METEOR: Landslide Hazard Report

Report Number: M6.2b/P

22 April 2020

Author:

C. Dashwood

METEOR Landslide Hazard Report

Document Verification

Project	METEOR: Modelling Exposure Through Earth Observation Routines
Report Title	METEOR Title of Report
Related Milestone	M6.2
Reference as	C. Dashwood (2020) METEOR Landslide Hazard Report. Report M6.2b/P
Release Type	Public / ~~Confidential~~ / ~~Confidential with Embargo Period~~

Prepared by: Contributors		
Name(s): C. Dashwood	Signature(s):	Date(s): 16 April 2020
Approved by: Project Manager		
Name: K Smith	Signature:	Date: 22 April 2020
Approved by: UKSA IPP Project Officer		
Name:	Signature:	Date:

Date	Version	Alterations	Editor

METEOR Landslide Hazard Report

About this report

The objective of this report is to summarise the methodology followed to co-develop landslide susceptibility and hazard assessments for rainfall and earthquake triggered landslides at national level in Nepal. The report is separated into sections detailing the methodology associated with the susceptibility maps followed by the hazard maps

Abbreviations

Acronym	Full Text	Description
BGS	British Geological Survey	An organisation providing expert advice in all areas of geoscience to the UK government and internationally
DMD	Disaster Management Department	Prime Minister's Office of Tanzania focused on disaster risk
DRM	Disaster Risk Management	
EO	Earth Observation	
FATHOM		Provides innovative flood modelling and analytics, based on extensive flood risk research
GCRF	Global Challenges Research Fund	
GEM	Global Earthquake Model	Non-profit organisation focused on the pursuit of earthquake resilience worldwide
HOT	Humanitarian OpenStreetMap Team	A global non-profit organisation the uses collaborative technology to create OSM maps for areas affected by disasters
ImageCat		International risk management innovation company supporting the global risk and catastrophe management needs of the insurance industry, governments and NGOs
IPP	International Partnership Programme	
METEOR	Modelling Exposure Through Earth Observation Routines	
NSET	National Society for Earthquake Technology	Non-governmental organisation working on reducing earthquake risk in Nepal and abroad

Acronym	Full Text	Description
ODA	Official Development Assistance	
OPM	Oxford Policy Management	Organisation focused on sustainable project design and implementation for reducing social and economic disadvantage in low-income countries
UKSA	United Kingdom Space Agency	
WP	Work Package	

Contents

Figures

Tables

Equations

METEOR Landslide Hazard Report

1. METEOR Project Introduction

1.1. Project Summary

Project Title	Modelling Exposure Through Earth Observation Routines (METEOR): EO-based Exposure, Nepal and Tanzania
Starting Date	08/02/2018
Duration	36 months
Partners	UK Partners: The British Geological Survey (BGS) (Lead), Oxford Policy Management Limited (OPM), SSBN Limited (Fathom) International Partners: The Disaster Management Department, Office of the Prime Minister – Tanzania (DMD), The Global Earthquake Model (GEM) Foundation, The Humanitarian OpenStreetMap Team (HOT), ImageCat, National Society for Earthquake Technology (NSET) – Nepal
Target Countries	Nepal and Tanzania for “level 2” results and all 47 Least Developed ODA countries for “level 1” data
IPP Project	IPPC2_07_BGS_METEOR

Table 1: METEOR Project Summary

1.2. Project Overview

At present, there is a poor understanding of population exposure in some Official Development Assistance (ODA) countries, which causes major challenges when making Disaster Risk Management decisions. Modelling Exposure Through Earth Observation Routines (METEOR) takes a step-change in the application of Earth Observation exposure data by developing and delivering more accurate levels of population exposure to natural hazards. METEOR is delivering calibrated exposure data for Nepal and Tanzania, plus ‘Level-1’ exposure for the remaining Least developed Countries (LDCs) ODA countries. Moreover, we are: (i) developing and delivering national hazard footprints for Nepal and Tanzania; (ii) producing new vulnerability data for the impacts of hazards on exposure; and (iii) characterising how multi-hazards interact and impact upon exposure. The provision of METEOR’s consistent data to governments, town planners and insurance providers will promote welfare and economic development and better enable them to respond to the hazards when they do occur.

METEOR is co-funded through the second iteration of the UK Space Agency’s (UKSA) International Partnership Programme (IPP), which uses space expertise to develop and deliver innovative solutions to real world problems across the globe. The funding helps to build sustainable development while building effective partnerships that can lead to growth opportunities for British companies.

1.3. Project Objectives

METEOR aims to formulate an innovative methodology of creating exposure data through the use of EO-based imagery to identify development patterns throughout a country. Stratified sampling technique harnessing traditional land use interpretation methods modified to characterise building patterns can be combined with EO and in-field building characteristics to capture the distribution of building types. These protocols and standards will be developed for broad application to ODA countries and will be tested and validated for both Nepal and Tanzania to assure they are fit-for-purpose.

Detailed building data collected on the ground for the cities of Kathmandu (Nepal) and Dar es Salaam (Tanzania) will be used to compare and validate the EO generated exposure datasets. Objectives of the project look to: deliver exposure data for 47 of the least developed ODA countries, including Nepal and Tanzania; create hazard footprints for the specific countries; create open protocol; to develop critical exposure information from EO data; and capacity-building of local decision makers to apply data and assess hazard exposure. The eight work packages (WP) that make up the METEOR project are outlined below in section 1.4.

