Research Project 2: Factor of Safety and Newmark's Formula

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This document describes the Factor of Safety and Newmark's Formula and their use in the workflow for the generation of earthquake-induced landslide susceptibility maps (LSM).

Additional Key Words and Phrases: Earthquake induced landslide, susceptibility maps, Monte-Carlo methods, machine learning,

CONTEXT AND OVERVIEW

In this note, we seek to:

(1) Understand the theoretical and operational basis of the generation of earthquake-induced landslide susceptibility maps (LSM).
(2) Review recent studies and new approaches.
(3) Identify theoretical weaknesses and operational bottlenecks and propose research pathways for their solution.
(4) Consult PHIVOLCS regarding:
   (a) data availability,
   (b) methods actually employed.

1 RESEARCH PROJECTS

The topics for research projects will be discussed with PHIVOLCS. There are 3 tentative propositions detailed below. Note that each project relies on the contents of the training program [1, 9, 11], and the lectures, examples will need to be restudied and completed as the research progresses. The work on the projects will be divided into teams, with each team concentrating on one of them. Cross collaboration between the teams is strongly encouraged.

1.1 Project 1: EIL Inventory using ML

- Use tree-based ML on a landslide inventory to generate a detailed susceptibility map.
- Dashboards (interactive) for DRRM and risk scenario exploration.
- Use ML to update the hazard maps by integrating real-time data and continuously (re)learning from new events.
- Post Qualification (Landslide Inventory): (PE)ML can be used to validate and update the hazard maps by comparing predicted hazards with actual landslide occurrences.

1.2 Project 2: ML for Soil Parameters and FoS

- Use PEML to predict the FoS by taking into account the Newmark physics formulas.
- Perform a feature importance study on the 7 covariates (geotechnical parameters in Newmark).
- Perform a causality study, based on Shapley values, and integrate the results into the hazard/susceptibility map.
- Evaluate predictive performance of past forecasts and hazard maps.

1.3 Project 3: SEM-Newmark Coupling for EILs

- Step 1: Simulate seismic wave propagation using SEM.
- Step 2: Predict landslide using Newmark displacement analysis.

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- Step 3: Couple the above to predict Earthquake Induced Landslides. Study effects of duration of seismic events as well as peak amplitude. Evaluate risk for extreme events.

2 FOS AND NEWMARK

Definition 2.1. The Factor of Safety (FoS) is a ratio used in geotechnical engineering to evaluate the stability of a slope. The ratio can be described as

$$\text{FoS} = \frac{\text{reisisting force}}{\text{driving force}}$$

and the decision,

$$\text{FoS} > 1 \implies \text{stability}$$
$$\text{FoS} < 1 \implies \text{instability.}$$

In terms of geotechnical soil and morphology parameters, the *static* factor of safety [Jibson1998, 2000] is,

$$\text{FoS} = \underbrace{\frac{c'}{\gamma h \sin\alpha}}_{\text{cohesive}} + \underbrace{\frac{\tan\phi'}{\tan\alpha}}_{\text{frictional}} - \underbrace{\frac{m\gamma_w \tan\phi'}{\gamma\tan\alpha}}_{\text{pore pressure}}, \tag{1}$$

where

- ϕ' is the effective friction angle (from tables, lithology map),
- c' is the effective cohesion (from tables, lithology map),
- α is the slope angle (obtained from the DEM),
- γ is the material unit weight (from tables, lithology map),
- m is the proportion of slab thickness that is saturated (from rainfall data),
- γ_w is the unit weight of water, and
- h is the slope-normal thickness of the failure slab (sliding plane, empirical constant = 3.33m).

This value is then used in the computation of the Newmark critical acceleration,

$$a_c = (\text{FoS} - 1) g \sin\alpha.$$

Finally, the exceedance is defined as the difference,

$$E = a_c - \text{PGA}, \tag{2}$$

where the peak ground acceleration, PGA, comes from seismic recordings (seismograms, shakemaps—see below). This exceedance gives rise to a probability of failure by performing a regression based on a Weibull distribution

$$P(f) = m\left[1 - \exp(-aD_N^b)\right],$$

where

- $P(f)$ is the proportion of landslide cells,
- m is the maximum proportion of landslide cells indicated by the data,
- D_N is the Newmark displacement (in cm.),
- a, b are the regression coefficients to be estimated.

