# LANDSLIDE SUSCEPTIBILITY MAPPING USING GIS-BASED WEIGHT-OF-EVIDENCE MODELLING IN CENTRAL GEORGIAN REGIONS

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***Summary:*** *This paper explains the procedure for the generation of a landslide susceptibility map at regional level in Georgia. At the first place, this research presents the results of the weight-of-evidence model applied to estimate the probability of landslides manifestation. A spatial database, including causative factors associated with landslides was constructed from geological maps and satellite data products. The factors that influence landslide occurrence, such as terrain slope, aspect, curvature, elevation, flow accumulation and distance from drainages were calculated from a Sentinel-1 digital terrain elevation data (DTED). Lithology is derived from the Georgia's geological map. Vegetation cover map is retrieved from Sentinel-2 multispectral satellite imagery.*

***Key words****: landslide, weight-of-evidence, landslide hazard mapping, remote sensing, digital terrain elevation data.*

## Introduction

Landslides have long been recognized as a frequent natural hazard in the mountainous terrain of tropical and subtropical environments [1]. Particularly, in accordance with EM-DAT International Disaster Database of the Centre for Research on the Epidemiology of Disasters (CRED) the landslides are the reason of around 26,000 deaths in a period from 2000 to 2014. Therefore, areas susceptible to landslides should be identified to prevent the damage at regional and local scale. In this case, landslide susceptibility assessment is required [2].

In this research, the effects of intrinsic and extrinsic variables associated with landslides are considered as causative factors. The intrinsic variables refers to landslide risk site internal factors such as bedrock geology, geomorphology, soil type, slope gradient, slope convexity and concavity, elevation, engineering properties of the slope material, land use pattern, drainage and escape network etc. The extrinsic variables are external factors such as heavy rainfall, glacier outburst, seismic activity that change over a very short time span and are thus very difficult to estimate.

In addition, the natural hazards statistics is required for landslide susceptibility assessment. Thus, our research is focused on the probability estimation of landslide occurrence prospects within the sites of historical landslides as well.

There are four different approaches to the assessment of landslide hazard: landslide inventory-based probabilistic, heuristic (which can be direct geomorphological mapping, or indirect qualitative map combination), statistical (bivariate or multivariate statistics) and deterministic. In addition, a wide range of models are used based on these approaches [3]. However, the main purpose of this study is to apply the weights-of-evidence modelling for central Georgia landslide hazard assessment.

Substantial contribution for landslide hazard mapping made the implementation of satellite data products as a source for causative factors generation and easier spatial results interpretations [4]. Complex using of Remote Sensing and Geographical Information Systems (GIS) have wide-range applications in the field of geo-sciences [5]. For example, global databases such as the EM-DAT International Disaster Database, the NASA Global Landslide Catalogue and the Global Fatal Landslide Database (GFLD) are usually based on these technologies [6]. Therefore, all causative factors thematic maps used in this research are entered into the GIS database and integrated with a landslide inventory map. The database will assist with landslides investigation through the implementation of satellite data products as a source for causative factors generation and easier spatial results interpretations. Particularly, the database will assist to determine the effect of each causative factor associated with historical or eventual landslides.

## Study area

Georgia belongs to the one of world's most complex mountainous regions according to the scale and frequency of natural hazardous processes. Complicated topography is one of the major condition for landslides activation in this country. The Lesser Caucasus Mountains and Greater Caucasus Mountain Range cross the country. The Greater and Lesser Caucasus are two fold-and-thrust belts separated by the Rioni Basin in the Black Sea and the South Caspian–Kura Intermontane Depression. Fault-bend folds and fault-propagation folds are widespread, with evidence of thin-skinned tectonics in both the Rioni and Kura fold-and-thrust belts. Therefore, the topography elevation ranges from sea level to the Black Sea to over 5000 m in the Caucasus Mountains [7, 8].

The climate of Georgia is different from west to east. Specifically, the western part of Georgia lies within the northern periphery of the humid subtropical zone. Eastern Georgia has a transitional climate from humid subtropical to continental. Thus, the annual precipitation ranging from 1000 to 4000 mm at the west and from 400 to 1600 mm at the east [8].