1.4. Work Packages

Outlined below are the eight work packages that make up the METEOR project, which are led by various partners. **Error! Reference source not found.** provides an overview of the work packages together with a brief description of what each of the work packages cover. BGS is leading WP.6: Multiple Hazard impact, which focuses on the multiple hazard impacts on exposure and how they may be addressed in disaster risk management by a range of stakeholders

Table 2: Overview of METEOR Work Packages

Work Package	Title	Lead	Overview
WP.1	Project Management	BGS	Project management, meetings with UKSA, quarterly reporting and the provision of feedback on project deliverables and direction across primary stakeholders.
WP.2	Monitoring and Evaluation	OPM	Monitoring and evaluation of the project and its impact, using a theory of change approach to assess whether the associated activities are leading to the desired outcome.
WP.3	EO Data for Exposure Development	ImageCat	EO-based data for exposure development, methods and protocols of segmenting/classifying building patterns for stratified sampling of building characteristics.

WP.4	Inputs and Validation	HOT	Collect exposure data in Kathmandu and Dar es Salaam to help validate and calibrate the data derived from the classification of building patterns from EO-based imagery.
WP.5	Vulnerability and Uncertainty	GEM	Investigate how assumptions, limitations, scale and accuracy of exposure data, as well as decisions in data development process lead to modelled uncertainty.
WP.6	Multiple Hazard Impact	BGS	Multiple hazard impacts on exposure and how they may be addressed in disaster risk management by a range of stakeholders.
WP.7	Knowledge Sharing	GEM	Disseminate to the wider space and development sectors through dedicated web-portals and use of the Challenge Fund open databases.
WP.8	Sustainability and Capacity-Building	ImageCat	Sustainability and capacity-building, with the launch of the databases for Nepal and Tanzania while working with in-country experts.

1.5. Multiple Hazard Impact

The multiple hazard impact work package (WP6) led by BGS includes four deliverables, which are focused on developing footprints of the hazards that have been designated as of most importance to our partner countries of Nepal (flooding, earthquake and landslide) and Tanzania (flooding, earthquake and volcanic activity) and modelling their potential impacts on exposure (Table 3).

Deliverable	Title
M6.1	Deliver national hazard footprints for Nepal and Tanzania
M6.2	Develop models for analysing multi-hazards with exposure
M6.3	Draft protocols on hazard and exposure modelling
M6.4	Final report on multiple hazard impact

Table 3: Overview of BGS multi-hazard impact deliverables

2. Landslide Susceptibility

Herein, we consider landslide susceptibility as the probability of spatial occurrence of slope failures, given a set of environmental conditions (Guzzetti et al., 2005). Susceptibility measures the degree to which a terrain can be affected by future slope movements; in other words, it is an estimate of "where" landslides are likely to occur (Reichenbach et al., 2018). In this approach, we did not consider landslide size (area, depth, volume) nor travel distance (as adopted in the definition of Fell et al. 2008). Therefore, no "hazard footprint" can directly be associated with the resulting susceptibility map.

This works is based on the following main assumptions:

- Conditions that cause landslides, or directly or indirectly linked with slope failures, can be identified and data associated with them can be collected and used to build predictive models of landslide spatial occurrence;
- Future slope failures are more likely to occur under the conditions which led to past and current instability;
- Spatial probability of landslide occurrence can be inferred from heuristic investigations and ranked in different classes for zonation purposes.

3. Data

3.1. Landslide Inventory

In this study the creation of a landslide inventory fulfils two roles as defined by Guzzetti *et al* 2012: A way of investigating the distribution, pattern and type of landslides in relation to morphological and geological factors and following this as a first step towards creation of landslide susceptibility and hazard maps.

Two separate **landslide inventories** (point data) were compiled for the rainfall and seismic triggering mechanisms (Figure 1). The former contained 359 points uniformly distributed over the entire study area. The latter contained 18593 points and was derived by combining three datasets related with the 2015 Gorkha seismic event from USGS Open Source (pre- and post-earthquake) BGS & Durham University (post Gorkha) inventory and an inventory on the ICIMOD website that was concentrated on the Koshi Basin/14 most affected districts (post Gorkha). The data were combined so that duplication across the different datasets was minimised.

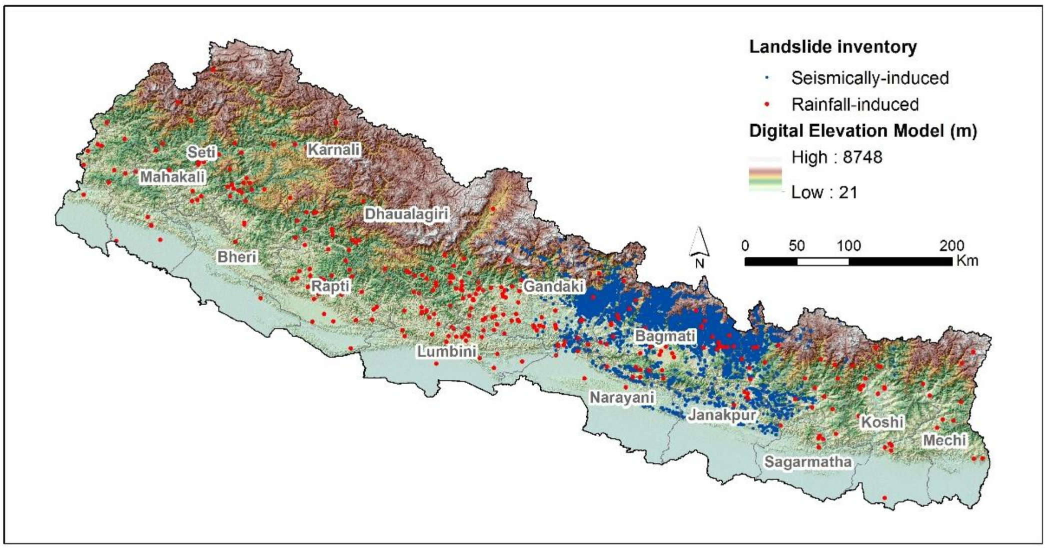


Figure 1: Inventory data for rainfall (n=359) and earthquake-induced (n=18096) landslides

3.2. Landslide predisposing factors (predictors)

For the assessment of susceptibility, several geological, geomorphological and hydrological datasets were required. The datasets are compiled from different sources, including national and international research institutes and non-governmental organisations (*AMR was only used in the production of the rainfall induced landslide susceptibility map

Table 4).

