road were considered as not affected by road-related instability and grouped into a single class.

3.2.7. Proximity to major fractures and lineaments

Faulting results in fracturing and destabilisation of rock and soils and thus was considered as a potential factor contributing to slope instability. Field observations indicate that rocks within the study areas are highly fractured and weathering is non-uniform. Faults and major fractures were extracted from the geologic map produced by the GRNP (Management of Natural Risks and Civil Protection) project (Thierry et al., 2008) and multiple buffers of 100 m incremental distance used to generate a distance-to-fault map. No accuracy constraint exists for the position of these faults which were mostly extracted from morphological interpretation. The existence and active nature of these structures is thus subject to uncertainty. The area is characterised by low magnitude earthquakes and not very active faults. Hence their destabilizing potential will tend to decrease with increasing distance from the fault line. A 100 m interval is thus dimmed appropriate to grasp the influence of faults on landslide occurrence.

3.2.8. Mean Annual Precipitation (MAP)

MAP is considered as a factor potentially contributing to slope instability as rainfall is the principal source of groundwater recharge coupled with the fact that the area is characterised by a long rainy season that lasts at least 8 months per year. The spatio-temporal distribution of rain is highly variable within this region. Mean annual rainfall distribution therefore provides a general picture of groundwater distribution within the study area and can better explain the long term effect of soil water on slope destabilization. The lack of long term daily rainfall data and of well dated landslide events limit our ability to analyse rainfall as a triggering factor controlling the timing of landslide occurrence. MAP is obtained by inverse distance interpolation of 20–34 years mean annual rainfall from 12 stations located within and directly outside of the study area (Fig. 3f). The Inverse Distance Weighted Interpolation method used here does not enable accounting for topographic control on rainfall distribution, but constraints are lacking to calibrate a more realistic interpolation. MAP ranges from ~2000 to ~4400 mm/year. This range was subdivided into 6 classes of 400 mm interval to cover the entire range of values.

4. Landslide susceptibility evaluation

Bivariate statistical analysis involves the determination of the abundance of landslides within each factor class. Fig. 4 is a schematic illustration of the steps involved in the susceptibility evaluation procedure used in this study. To evaluate the influence of each factor class on landslide susceptibility, the distribution of the seed cells derived from the training dataset for each factor classes was calculated. The frequency of the seed cells per factor class (seed cell density) was then used to calculate the landslide density per factor class based on the following formula

\[
D_j = 10000 \times \frac{\text{Npix}(SC)_j}{\text{Npix}(F_j)}
\]

where

- \(D_j\) = slide density for the factor class \(j\);
- \(\text{Npix}(SC)_j\) = number of seed cells within a factor class \(j\);
- \(\text{Npix}(F_j)\) = number of cells within the factor class for the entire study area.

To determine the influence of each factor on the entire area, weighting values were introduced, which, following Süzen and Doyuran (2004) enable the comparison of the slide density per factor class to the slide density in the entire study area. This is done by subtracting the landslide density of the entire area from the landslide density of each factor class, that is,

\[
W_j = D_j - 10000 \times \frac{\sum \text{Npix}(SC)}{\sum \text{Npix}(F)}
\]

where

- \(W_j\) = weighted factor for class \(j\) (Infoval or Information value);
- \(\sum \text{Npix}(SC)\) = total number of seed cells within the study area;
- \(\sum \text{Npix}(F)\) = total number of pixels within the study area.

To avoid negative weighting values, the weighted values are rescaled by adding the absolute value of the minimum weighted value in each factor (the largest negative value) to the weights of all the other factor classes in each factor. A low weighting value indicates a low tendency for landslides to occur within a given factor class. The rescaled weights (Infoval) are assigned to each factor class to obtain weighted factor maps. These factor maps are then summed up using the raster calculator to obtain a landslide susceptibility index value for each pixel.

The resulting susceptibility indices which are continuous variables are then reclassified into five susceptibility classes (very low, low, moderate, high and very high susceptibility). It should be noted that there are no universally acceptable norms with regards to the division of continuous data into discrete values (Ayalew et al., 2005). In this study, the susceptibility indices were reclassified into five classes with the mean susceptibility index taken as the lower boundary of the moderate susceptibility class. Other classes were then defined using the standard deviation as the class boundaries. Pixels with a susceptibility index value greater than the mean plus twice the standard deviation were thus considered to belong to the very high susceptibility class.