Terrane is mainly composed of pre-Cambrian and Paleozoic rocks. Paleozoic granites have intruded Granitic-metamorphic complex presented by different crystalline schists and paragneisses. Lower Jurassic rocks here presented by shallow sea sandy-argylleous rhythmical sediments with lenses of limestones. This massif consists of Paleozoic schists intruded by numerous Paleozoic and Jurassic gabbros, quartz diorites, granites accompanied by pegmatite veins. Paleozoic rocks are overlapped by shallow water Jurassic clays and Cretaceous limestones [8].

In this research we apply the weight-of-evidence modelling for the three of Georgian administrative regions Shida Kartli, Mtskheta-Mtianeti, Kvemo Kartli. We concentrate the study in this region because of the known landslide potential, slope angle and complex drainage system.

We concentrate our study on a site located in the central western part of Georgia (42.30°N, 43.48°E) because of the known landslide potential, slope angle and field access there.

## Weight-of-evidence model

The Bayesian inference was used to simulate the influence of selected geophysical factors onto the landslide overall hazard. The likelihood ratio was assigned as the basic weight $w_i$ of each $i$-th influencing factor $F_i$:

$$w_i = \ln \frac{P(F_i \mid A)}{P(F_i \mid B)} = \ln P(F_i \mid A) - \ln P(F_i \mid B)$$

where $P(F_i|A)$ is a conditional probability of $F_i$ under landslide occurrence constraint, $P(F_i|B)$ is the same one otherwise [9].

The conditional probabilities of each factor for landslide occurrence/missing were determined on the basis of previously known statistics, and in the case of its insufficiency – by approximating with exponential model from the most likely down to the least likely factor values. When considering the significant number of factors then ones' expert ordering additionally used.

## Data acquisition

A DTED is a key to generate various topographic parameters, which influence the landslide activity in an area. Thus, the DTED were acquired by the phase interferometry of Sentnel-1 synthetic aperture radar (SAR) satellite system.

In this research the slope angle, lineament density, drainage effect buffer, flow accumulation and slope curvature are estimated using DTED derived from Sentinel-1A Single Look Complex (SLC) data products. The Sentinel-1 SLC stereo pair of 31 October 2018 and 12 November 2018 were retrieved for phase interferometry using Sentinel Application Platform (SNAP) software (http://step.esa.int/main/ download/ snap-download/). The 10×10 m pixel size DTED were obtained as an output of interferometric data processing.

The resulted DTED were used as a relative relief to derive thematic data layers like slope, aspect, drainage effect buffer, flow accumulation and lineament density.

Slope angle map. When the slope angle in our model increases, the geometry of the potential critical slip surface changes and probability of failure distributions rises extremely with slope angle increasing [10]. After the radar interferometric DTED were generated, it were used to calculate slope angle map using QGIS software (https://grass.osgeo.org/grass64/manuals/r.slope.aspect.html).

Lineaments' density map. Lineaments are straightened sections of terrain's relief. Their density is calculated as the aggregated length of lineaments per one km2. The higher the lineaments' density, the greater the probability of landslide [11].

Vegetation cover map. Vegetation density is an essential parameter for landslide hazard due to natural prevention ability. Sentinel-2 multispectral imagery in visible and near infrared bands is used to estimate vegetation cover fraction (VCF) [12].

Precipitation Map. The map of rainfall precipitation over the study area was obtained by averaging of 366 MODIS Total Precipitable Water satellite data product (MOD05_L2) for the period from 31 October 2017 to 31 October 2018. MOD05_L2 data product is available from Atmosphere Archive and Distribution System Data Download Scripts (LAADS DAAC) (https://ladsweb.modaps.eosdis.nasa.gov).

Geological map. Geological environment plays an important role in landslide susceptibility studies because different geological units have different susceptibilities to active geomorphological processes. Geological map of Georgia for 2004 developed by Georgian Department of Geology was used to map the study area and classify the lithology by rocks hardness [13].