No	Type of Data	Source organisation	Scale/resolution
1	Geological map	Geological Map of Nepal. Department of Mines and Geology	National; 1:1,000,000 scale
2	Faults and lineaments	Global Active Faults Catalogue (GEM), Geological Map 1:1M (1994)	Global; national
3	Landslide inventory (rainfall-induced)	Global Landslide Catalogue (NASA)	Global
4	Landslide inventory (earth-quake induced)	ICIMOD (2016)	Regional (14 districts)
		BGS & Durham University (post-Gorkha inventory)	Regional
		USGS (Open Source Repository)	National
5	Drainage Density	Derived from ICIMOD River Network of Nepal	National/ 1:250,000
6	Land Cover	Uddin *et al.*, 2015- Land Cover map of Nepal 2010	National
7	DEM derivatives (Slope, Aspect)	MERIT DEM	National; 90m
8	Annual Mean Rainfall*	Marahatta *et al.*, (2009)	

*AMR was only used in the production of the rainfall induced landslide susceptibility map

Table 4: Data and data sources used in this study

Slope gradient was introduced into the model as a continuously-scaled variables, while the rest of the predictors- as categorical variables. The **slope gradient** and **aspect** (slope orientation) maps were computed from a 90m resolution DEM. The drainage density was derived using ArcHydro tools from the **River Network of Nepal** dataset created from the 1988 topographic zonal map of Nepal. Geology was derived from an amalgamation of the digital 1:1,000,000 geological map and a paper copy of the same scale produced by the Department of Mines and Geology (1994). The **distance from faults** predictor was utilised because it was assumed that the mechanical and hydrogeological properties of rocks adjacent to the fault zone are more favourable to landslides than in the surrounding non-faulted rocks. The **geological** map, originally with 55 classes, was grouped into six lithology classes according to their approximated soil/rock mechanical properties (e.g., their competence when fractured/tectonised and/or weathered).

3.3. Data Limitations

The quality of landslide susceptibility models is known to be highly dependent on the quality and completeness of the input data. The available datasets were not complete nor unbiased, as they were originally created by investigators with different skills and experience, for different purposes (including extent of the study area) using different methods (e.g., compilation from the literature, image interpretation, etc.) and resources to complete the work. The accuracy of the landslide inventories and the spatial and temporal distribution of earthquake-triggered landslides are some of the major data limitations. For example, the inventories do no dissociate between different landslide types (i.e., based on the movement and material type) which has negative consequences for the predictive power of the susceptibility model and associated terrain zonations. Another limitation is related with the type and quality of geo-environmental information. In this study, a combination of morphological, hydrological and geological factors was used to assess landslide susceptibility. However, the selection was based on a limited number of studies in the area and their relevance for the good performance of the model is yet to be determined. Limitations over availability and resolution of data exist so that event though input from in country experts indicated that curvature would have been a valuable addition to the conditioning factors it was not scientifically valid to use the 90m resolution DEM for this purpose.

4. Models

Different techniques exist to assess landslide susceptibility from direct geomorphic mapping through to complex, quantitative conceptual process models. Suitability of a given approach is dependent on upon the availability of inventory data as well as the quality of appropriate baseline data (geology, topography and environmental data).

The methodology followed in this study is based on a hybrid approach, whereby a fuzzy logic technique is informed by landslide inventories (data-driven frequency analysis) and subsequently by local expert knowledge (heuristic index-based with ranking and rating of predisposing factors through expert elicitation) to derive information about the susceptibility of slopes to landsliding (Figure 2).

Firstly, the influence of each selected predisposing factor on the spatial distribution of landslides was assessed using a conventional frequency ratio analysis. This approach was supported by two assumptions: i) the quality of available landslide inventories is appropriate for deriving strong relationships between landslide occurrence and geo-environmental conditions; and ii) no local expert knowledge is available.

In a second stage, local expert knowledge was sought to ensure the co-production aspect of METEOR and also to make certain that the data driven results reflected the tacit knowledge and experience of local experts. The assumption behind this approach is that good quality information about the geo-environmental conditions elicited from local experts leads to better modelling results than when using inventory data that may be flawed. For the present work, the EXCALIBUR structured expert judgment procedure (**Cooke and Solomatine, 1992**), formulated by **Cooke (1991)** as the Classical Model, has been selected for application.

The results of the frequency analysis and expert elicitation were used as input in a fuzzy logic model (**Zhu et al., 2014**), where three generic steps are followed: i) **frequency-ratio distributions** were used to investigate the correlation between landslides and predisposing factors, ii) These distributions were used to define **rule sets** and **parameters** for **each fuzzy logic function associated with a predisposing factor map** and iii) Finally, the fuzzy predisposing factor maps were **aggregated using a weighted approach informed by expert ranking**.