This classification methods is based on methods used in mineral exploration, where element concentration less than the mean plus two standard deviations of world averages are considered as normal background values whereas values above the mean plus two standard deviation are considered as enrichment zones or ores. Although this classification is based on a subjective choice, it was shown to result in acceptable results and as it is based on the statistical distribution of susceptibility values, it can be reproduced in a comparable manner for different factor combinations. Model accuracy was evaluated with the training seed cell dataset and its performance in predicting future landslides was evaluated with the validation datasets. Success rate curves are drawn to test the prediction potential of the susceptibility model.
5. Relationship between factors and seed cells

Histograms of the number of pixels in each factor class and the corresponding number of training seed cells within each factor class in the study area are shown on Fig. 5. From calculated Infoval, rock types and slope gradients are the most influential parameters for landslide occurrence in the study area with values of 15.5 and 12.0, recorded on pyrolastic materials and on slope gradient 25–30°, respectively. 68% of the seed cells fall in porphyritic basaltic lava flows, 28% in pyroclastic deposits, and 3% in mudflow deposits (Fig. 5a). Looking at the relatively high proportion of seed cells on the pyroclastic material relative to its surface extent, it can be noted that pyroclastic materials are more susceptible to failure than the lava flows and mudflow deposits.

Based on soil types, 77% of the training seed cells occur within old volcanic soils, 12% in valley clay soils, 8% in ash soils, while the others contain very low proportions or no seed cells at all (Fig. 5b). It is worth noting that old volcanic soils which make up 28% of the study area, host 77% of the seed cells, resulting in the highest Infoval (6.7) suggesting that old volcanic soils are more susceptible to failure than other soil types, probably due to their greater thickness. Lower but significant weights are assigned to rocky and valley clay soils. All other classes show extremely low weights suggesting lower susceptibility to failure.

Of the 4 land cover classes mapped in the area, forest covers 58%, plantations 36% and built-up areas 6% of the study area (Fig. 5c). These land cover types are associated with 64, 18, and 18% of the seed cells, respectively, resulting in the highest Infoval for built-up areas, followed by forest.

Slopes with gradients<10° make up 69% of the study area and contain less than 15% of the seed cells (Fig. 5d), whereas slopes with gradients from 10–30° represent 31% of the study area and contain 87% of the seed cells. Only one seed cell is recorded on slopes<5°. Maximum Infoval for the slope factor is associated with the slope gradient interval 25–30°, followed by the intervals 20–25° and 15–20° indicating a high probability of failure within these slope categories. It is worth noting that the slope gradients measured in the field are slightly different and generally higher than those obtained from the DEM probably due to the DEM resolution and the interpolation method used. In the field slides occurred only on slopes greater than 15° but were dominant on slopes with gradients between 26 and 40° (Che et al., 2011).

The most dominant slope direction are slopes oriented to SE, S and E making up 32%, 24% and 15% of the study area, respectively (Fig. 5e). Each of the other classes represents less than 9% of the study area. The number of seed cells is highest on S facing slope while N, SE, SW, NW, and W facing slopes have almost the same number of seed cells. High Infoval is recorded on W, N and NW facing slopes while moderate values appear on SW and NE facing slopes. All other classes represent low to very low probability of failure. S and SE facing slopes mostly characterise the low angle foot slopes of Mt Cameroon where no or limited slides occur (Fig. 5e). No straightforward explanation has so far been found for the relative concentration of slides. One hypothesis is that it is related to rainfall distribution patterns with rain brought in by the SW-NE Tropical Monson Winds from the St Helena anticyclone.

From the existing relationship between the training seed cells and the factor proximity to streams, it is noted that the distribution...
of seed cells does not vary significantly among the factor classes. However, minimum values are recorded for the class interval 250–300 m. Similarly, calculated Infoval do not vary greatly and range from 0–3.5 (Fig. 5f). These values are small when compared to maximum Infoval calculated for other factor classes, and thus suggest that proximity to streams does not play a major role in the location of landslide scars within the study area. These results are in contrast with field observations where stream undercutting was noted to be an influential factor in some of the observed landslides. The low Infoval might be accounted for by the fact that streams were digitised from a 1:50,000 map and it is likely that not all streams could be observed and accounted for at this scale. The low Infoval might also result from the fact that only a few landslides are caused by stream undercutting but most of them are not.