The Newmark displacement is itself defined as an integral of the acceleration difference,

$$D_N = \int_{t_0}^{t_1}\int_{t_0}^{t_1} (a_s - a_c)\ \mathrm{d}t,$$

where a_s is the seismic acceleration. This can be integrated directly over map units. Alternatively, one can use an empirical (regression) formula relating D_N to the Arias Intensity I_A,

$$\log I_A = M - 2\log R - 4.1,$$

where M is the Richter magnitude and R (m) the distance to the seismic source, or use

$$I_A = 0.9 t_d (\mathrm{PGA})^2,$$

where t_d is the Dobry time, itself estimated from

$$\log t_d = 0.423M - 1.83.$$

Then, an empirical formula that relates D_N (m) to I_A (m/s) and a_c,

$$\log D_N = 0.7605 \log I_A - 0.9965 \log a_c - 0.733.$$

2.1 Newmark Parameters

Newmark's model requires knowledge of several parameters:

- estimated from geotechnical field work: cohesion c', friction angles ϕ',
- obtained from seismic records: Arias intensity I_A,
- topographic data (DEM): slopes α.

The geotechnical data itself, composed of soil types, is obtained from a combination of laboratory tests and geological maps. But lithological distributions are rarely known with any accuracy, and often one has to assume a homogeneous distribution for different lithologies of the same geological unit. There is also the issue of poor spatial accuracy. Therefore one should consider these model parameters as probabilistically distributed [10, 11]. This raises the tricky question of their estimation. Possible approaches include:

- Kriging [7]?
- Monte Carlo simulations [10]?
- Regression to a chosen distribution [4]?

2.2 Shakemaps

Definition 2.2. A ShakeMap is a representation of ground shaking produced by an earthquake. The information it presents is different from the earthquake magnitude and epicenter that are released after an earthquake because ShakeMap focuses on the ground shaking produced by the earthquake, rather than the parameters describing the earthquake source. So, while an earthquake has one magnitude and one epicenter, it produces a range of ground shaking levels at sites throughout the region depending on distance from the earthquake, the rock and soil conditions at sites, and variations in the propagation of seismic waves from the earthquake due to complexities in the structure of the Earth's crust.

ShakeMap is an open-source software program of the USGS, employed to automatically produce a suite of maps and products that portray the geographical extent and severity of potentially damaging shaking following an earthquake. It is routinely used to provide post-earthquake situational awareness for emergency management and response and for damage and loss estimation.

A ShakeMap can also be employed as the primary shaking hazard input for many other downstream earthquake products, including

- assessments of critical facilities,
- societal losses, and
- estimates of ground failure.

PERCEIVED SHAKING	Not felt	Weak	Light	Moderate	Strong	Very strong	Severe	Violent	Extreme
POTENTIAL DAMAGE	none	none	none	Very light	Light	Moderate	Mod./Heavy	Heavy	Very Heavy
PEAK ACC.(%g)	***<0.1***	***0.5***	***2.4***	***6.7***	***13***	24	44	83	>156
PEAK VEL.(cm/s)	<0.07	0.4	1.9	5.8	***11***	***22***	***43***	***83***	***>160***
INSTRUMENTAL INTENSITY	**I**	**II-III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X+**

Scale based upon Wald, et al.; 1999

Fig. 1. Instrumental Intensity based on a combined regression of peak acceleration and velocity amplitudes vs. observed intensity for eight significant California earthquakes - source CISN.

Class	Values	Displacement (cm)
very low	$0 < p < 0.2$	
low	$0.2 \leq p < 0.4$	$0 < D_N < 1$
moderate	$0.4 \leq p < 0.6$	$1 \leq D_N < 5$
high	$0.6 \leq p < 0.8$	$5 \leq D_N < 15$
very high	$0.8 \leq p < 1$	$D_N \geq 15$

Table 1. Susceptibility classification for EILs.

Mathematically, or algorithmically, geospatial interpolation can take many forms. There are some good reasons to employ geospatial kriging-with-a-trend. However, the complexity of the trends (GMPE, as well as inter-event bias corrections per Intensity Measure or IM), the use of multiply-weighted strong-motion and macroseimic data, and the real-time nature of the processing require other considerations. The approach ShakeMap currently employs for interpolation (Worden et al., 2018) applies a conditional multi-variate normal distribution, within which some or all of the points upon which the distribution is conditioned may themselves have uncertainty.

Estimating motions where there are few stations, and then interpolating the recordings and estimates to a fine grid for mapping and contouring, requires several steps. The shakemap provides the following values:

- peak ground acceleration PGA (horizontal).
- peak ground velocity (PGV).
- pseudo spectral acceleration (PSA).

2.3 Susceptibility Classes and Maps

For the final step, the actual production of the LSM, we need a classification scale. One possible classification for earthquake induced (or co-seismic) landslide susceptibility is given in Table 1, based on the probability p of occurrence of an EIL, or on the terrain displacement itself.

2.4 The global workflow for LSM

To actually generate an LSM, a global workflow, originally presented in [7, 8] is used. This can be found in PHIVOLC's ArcGIS setup. In Figures 2 and 3 we present a version that includes all the important parameters.