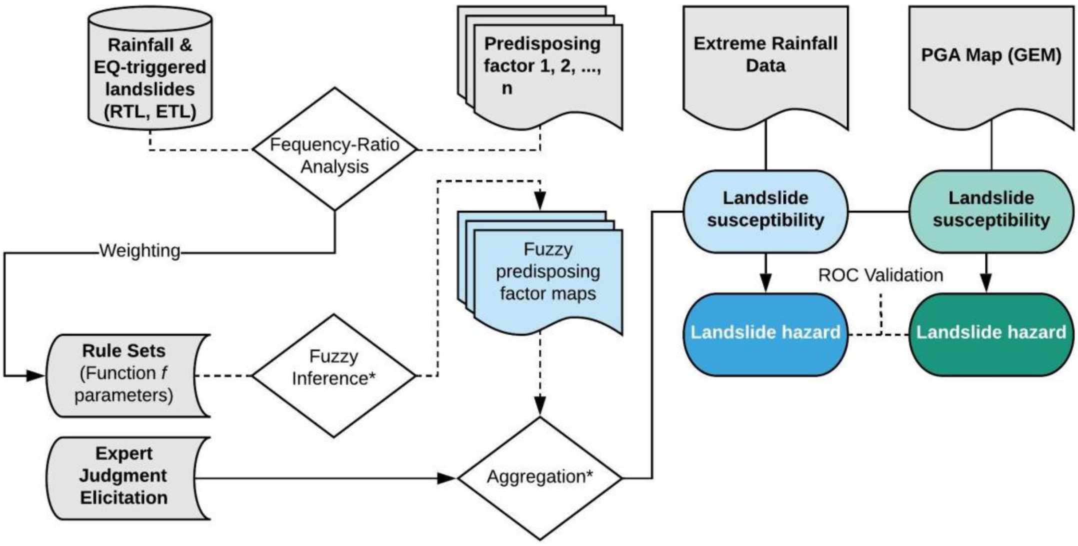


Figure 2: Methodological workflow

4.1. Frequency Statistics

Prior to applying the frequency statistics, the predictor layers where rasterised at a 90 × 90 m grid cell resolution and all distance-related predictors were buffered in ArcMap (ArcGIS). The resulting maps were used as input data in all subsequent calculations.

The conventional frequency ratio method calculates a Landslide Susceptibility Index (LSI) by summing up the frequency ratios of all landslide predisposing factors at a given location. The frequency ratio of a given landslide susceptibility factor is calculated using Equation 1 (Li et al., 2017).

Equation 1

$$FR_i = \frac{PL_i}{PF_i}$$

$$= \frac{\text{the frequency of landslides in the } F_i \text{ area}}{\text{the frequency of the } F_i \text{ area}}$$

$$= \frac{\text{the area of landslides in the } F_i \div \text{the area of landslides in the study area}}{\text{the area of the } F_i \text{ area} \div \text{the area of the study area}}$$

In this study, landslide areas were not available, so the counts (point locations) of landslides were used instead. The FR of all predisposing factors were then applied to i) eliminate those predictors that do not show any relationship with landslide occurrence and ii) define rule sets and parameters (threshold values) for the fuzzy inference.

5. Expert Elicitation (Cooke's Classical Model)

Models inferred from empirical observations inevitably carry some uncertainty, which can be expected to increase and be difficult to quantify when generalised beyond the sample or type of structure used in the original inference (**Lamb et al., 2017**). Moreover, given the limited knowledge of local geo-environmental conditions, there was a need to harvest the tacit knowledge and experience of local experts.

We acknowledge that some subjectivity in expert-driven approaches is inevitable in the interpretation of data and problem at hand. Nevertheless, a structured approach has been taken to elicit expert judgment from a range of recognised specialists in landslides from NSET, ICIMOD, DoLI and TU. The quantitative elicitation method developed by **Cooke (1991)**, known as the classical model, was adopted. In this approach, distinct weights are given to individual experts based on a statistical test of the expert's ability to judge uncertainties. This is determined empirically by calculating performance metrics derived from a set of control questions. The results of the elicitation were used to inform the aggregation of factors into the overall susceptibility map based on expert weighting of the factors.

5.1. Fuzzy Logic Component

The fuzzy logic model is adapted after **Zhu et al. (2014)**, who applied it in the Kaixian and Three Gorges area, China, in an attempt to overcome the deficiencies of data-driven approaches. The main difference between our model and the one proposed by Zhu et al. (2014) is the expert knowledge elicitation method: in our approach, the information was obtained from a group rather than a single expert and the uncertainty associated with the expert estimates is quantified.

The main component of the fuzzy logic model is the construction of the fuzzy membership functions to formulate the expert knowledge. As opposed to the frequency ratio approach, where the relationship between landslide susceptibility and an individual predisposing factor is described using a ratio (FR), here a function (f) is employed instead. Three main basic curves are used for continuous-scaled predictors: bell-, Z- and S-shaped (Figure 3); these are determined and adjusted by the expert using function parameters (minimum, maximum and average) based on the availability and importance of the predisposing factor. In other words, the function describes how landslide susceptibility varies in relation to changes in the predisposing factor.