The factor stream density distribution (Fig. 5g) categorises 68% of the training seed cells into the moderate and high stream density categories and thus a higher Infoval is obtained for these categories relative to the low or very high stream density classes. Assuming that stream density gives an idea of the regional distribution of groundwater conditions, regions with very high and extremely high density should correspond to low lying water-saturated areas, flood plains and stream channels where slope failure is less likely to occur. Areas with high and medium densities are more likely to fail because of high soil water content, positive pore water pressure and a net negative influence on soil strength. Lowest stream densities indicate dryer soils where negative or low pore water pressure increases stability.

The factor proximity to roads shows a bimodal distribution for the seed cells within the various classes. 21% of the seed cells are located

Fig. 5. Distribution of factor class associated seeds and normalised factor rating (Infoval). Py: pyroclastic material; AD: Alluvial deposits; PBF: porphyritic basaltic lava flows; MB: massive basalt; MF: mudflow deposit; PVB: porphyritic vesicular basalt; BSPL: beach sand, shingle and pillow lava; AS: Ash soil; F: fragipan; LS: lava soils; L: Lithosol; VCS: valley clay soil; RS: rocky soil.
within <50 m from roads. This percentage drops to 8% in the interval 50–100 m and then increases progressively with maximum value at distance above 150 m suggesting that there are two types of slides in this area: road-related and non road-related slides. Calculated Infoval indicates that maximum Infoval is recorded in the 0–50 m category, followed by the 100–150 categories (Fig. 5h). This suggests that the presence of roads affects the occurrence of some of these slides while others occur in areas which are not impacted by roads.

The total number of pixels per class decreases progressively with increasing distance from lineaments (Fig. 5i). Similarly, Infoval decreases gradually with increasing distance. However, maximum Infoval (4.79) is relatively low when compared with other factors. In addition, the variation in Infoval for various classes is not significantly large as most values range between 2 and 4.8 with only the class >600 m having Infoval less than 2. This means that the presence of fractures in this area contributes positively to failure although the contribution is not significant. Fractures probably enhance infiltration of ground water resulting in positive pore pressure build-up. Furthermore, seismic activity in this area is characterised by low magnitude earthquakes (Atiba and Ntepe, 1997). The potential influence of low magnitude seismic activity cannot be completely ruled out.

High Infoval is observed for areas that receive between 3600 and 4000 mm of rain annually, followed by those that receive 3200 to 3600 mm (Fig. 5j). Lower values are obtained for areas that receive less amounts of rain per year. As earlier stated MAP is assumed to provide a general picture of groundwater distribution within the study area and can better explain the long term effect of soil water on slope destabilization.

### Table 2

<table>
<thead>
<tr>
<th>Susceptibility ranking</th>
<th>Susceptibility index</th>
<th>Pixel % in study area</th>
<th>Proportion of Training seed cells</th>
<th>Proportion of validation seed cells</th>
</tr>
</thead>
<tbody>
<tr>
<td>All factors considered (10 factors)</td>
<td>Very low</td>
<td>2.5–9.8</td>
<td>13.8</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>9.8–20.1</td>
<td>43.6</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Moderate</td>
<td>20.1–30.5</td>
<td>25.5</td>
<td>16.5</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>30.5–40.4</td>
<td>12.5</td>
<td>36.5</td>
</tr>
<tr>
<td></td>
<td>Very high</td>
<td>40.8–69.2</td>
<td>4.6</td>
<td>46.5</td>
</tr>
<tr>
<td>X = 20.1, sd 10.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All factors except distance to streams and distance to faults/lineaments (8 factors)</td>
<td>Very low</td>
<td>2.5–7.2</td>
<td>12.2</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>7.2–16.7</td>
<td>46.9</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Moderate</td>
<td>16.7–26.1</td>
<td>24.5</td>
<td>22.0</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>26.1–35.6</td>
<td>11.6</td>
<td>31.5</td>
</tr>
<tr>
<td></td>
<td>Very high</td>
<td>35.6–65.5</td>
<td>4.7</td>
<td>46.0</td>
</tr>
<tr>
<td>X = 16.7, sd 9.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Best factor combination (slope, land use, MAP, Stream density, Slope orientation and distance from roads) 6 factors without mask</td>
<td>Very low</td>
<td>1.5–5.6</td>
<td>14.8</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>5.6–11.8</td>
<td>41.8</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Moderate</td>
<td>11.8–18.0</td>
<td>26.5</td>
<td>17.5</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>18.0–24.2</td>
<td>12.2</td>
<td>38.0</td>
</tr>
<tr>
<td></td>
<td>Very high</td>
<td>24.2–42.5</td>
<td>4.7</td>
<td>44.0</td>
</tr>
<tr>
<td>X = 11.8, sd 6.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Best factor combination (slope, land use, MAP, Stream density, Slope orientation and distance from roads) 6 factors with mask</td>
<td>Very low</td>
<td>1.5–5.6</td>
<td>27.0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>5.6–11.8</td>
<td>33.5</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Moderate</td>
<td>11.8–18.0</td>
<td>23.8</td>
<td>17.5</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>18.0–24.2</td>
<td>11.4</td>
<td>38.0</td>
</tr>
<tr>
<td></td>
<td>Very high</td>
<td>24.2–42.5</td>
<td>4.4</td>
<td>44.0</td>
</tr>
<tr>
<td>X = 11.8, sd 6.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
factors was considered for this selection and prediction performance of several factor combinations was assessed. The factor combination that categorises most of the training and validation seed cells in the high and very high landslide susceptibility classes while at the same attributing the smallest proportion of the study area into the high and very high susceptibility classes was selected as the preferred model to construct the final susceptibility map.