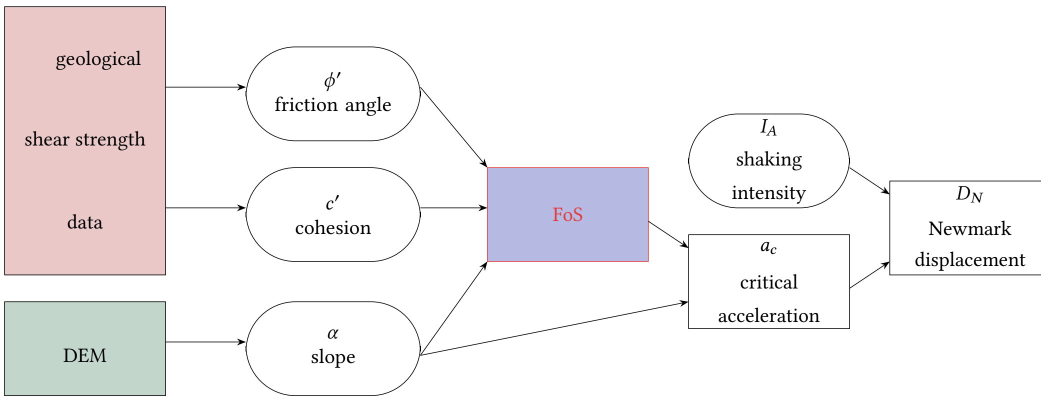

Fig. 2. Generic workflow for computation of Newmark displacement D_N.

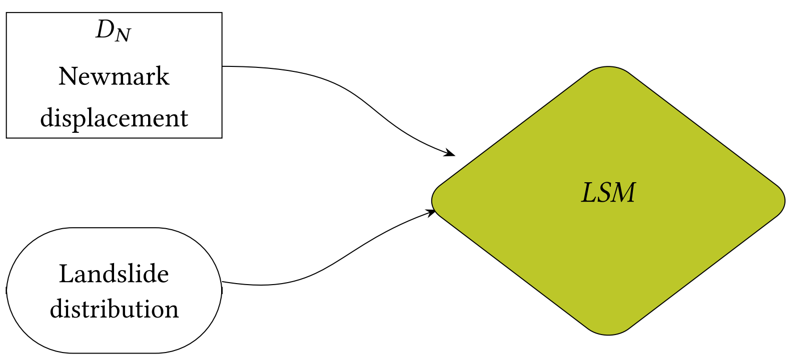

Fig. 3. Generation of the final Landslide Susceptibility Map (LSM)

3 POSSIBLE RESEARCH DIRECTIONS

In order to enhance and enrich the PHIVOLCS workflow for LSMs, we could consider the following topics:

- Evaluate the influence of seismic event frequency (period) and duration—see [9];
- Perform a feature importance study on the 7 covariates—the geotechnical parameters in Newmark's formula (1).
- Perform a causality study on the features, based on Shapley values, and integrate the results into the hazard/susceptibility map.
- Use Monte-Carlo simulations (with LHS sampling?) to quantify the uncertainty in the shear strength parameters, following [10].
- Integrate ShakeMap displays into the workflow. These can also be obtained from simulations by SPECFEM—see Project 3.

NOTE: All the above must be presented to PHIVOLCS and discussed with them. In addition, we need to either collect all the PHIVOLCS data for LSMs, or download benchmark data from the internet.

THINGS TO DO

(1) Interrogate PHIVOLCS: methods, data, bottlenecks in LSM production workflow.

(2) Investigate LandLab to see if it has any value for us.
(3) Are ShakeMaps of interest to PHIVOLCS? Could we integrate them (and by-products) into the overall workflow? What link with VaR analysis of Project 1?
(4) Break the workflow into sub-projects, and assign a sub-team to each piece.
(5) Evaluate the feasibility of a data-driven approach, based on RF for example. Do we have sufficient data? Can a transfer learning approach be applied here? How does this stand up against an MC-based Newmark model approach?

REPLACE ENTIRE WORKFLOW BY ML?

PHIVOLCS uses the workflow of Figure 2, starting from the geotechnical and slope parameters and ending with the exceedance (2), and then they generate a *hazard* map that does not include the landslide data used for the generation of susceptibility maps. In other words, the PHIVOLCS workflow is a "mapping"

$$f \colon \{\phi', c', \gamma, \alpha\} \longmapsto E.$$

The proposition is to learn the mapping f with ML techniques, probably a neural network.

This requires the following steps:

(1) Collect data pairs, $\{x_i, y\}$ of input (explanatory variables) and output (response variables) and create a dataset. For this we need to interrogate PHIVOLCS as to availability of data, and concerning the reliability of the target variable. If not, select a more reliable target variable.
(2) Perform EDA on the data.
(3) Perform a feature importance analysis on the dataset using RF and/or Shapley values.
(4) Find a suitable machine learning model that can provide satisfactory predictive performance.
(5) Option: instead of replacing the entire workflow, we can identify sub-parts that could each be "replaced" by a suitable, tailor-made machine learning model.

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