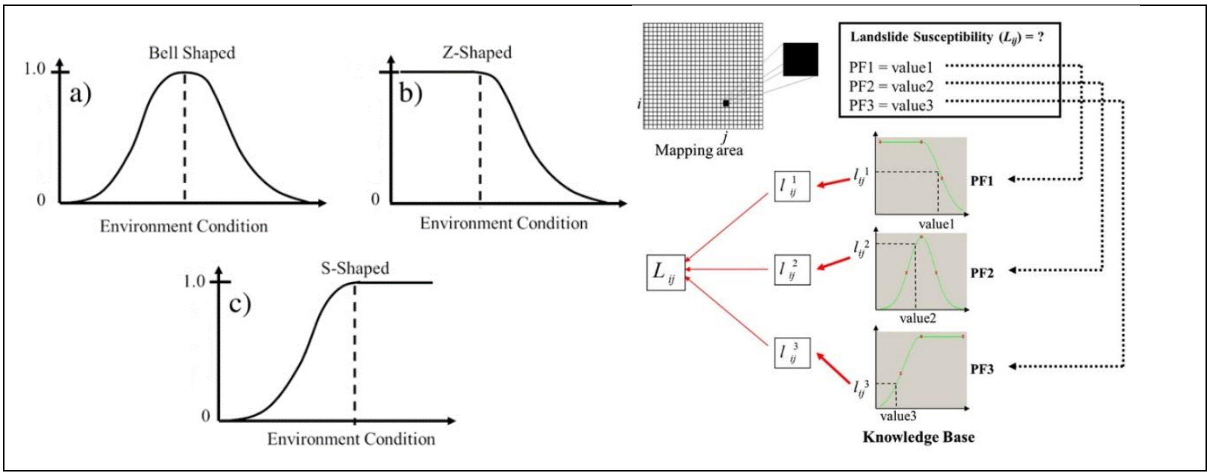


Figure 3: Illustration of the three basic curves for continuous-scaled variables (left); and the fuzzy inference process (right) (after Zhu et al, 2014)

The general Gaussian-style function that controls the shape of the curves for continuous-scaled predictors is denoted in Equation 2 (Zhu et al., 2008):

Equation 2

$$f_v\left(e_{ij,v}\right) = \exp\left[-\left(\frac{\left|e_{ij,v} - e_v\right| \times 0.8326}{w}\right)^2\right]$$

Where f_v is the function describing the relationship between landslide susceptibility and the predisposing factor v and $e_{ij,v}$ is the value of predisposing factor v at location (*ij*); w is a parameter controlling the shape of the curve and is defined as the difference between the value of the predisposing factor when the membership is at unity (1) and when it is 0.5 (cross-over).

The curve type and parameters are determined based on the knowledge of experts. For example, if the expert stated that landslide susceptibility increases as the slope gradient increases, an S-shaped curve is employed. If an expert suggested that susceptibility is very high (S = 1) for areas with a slope gradient over 40° ($e_{gradient}$=40) and susceptibility is reduced by roughly half (S = 0.5) at 15° ($w = |40 - 15| = 25$), this knowledge provides us with the following membership function (Equation 3):

Equation 3

$$f_v\left(e_{ij,v}\right) = \begin{cases} 1 & \text{if } e_{ij,v} > 40^\circ \\ \exp\left[-\left(\frac{\left|e_{ij,v} - 40\right| \times 0.8326}{25}\right)^2\right] & \text{otherwise} \end{cases}$$

For categorical variables the following formula is applied (Equation 4):

Equation 4

$$f_v\left(e_{ij,v}\right) = \begin{cases} w_{1,v} & if\ e_{ij,v} = c_{1,v} \\ w_{2,v} & f\ e_{ij,v} = c_{2,v} \\ \cdots & \\ w_{m,v} & f\ e_{ij,v} = c_{m,v} \end{cases}$$

Where f_v and $e_{ij,v}$ (e_v) have the same meaning as above; and $w_{1,v}$, $w_{2,v}$, …, and $w_{m,v}$ are the corresponding landslide susceptibilities when factor v takes the value of $c_{1,v}$, $c_{2,v}$, …, and $c_{m,v}$.

The fuzzy inference process is repeated for every grid cell in the raster layer by using the Model Builder tool in ArcMap 10.3. The aggregation methodology proposed by Zhu *et al.,* (2014) was replaced with that of Ruff & Czurda (2008) in order to utilise the expert ranking of predisposing factors carried out as part of the elicitation process outlined above.

Once a fuzzy map has been obtained for all predisposing factors, the fuzzy landslide susceptibility is calculated by aggregating all fuzzy maps into a single map which can be categorised in different susceptibility classes (e.g., very low, low, medium, high, very high). Each factor class receives a weight as defined by the fuzzy map for that factor map (I_1). The predisposing factors are divided into groups (geology, morphology and environment) with an index value assigned to each group to indicate its relative importance to susceptibility as defined by the expert elicitation results (I_3). Each factor within the group (e.g. slope aspect) is assigned an index value reflecting its importance within the group informed by the elicitation process (I_2). A map for each predisposing factor is created using Equation 5, whilst overall susceptibility in a grid cell was defined by Equation 6. An example of the values used for the assessment of rainfall induced landslide susceptibility is shown in Table 5.

Equation 5 $$I_{\text{factor}} = I_1 \times I_2 \times I_3$$

Equation 6 $$\text{Rainfall Susceptibility} = I_{\text{slope}} + I_{\text{aspect}} + I_{\text{lithology}} + I_{\text{drainage density}} + I_{\text{Landover}} + I_{\text{AMR}}$$

Factor (I_1)	**(I_2)**	**(I_3)**
Slope	0.8	0.4
Aspect	0.2	
Lithology	0.8	0.4
Distance to faults	0.2	
Drainage density	0.5	0.2
Land cover	0.1	
AMR	0.4	

Table 5: Index values assigned to factors in the production of the rainfall induced landslide susceptibility map

6. Deriving the Landslide Hazard Maps

Reichenbach *et al.,* (2018) define hazard as "*the probability that a landslide of a given magnitude will occur in a given period and in a given area*". So, whilst susceptibility represents the spatial probability of landslide occurrence, hazard represents the temporal probability of a landslide (of a given magnitude) occurring. Hazard in this study is expressed through the combination of susceptibility and a trigger value following Varnes (1984) and is similar in approach to assessments carried out by Jaedicke *et al*., (2014) and Nadim *et al*., (2006). Susceptibility values are multiplied by a triggering factor to derive national scale maps depicting the hazard arising from both earthquake triggered and rainfall induced landslides (Table 6).