First, a model where all the factors were included was assessed. Generated susceptibility indices were evaluated and a success rate curve was constructed. The success rate curve (plots of the cumulative percentage of training seed cells in each of the susceptibility class against the cumulative sum of pixels in each susceptibility class arranged in decreasing susceptibility ranking (Chung and Fabri, 1999, 2003; Conoscenti et al., 2008) were constructed. It allows us to estimate the goodness of fit of the predictive model by representing the proportion of training seed cells that are correctly categorised into the high and very high categories.

Second, a series of models with an increasing number of controlling factors was assessed. Each successive model introduced one additional factor, with factors being introduced by decreasing order of recorded maximum Infoval. The accuracy of each model was evaluated by the construction of success rate curves. If the added factor did not increase the slope of the first portion of the curve, it was considered redundant and eliminated from the set of factors because its impact is already accounted for by the other factors. This way, the factors proximity to streams and proximity to lineaments and major fractures were excluded. For two models with a comparable success rate curve, the one with the lowest number of controlling factors would be favoured. It is worth noting that a factor combination that shows the highest true positive value with the training seed cells does not necessarily mean the best factor combination. It just indicates that it provides an accurate estimate of the quality of the analysis.

A third set of models similar to the second one was assessed with the factor lithology eliminated from the set of factors due to uncertainties in the boundaries on the geological map. This was required despite the high Infoval of 15 for pyroclastic rock as it resulted in high to very high susceptibility classes in the centre of Limbe, despite low angle to flat topography. This highlights the need to reassess the exact position of lithological boundaries in the study area.

7. Model validation

All the susceptibility maps generated were validated with the validation dataset and sensitivity ratio i.e. ratio between true positives observed with the validation dataset and the proportion of the

Fig. 7. Landslide susceptibility map of Limbe generated from a combination of seed cells and the Infoval bivariate method based on a combination of six weighted factors: slope gradient, land cover, mean annual precipitation, stream density, slope orientation and proximity to roads.
study area categorised into the high and very high susceptibility classes calculated.

Success rate curves from the training and validation seed cells for the three factor combinations discussed above are shown in Fig. 6. The susceptibility map generated using all factors (10) considered in this study correctly classifies 83% of the training seed cells and shows a lower prediction performance of 78.6% for the validation seed cells. With this combination, 17.1% of the total area is categorized in the high and very high susceptibility classes.

Eliminating the factors proximity to streams and proximity to lineaments and major fractures, the accuracy decreases to 77.5% for the training seed cells and 77.4% for the validation seed cells with 16.3% of the study area categorized in the high and very high susceptibility classes. The best trade-off between the model accuracy and the number of factors was obtained using only six factors: slope gradient, land cover, MAP, stream density, soil type, and proximity to roads. This model enables to categorize 82% of training seed cells and 78.6% of the validation seed cells in the high and very high susceptibility classes (47.6% in the very high, and 31% in the high susceptibility class, respectively). Based on this factor combination, 16.9% of the study area falls in the high and very high susceptibility categories. These results are similar to the ones of the first model including 10 factors. Only 7% of the validation seed cells are attributed to the low susceptibility class and none to the very low susceptibility class (Table 2).

This is an indication that the model has a high predictive power. The distribution of various susceptibility ranking, training and validation results for the 3 scenarios described above are given in Table 2.

