Title

Framework for Regional Earthquake-Induced Landslide Assessment using a Data-Informed Probabilistic Approach

Authors
Ojomo, Olaide
Rathje, Ellen M
Bullock, Zach
et al.

Publication Date
2022-07-01

Peer reviewed

12th National Conference on Earthquake Engineering
Salt Lake City, Utah
27 June - 1 July 2022
Hosted by the Earthquake Engineering Research Institute

Framework for Regional Earthquake-Induced Landslide Assessment using a Data-Informed Probabilistic Approach

Olaide Ojomo[1], Ellen M. Rathje[2], Zach Bullock[3], Pengfei Wang[4], Paolo Zimmaro[5], Domniki Asimaki[6], Jonathan P. Stewart[7]

ABSTRACT

This paper presents a data-informed, probabilistic methodology employed to assess regional co-seismic landslide hazards in California, primarily by jointly analyzing geologic data and geotechnical properties of various geologic units and incorporating uncertainties in the prediction analyses. Geotechnical data from a borehole database, a California statewide geologic map, and judgment in consultation with local geologists/geotechnical engineers are integrated to estimate a range of plausible shear strength parameters and slope properties that represent the epistemic uncertainty in these parameters. A logic tree approach is implemented to account for the epistemic uncertainties in the input model parameters, as well as in empirical displacement models, that may influence the accuracy of the co-seismic landslide displacement predictions.

Introduction

The state of California is seismically active and has a high likelihood of earthquake-induced landslides that may cause damage to aboveground and buried infrastructure, causing concerns for public safety and economic losses. The possibility of occurrence of such landslides needs to be assessed to minimize potential exposure to damage and to aid emergency response management plans. This issue is of particular importance for distributed infrastructure, such as pipeline and transportation networks.

The resistance of slopes to earthquake-induced landslides is largely dependent on the material shear strength, geology, slope configuration, groundwater table and ground shaking intensity. The rigid sliding block approach has been used extensively to estimate earthquake-induced displacements of slopes on a regional scale [1-4]. To estimate displacements, the approach requires the yield acceleration, k_y, which is defined as the horizontal acceleration that results in a factor of safety (FS) of 1.0. The calculation of k_y for regional-scale analysis often utilizes an infinite slope assumption, and the resulting expressions (Eqs. 1 and 2) are a function of the factor of safety (FS), the effective

[1] Graduate Student Researcher, Department of Civil, Arch. and Env. Engineering, Univ. of Texas, Austin, TX 78712
[2] Professor, Dept. of Civil, Arch. and Env. Engineering, Univ. of Texas, Austin, TX 78712 (email: e.rathje@mail.utexas.edu)
[3] Assistant Professor, Department of Civil Engineering, University of British Columbia, Vancouver, BC Canada V6T 1Z4
[4] Postdoctoral Scholar, Dept. of Civil and Environmental Engineering, University of California, Los Angeles, CA 90095
[5] Visiting Project Scientist, Dept. of Civil and Environmental Engineering, University of California, Los Angeles, CA 90095
[6] Professor, Department of Mechanical and Civil Engineering, California Institute of Technology, Pasadena, CA 91125
[7] Professor, Department of Civil and Environmental Engineering, University of California, Los Angeles, CA 90095

Ojomo O. et al. Regional Co-Seismic Landslide Susceptibility Mapping for California using Data-Driven Probabilistic Approach. *Proceedings of the 12th National Conference in Earthquake Engineering*, EERI, Salt Lake City, UT. 2022.

cohesion (c'), the effective friction angle (ϕ'), the material and water unit weights (γ and γ_w, respectively), the slope angle (α), the thickness of the sliding mass (t), and the proportion of sliding mass that is saturated (m).

$$k_y = (FS - 1)g/(\cos\alpha \cdot \tan\phi' + 1/\tan\ \alpha) \quad (1)$$
$$FS = c'/(\gamma \cdot t \cdot \sin\ \alpha\ ) + \tan\phi'\ (1 - m \cdot \gamma_w/\gamma\ )/\tan\ \alpha \quad (2)$$

Shear strength parameters can vary significantly, even within the same geologic unit, due to spatial variability and continuity, the reliability of testing procedures, and interpretation of data. This paper describes the process of (1) assigning shear strengths on a regional scale based on geologic units and geotechnical data, and (2) utilizing the logic tree approach to incorporate uncertainties related to material strength parameters, slope properties and predictive displacement models in seismic landslide analyses.

Previous Work

Previous studies have evaluated the prediction of seismic landslides using the rigid sliding block approach. These studies used a limited amount of shear strength data and found that only a fraction of observed landslides is captured, and the total area of predicted landslides is much larger than observed [2-4]. These studies only used single values of the input parameters without accounting for uncertainties and concluded that the overprediction of landslides may be due to the use of one set of shear strength parameters per geologic unit. More recent studies [5, 6] highlighted the importance of considering the spatial variability of shear strengths across geologic units and accounting for uncertainties in seismic landslide predictions. One approach to incorporating epistemic uncertainties in the analysis is the use of logic trees, which is common practice in probabilistic seismic hazard analysis [7-9]. This study builds upon previous work to develop a logic tree for seismic landslide analysis that can be utilized at the state-scale and incorporates not only parametric uncertainty but also differences in the displacement prediction models.