6.1. Seismic Trigger

Seismic trigger data comprising PGA data was supplied by GEM and developed by NSET using a standard Probabilistic Seismic Hazard Assessment approach (Stevens et al*.,* 2018). The seismic trigger data has a 0.1 probability of exceedance in 50 years (return period of 475 year) reflecting the standard design life of buildings. The PGA values derived from the GEM/NSET data were categorised into 12 classes following Jaedicke *et al.,* (2014) with an additional number of classes to reflect the higher PGA values in Nepal.

6.2. Rainfall Trigger

24 hr extreme rainfall data taken from Marahatta *et al.,* (2009) was used as the trigger factor for the rainfall induced landslide hazard map. Data comprised extreme rainfall values (mm/day) recorded monthly at 166 weather stations across Nepal between 1976 and 2005. A range of return periods were produced in Marahatta *et al.,* (2009) and the 1 in 50 year extreme rainfall event was chosen for this study. Other return periods in the report (2, 5, 10, 15, 20, 25, 50 and 100 years) could be used to produce different hazard magnitudes.

Data	Source organisation	Scale/resolution
Extreme rainfall (50 year return period)	Marahatta *et al.*, 2009	National
Seismic trigger (PGA)	GEM/NSET (current project)	National; Interpolated to a 90m grid from point data at 2.5km spacing.

Table 6: Data used to derive the trigger for the landslide hazard maps

The final hazard maps categorise the terrain into five zones that are representative of the landslide hazard given a defined rainfall or earthquake scenario. The 5 categories of hazard, defined using a natural breaks method (Jenks, 1967), are: (1) very low; (2) low; (3) moderate; (4) high; and (5) very high.

7. Limitations of the Data/Methodology

Whilst all care and attention has been taken to produce a robust landslide hazard model that is as accurate as possible, the BGS and partner organizations do not guarantee that the input data or the model are accurate, up to date, complete or suitable for site-specific engineering purposes. Like most national level landslide hazard assessment this study has limitations stemming from:

1) *Model assumptions*: The central assumption of landslide susceptibility modelling is based on the concept that states that “the past and present are keys to the future”. This is a clear source of uncertainty in the model because it implies that the predisposing and triggering factors (i.e., extreme rainfall) of landslides do not change in the future. Therefore, the natural variability of the triggering mechanisms and climate system changes are not considered. This project did not consider the effect of future climate scenarios on landslide susceptibility or hazard.

2) *Accuracy, consistency and suitability of source datasets*: Limitations exist around the availability of suitable source datasets such as the geological map, DEM and the availability of a national landslide inventory for rainfall-triggered events (see also the Rainfall-triggered Landslide Susceptibility Model). Several sources of historic landslide information meant that disparate approaches of mapping and recording data (e.g., event date, landslide representation and characteristics, type, volume/depth, failure mechanism, etc.) would impede the calculation of a quantitative relationship between a landslide event and a rainfall event of a given return period. To avoid inconsistencies, a separate rainfall dataset was used for the Rainfall-triggered Landslide Hazard Model. The resulting map is affected by the distribution and number of meteorological stations; data is spatially limited in the high mountains compared to Terai, lower and middle hills.

3) *Model output*: Specific landslide characteristics (such as expected magnitude/volume, intensity, travel distance, type) are not considered in the model and therefore no information with regards to their spatial distribution or typology can be inferred from the map. The map was designed to indicate the main scarps (initiation/source area) of landslides and does not reflect the spatial extent of the likely debris transport pathways or accumulation zone.

4) *Non-correspondence between the available data/information and the actual physical mechanisms responsible for landsliding*: when interpreting and using the map, it should be noted that no information about the material effects of prior seismicity, material strength and weathering conditions, slope loading, soil depth, saturation and permeability, were directly included in the susceptibility model. This endeavour was out of the scope of the project and impracticable at the selected scale of analysis. Although human activities (e.g., mining, poor drainage management, excavation, road building, etc.) can be key triggering factors for landslides, the current project focused on two main natural triggers only – rainfall and seismicity. It does not account for seismic site effects or slope strength degradation resulting from previous earthquakes and the interplay with rainfall-triggered landslides (multi-hazard context).

5) *Limitations of the modelling approach*: This map was produced using a combination of heuristic and statistical methods. The statistical method assessing the spatial probability based on landslide inventories is complemented by the heuristic model, which takes advantage of the local expert knowledge captured through a project workshop in Kathmandu held in April 2019, and is suitable for assessments at district to national level. The drawbacks relate to the tendency to simplify the dynamic

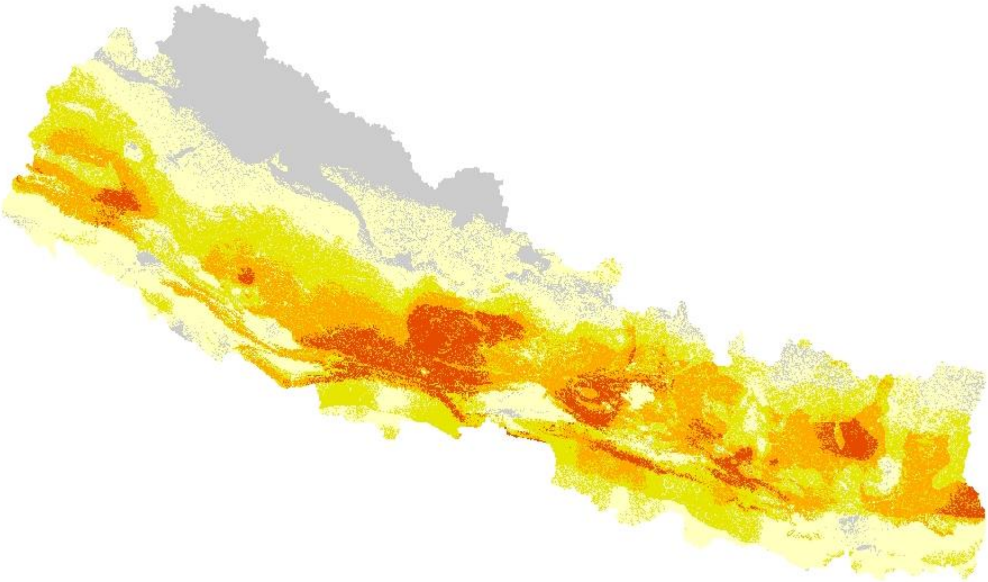
factors that condition landslides (land use, water table fluctuations, slope morphology, material conditions, etc.) and generalization of the triggering factors, assuming that landslides initiate under the same combination of conditions throughout the study area and in time (no changes in weather patterns and climate). The extreme rainfall model is a national level model and does not reflect the highly localized effects of intense rainfall.