Despite the good prediction performance of the model, some areas observed to have slopes less than 2° in the field appear in the high and very high categories, particularly in the town of Limbe. These areas are characterized by a combination of parameters with high Infoval, such as built-up areas, a close proximity to roads, and high mean annual rainfall, resulting in a high susceptibility despite the low slope gradient. To correct for this, a mask that attributes very low susceptibility to areas with slope gradient less than 2° irrespective of all other factor combinations was applied. The applied mask however did not change the success rate of the model but reduced the total amount of pixels classified in the high and very high susceptibility classes by 0.8 and 0.2%, respectively, ie it categories 15.8% of the study area into the high and very high susceptibility classes (Table 2). Fig. 7 shows the susceptibility map of the Limbe area obtained from the best factor combination after the application of the mask.

8. Landslide risk assessment

Landslide risk is defined as the combination of high hazard susceptibility and the presence of population or infrastructure that can...
be affected by the landslide (Varnes, 1984). In this study, risk is perceived as the likelihood that a specific structure would be affected by a landslide. It can be estimated by overlaying elements at risk and the landslide susceptibility categories. Elements located in the high and very high landslide susceptibility zones are considered to be at high to very high risk.

To estimate the degree to which humans and infrastructure in the study area are at risk of being affected by landslides, an inventory of roads and key individual structures frequently occupied by a large number of people at the same time (e.g. churches, markets, hospitals, schools, financial institutions) was made and the outline of built-up areas was used. The outline of built-up areas acts as a proxy for the total population, while the road network acts as a fingerprint to the disruption of economic activities. Limits of built-up areas in 2000 and 2008 were extracted from two Landsat ETM+ images acquired on December 10, 2000 and January 31, 2008, respectively (Fig. 8). These were converted to raster files and zonal statistics were performed in comparison with the susceptibility map to identify the proportion of these areas in each of the susceptibility classes. The specific location of the newly built-up areas between 2000 and 2008 will indicate if urban expansion is occurring in zones of higher landslide susceptibility or not.

Built-up areas covered 22 km² in December 2000, i.e. about 6% of the study area. 6 km² of this area lies in the high to very high susceptibility class. By 2008, the total built-up area had doubled to 45.6 km², i.e. 12.6% of the study area. Of the 24.2 km² increase in built-up areas between 2000 and 2008, 9% (2.2 km²) of it lies in the high and very high susceptibility classes (Table 3). These values suggest a tremendous increase in urbanisation and a corresponding extension of life-line into both hazardous and safe areas. Approximately 253 km of both paved and unpaved roads exist in this region. Of this length, 69.3 km, i.e. 23% of the road network is likely to be affected by future failures (Table 3). Of the 172 individual structures recorded, 27.9% of them are located in the high and very high susceptibility categories and are thus highly vulnerable. Individually, there are 10 schools, 8 bridges, 3 health facilities and 14 government administrative structures in the high and very high susceptibility categories (Table 4).

9. Limitations of the model

Despite its high predictive power, the proposed model has some limitations.

- The model assumes that landslides will happen under influence of the same combination of factors (principle of uniformitarianism) whereas field observations indicate that some slides are caused by a specific set of factors (e.g. proximity to a river in conjunction with other factors like land cover and slope gradient; Che et al., 2011).
- This susceptibility analysis requires continuous updating of the input factors: a change in the land cover might, for example, significantly increase the landslide susceptibility of a specific area.

<table>
<thead>
<tr>
<th>Susceptibility class</th>
<th>Proportion of built-up area in 2000 (%)</th>
<th>Proportion of built-up area between 2000 and 2008 (%)</th>
<th>Road network at risk (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very low</td>
<td>33</td>
<td>36</td>
<td>23</td>
</tr>
<tr>
<td>Low</td>
<td>16</td>
<td>40</td>
<td>21</td>
</tr>
<tr>
<td>Moderate</td>
<td>24</td>
<td>15</td>
<td>33</td>
</tr>
<tr>
<td>High</td>
<td>13</td>
<td>06</td>
<td>16</td>
</tr>
<tr>
<td>Very high</td>
<td>13</td>
<td>03</td>
<td>07</td>
</tr>
<tr>
<td>Total</td>
<td>22.6 km²</td>
<td>24.2 km²</td>
<td>261 km</td>
</tr>
</tbody>
</table>

- This model tends to oversimplify factors that condition sliding by considering only those factors that are easily mappable or can be derived from the DEM. It neglects geotechnical characteristics of the soil which vary enormously in space.
- Only the depletion or release zones of the landslides are considered and the run out distance is neglected, thus the risk for future slides is underestimated.
- The bivariate approach takes into account the independent relationships of individual factors with landslide occurrence, without accounting for the possible combination of factors that might act together in increasing the slope instability.