## Analysis and results

All thematic maps of study area were stored in raster format with a 10×10 m pixel size. The weight-of-evidence calculation procedure was performed using SciLab numeric computation software (www.scilab.org). Since all of the maps are multi-class maps, containing several classes, the presence of one factor, such as dense forest implies the absence of the other factors of the same land use map. Therefore in order to obtain the final weight of each factor, the positive weight of the factor itself was added to the negative weight of the other factors in the same map.

The final result is the landslide hazard susceptibility map shown in figure.

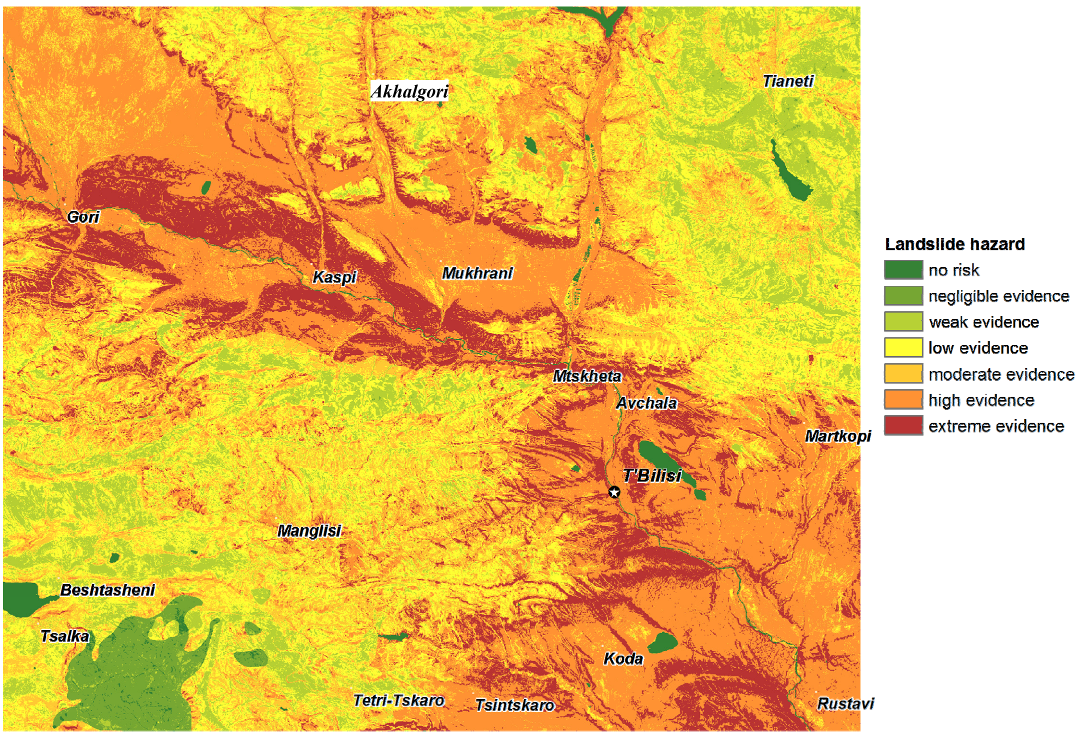


**Figure. Final landslide susceptibility map.**

On the resulting map, areas of a high evidence of landslide hazard mostly correspond to sharp slopes without vegetation. The areas of least probability of landslides are associated with the presence of hard rocks such as granite or carbonates. Water bodies excluded from landslide risk assessment by default. The presence of substantial vegetation cover significantly reduces the landslide hazard evidence down to low or weak inside the vegetative plots of terrain.

## Conclusion

GIS-based weight-of-evidence modelling is a convenient and efficient tool for preliminary mapping of landslide susceptibility, especially in difficult access regions.

Since terrain slope is the main contributor to landslide hazard, the use of up-to-date products of satellite radar interferometry is a mandatory stage in the remote sensing data processing for this purpose.

The data integration carried out in the assessment of landslide susceptibility allows to quantify and human-friendly visualize in a single map a lot of geospatial layers of landslide hazard factors.

The data obtained as a result of landslide susceptibility mapping have a good spatial correlation with the distribution of actual recorded landslide processes in the central regions of Georgia.

Future works should be focused on the development and verification of quantitative models for the various geophysical factors effect upon the landslide probability, as well as on the large-scale testing and accuracy evaluation of the proposed technique.

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