APPENDIX A: Frequency ratio values and weights for rainfall (R) and earthquake (EQ) induced landslide predictors

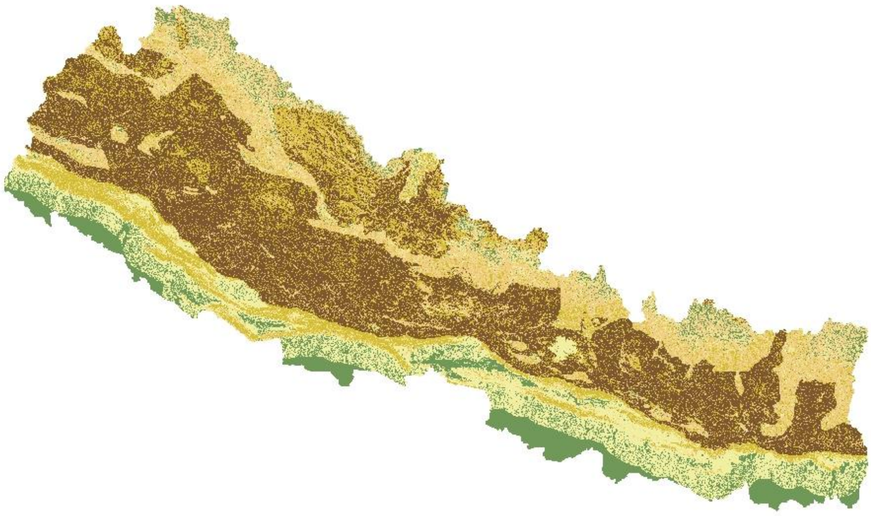
Predictor	Class	Frequency Ratio (FR)		Weight	
		R	EQ	R	EQ
Slope(°)	0 – 15	0.86	0.06	0.5	0.1
	15 – 20	1.35	0.83	1	0.3
	20 – 35	1.22	1.10	0.8	0.5
	35 – 45	0.61	2.65	0.3	0.8
	>45	0.45	3.05	0.1	1
Aspect	Flat	0.00	0.62	0	0
	N –NE	0.54	0.62	0.2	0.3
	NE - E	0.73	0.93	0.3	0.5
	E – SE	0.89	1.35	0.4	0.9
	SE – S	1.26	1.43	0.8	1
	S – SW	1.32	1.21	0.9	0.8
	SW -W	1.68	0.95	1	0.6
	W – NW	1.02	0.71	0.6	0.4
	NW - N	0.53	0.59	0.1	0.2
Geology	1 - Mid-Miocene Pleistocene Siwaliks	0.47	0.18	0.4	0.2
	2 - Limestones, quartzites, granite gneiss	1.85	8.09	1	1
	3 - Shales, slates, limestone and quartzites, phylites, schists	2.00	1.69	0.9	0.7
	4 - Cretaceous-Eocene Shales and Sandstones	2.28	0.00	0.8	0
	5 - Himal Group- Gneiss	0.30	0.88	0.1	0.5
	6 - Quaternary	0.37	0.02	0.2	0.1
Distance from faults (km)	<1	0.86	1.21	0.7	1
	1 – 5	1.14	1.21	0.8	0.8
	5 – 10	1.22	1.03	1	0.6
	10 – 20	1.13	1.17	0.9	0.8
	20 – 50	0.40	0.35	0.6	0.3
	>50	0.00	0.00	0	0
Drainage Density	0 – 0.15	0.37	0.24		
	0.14 – 0.45	2.72	2.94		
	0.45 – 0.75	3.99	4.59		
	0.75 – 1.05	3.85	6.07		
	1.05 – 1.45	4.99	2.86		
	> 1.45	1.74	1.11		
Annual Mean rainfall	0 - 100	0.19			
	100 - 500	0.09			
	500 - 1000	0.5			
	1000 - 1500	0.9			
	1500 - 2000	0.86			
	2000 - 2500	1.32			
	2500 - 3000	1.46			
	3000 - 3500	3.74			
	3500 - 4000	2.74			

	>4000	3.85	
Land Cover	Unclassified	n/a	n/a
	Forest	0.96	1.34
	Shrubland	0.72	1.30
	Grassland	0.53	1.70
	Agricultural Area	1.69	0.80
	Barren area	0.13	0.10
	Water body	1.57	0.21
	Snow/glacier	0.10	0.02
	Built-up area	9.09	0.14