10. Discussion and conclusions

Understanding the factors and processes that lead to the occurrence of landslides is fundamental in managing hazards and in understanding landscape evolution. Based on this fundamental principle, this study presents the results of a comprehensive landslide susceptibility assessment for the Limbe area. The resulting susceptibility map describes the zonation of relative probability of future landslide occurrence based on field identification and statistical analysis of possible contributing factors. Landslide densities for 10 different potentially contributing factors and their weight values (Infoval) are computed and used to rank the importance of each factor class.

The quality and accuracy of the output susceptibility map depends on the quality of the input parameters. In this case, the geologic map proved to be affected by too many uncertainties and was not used in the model despite the fact that the bivariate analysis highlighted the concentration of landslides on pyroclastic rocks. Uncertainties in the quality of the geologic map used in this study might have a neutralising effect on the contribution of distance to lineaments and major fractures. Decreasing Infoval with increasing distance from the lineaments and major fractures is understandable considering that the area is characterised by low intensity earthquakes. A decreasing influence of seismic acceleration with increasing distance from the fault line could play a role in the landslide distribution but a more detailed study of the distribution and characteristics of active geological structures is required to constrain this potential control.

In this study, the seed cell approach is combined with the Infoval method which is a bivariate statistical method to assess the spatial distribution of susceptibility of rain-fall induced shallow translational slope destabilisation in the Limbe study area. This method was adopted because the major failure type within the study area involves small shallow translation slides which are most suitable for the seed cell approach since the slope form does not change significantly after failure (Süzen and Doýuran, 2004). In addition, the method reduces the impact of expert opinion in susceptibility determination since no special ranking measures are introduced except for those that result from data-driven factor weight calculation. This implies
that the combined seed cell/Infoval method is an objective method when compared to other bivariate statistical methods.

Generally, the model has a good predictive power as it categories 78.6% of validation seed cells into the high and very high landslide susceptibility classes. It is possible that the seed cells in the medium and low susceptibility classes result from the fact that the observed slides are rather small when compared to the dimensions of the buffer used in generating the seed cells. They may also be resulting from errors in mapping the boundaries of some parameter classes or to locally steep slopes not accurately represented in the 20 m DEM (e.g. terraced hill slopes with local sub-vertical slopes).

In an earlier study, Thierry et al. (2008) used slope as the principal factor in landslide susceptibility zonation and categorized ca 80% of the Mabeta massif in the high and very high susceptibility categories. According to our field observations and our susceptibility assessment, these previous results overestimate the susceptibility of this area as slope alone is not able to account for the spatial distribution of landslide probability. Our analysis suggests that the best factor combination that accounts for landslide spatial distribution in the region includes slope gradient, land cover, mean annual precipitation, slope orientation, distance to road and stream density. Distance to streams, and the proximity to faults have minimal influence on the occurrence of landslides in this area although field observations suggest that proximity to streams did control the occurrence of some landslides. This indicates that factors which are the actual cause of a specific landslide cannot always be used to account for the spatial distribution of all landslides in a region, as the specific controlling factors differ from one slide to another. Instead, stream density which acts as a proxy to groundwater distribution (Vijith et al., 2009) or provides clues of the regional hydrogeological properties of the rock (Süzen and Doyuran, 2004), and the mean annual rainfall are more significant factors in accounting for the spatial distribution of observed landslides.

From field surveys, it was noted that construction works, particularly on weathered pyroclastic cones, are abundant (Che et al., 2011). These are not usually accompanied by any stabilisation measures thereby enhancing susceptibility particularly in steep areas made up of pyroclastic material. Excavation for any form of construction changes the slope line by creating terraces and sub-vertical slopes while addition of material results in extra load on the slope. This might account for the high weighted values observed for areas very close to roads and in built-up areas.

From the susceptibility map, it is observed that significant portions of the study area, especially around Limbe and in the Limbe West of Limbe there are low susceptibility areas that could also be risk of loss of life and to minimize other adverse impacts. Stabilisation and remediation measures are essential to decrease the erosion of built-up area on meta-stable slopes is unavoidable, adequate construction and maintained, particularly in areas characterized by loose soils in order to divert runoff or decrease water saturation in the soil. The landslide susceptibility map produced here can be used by local authorities to raise the awareness and preparedness among the population for future landslide occurrence. Billboards explaining the adverse impacts of landslides have already been placed in built-up areas located in the high hazard zones. For detailed urban planning and enforcement of exclusion zones in high hazard areas however, detailed site specific investigations are strongly recommended.

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