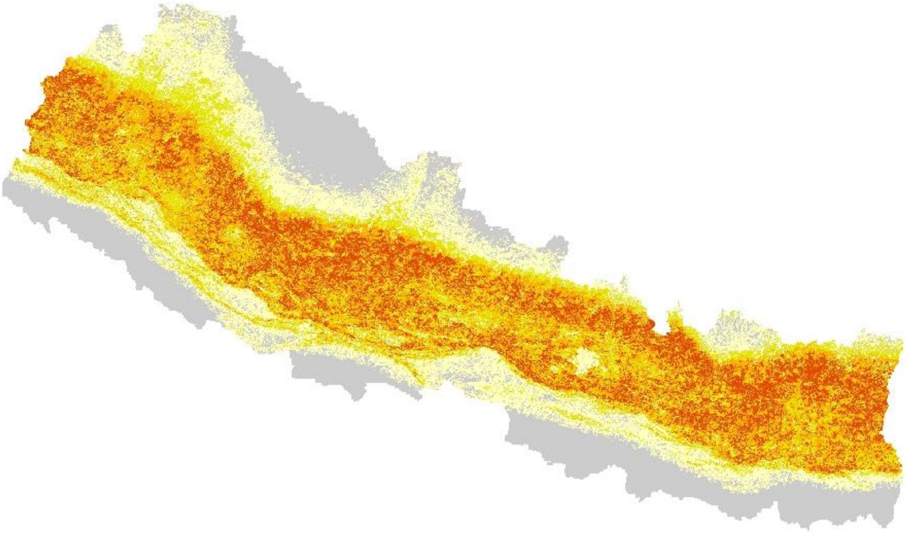
APPENDIX B: Hazard and Susceptibility Maps



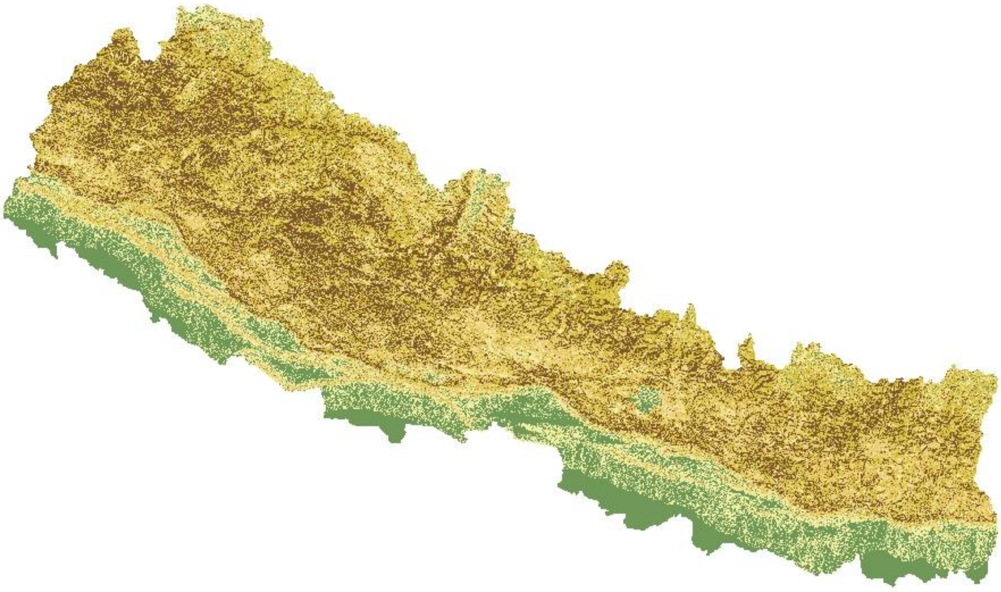
Rainfall triggered landslide hazard map for Nepal



Rainfall triggered landslide susceptibility map for Nepal



Earthquake induced landslide hazard map for Nepal



Earthquake induced landslide susceptibility map for Nepal

References

Guzzetti, F., Reichenbach, P., Cardinali, M., Galli, M. & Ardizzone F. (2005) **Probabilistic landslide hazard assessment at the basin scale.** Geomorphology, 72 (2005): pp.272-299

Guzzetti, F., Mondini, A.C., Cardinali, M., Fiorucci, F., Santangelo, M. & Chang. K.T. (2012) Landslide inventory maps: new tools for an old problem. Earth-Science Reviews, 112 (1) (2012): pp.42-66.

Marahatta, S., Dongol, B. & Gurung, G. (2009) Temporal and spatial variability of climate change over Nepal (1976 - 2005). Practical Action Nepal.

Nadim, F., Kjekstad, O., Peduzzi, P. & Jaedicke, C. (2006) Global landslide and avalanche hotspots. Landslides 3(2):159-173

Reichenbach, P., Rossi, M., Malamud, B., Mihir, M. & Guzzetti, F. (2018) A review of statistically-based landslide susceptibility models. Earth-Science Reviews. Volume 180: pp 60-91

Stevens, V. L., Shrestha, S.N. & Maharjan, D. K. (2018) Probabilistic Seismic Hazard Assessment of Nepal. Bulletin of the Seismological Society of America (2018) 108 (6): 3488–3510.

Uddin, K., Shrestha, H. Murthy, M.S.R., Bajracharya, B., Shrestha, B., Gilani, H., Pradhan, S. & Dangol, B. (2015) Development of 2010 national land cover database for the Nepal. Journal of Environmental Management. Vol 148: pp82-90

Varnes D. J. (1984) The International Association of Engineering Geology Commission on Landslides and Other Mass Movements (1984) Landslide hazard zonation: a review of principles and practice. Natural Hazards, Vol 3. United Nations educational scientific and cultural organization. 60pp

Zhu, A.X. (2008) Rule based mapping. In: Wilson, J.P., Fotheringham, A.S. (Eds.), The Handbook of Geographic Information Science. Blackwell, Malden, MA, pp. 273–291.

Zhu, A.X., Wang, R., Qiao, J., Qin, C. Z., Chen, Y., Liu, J., Du, F., Lin, Y. & Zhu, T. (2014) An expert knowledge-based approach to landslide susceptibility mapping using GIS and fuzzy logic. Geomorphology, 214: 128-138pp