General Methodology and Data

The primary geospatial inputs essential for the estimation of seismic landslide displacements include digitized regional-scale geologic maps, a digital elevation model (DEM) for computing slope angle, sliding mass thickness, water table data, material unit weight, shear strength parameters and earthquake ground motion parameters. This study used the statewide geologic map developed by [10] for assigned shear-wave velocities, which consists of fifteen geologic units (Fig. 1). The geologic map provides a consistent representation of the spatial distribution of geologic units across the state; however, there are regional geologic differences between northern and southern California. Although the boundary between the two regions is not well defined, this study presumes the red line shown in Fig. 1 to be the geologic boundary between northern and southern California for strength assignment purposes. The red line, which generally follows the Santa Ynez and Garlock faults, also shows the approximate southern extent of the Franciscan Complex (KJf), a rock complex consisting mostly of mélange, sandstone, shale, chert and greenstone.

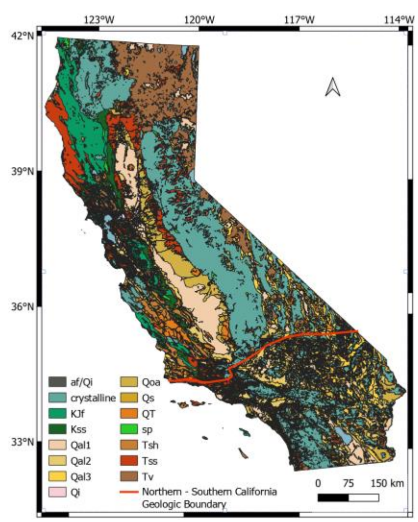

Figure 1. Geologic Map of California [10]

A 10-m resolution DEM from the CGS was used to derive the slope angles for the entire region. Slopes in California are as steep as about 80° in hilly terrains with slopes less than 10° associated with alluvial fans and floodplains. Most landslides triggered by earthquake events are shallow in nature and occur on steeper slopes [11]. Minimum slope inclination for observed earthquake-induced soil slides and rock slumps is about 15° [12]. The unit weight is assumed to be 18 kN/m^3 for the entire region. The thickness of the sliding mass was derived from judgment in consultation with local landslide experts. Low, best and high estimates of the sliding mass thickness are 5 m, 10 m and 15 m respectively for northern California and 1.5 m, 3 m and 4.5 m for southern California respectively. The degree of saturation of the sliding block are computed from water table depths obtained from the California well database [13].

Shear Strength Estimation

Shear strength parameters (c' and ϕ') were obtained from a borehole database maintained by the California Geologic Survey (CGS). The database includes results from geotechnical testing, mostly direct shear tests conducted by consultants and observation reports of geologic properties and lithology of borehole samples. The data was statistically analyzed and used in conjunction with geologic data to characterize the strength properties of the geologic units. The geologic subunits defined in the borehole logs were grouped and matched with the geologic units described in [10] according to their descriptions and the interpretation of the lithology and grain sizes. Subsequently, best estimates of c' and ϕ' mapped to the geologic subunits were assigned to the corresponding statewide geologic units. The computed values of c' and ϕ' were compared with values documented in Chapter F of the Hayward fault scenario report [14] and CGS seismic hazard reports. The properties were adjusted for some units to ensure the relative strengths of the geologic units was appropriate. As c' tends to follow a lognormal distribution [15, 16], the mean and standard deviation of the natural logarithm of c' (in units of kPa) are used in the analysis. Table 1 presents the shear strength parameters and water table depth information for each of the geologic units considered in this study. Statistical analysis of the

Table 1. Computed shear strength and water table depth data for each geologic unit

Map Symbol	Geologic Unit Description	$\mu_{\ln c}$	$\sigma_{\ln c}$	μ_ϕ (°)	σ_ϕ (°)	Water table depth (m)		
						Low	Best	High
Qal3	Quaternary (Holocene) alluvium on slopes steeper than 2%	3.04*	1.37	24.3	9.8	1.02	1.96	4.34
		2.293*	0.80	32.2	6.6	1.49	2.72	4.47
Qoa	Quaternary (Pleistocene) alluvium	3.30	1.07	26.8	10.3	1.27	2.33	5.21
		2.41	0.90	32.0	7.7	1.98	3.22	5.81
QT	Quaternary to Tertiary alluvial deposits such as Saugus of SoCal, Paso Robles of central coast ranges, and Santa Clara of the Bay Area	3.37	0.78	28.5	12.1	2.6	4.81	10.72
		2.85	0.81	31.4	8.1	2.55	5.64	17.71
Tsh	Tertiary shale/siltstone such as Repetto, Fernando, Puente and Modelo in LA	3.37	1.07	26.8	11.1	0.82	3.21	10.87
		3.05	0.72	30.2	8.5	1.32	2.54	5.67
Tss	Tertiary sandstone such as Topanga in LA and Butano sandstone in SF Bay area	3.40	0.72	28.3	10.4	1.14	2.04	3.72
		2.89	0.90	32.8	8.3	1.81	3.08	4.69
Tv	Tertiary volcanic such as Conejo Volcanics in Santa Monica Mountains and Leona Rhyolite in East Bay Hills	2.96	0.86	33.0	8.3	0.99	1.76	2.74
		3.18	0.82	30.5	9.1	0.94	1.17	1.83
sp	Serpentine, generally considered part of the Franciscan complex	3.30	0.93	28.0	12.7	0.73	1.18	2.18
		not present in southern California						
Kss	Cretaceous sandstone of the Great Valley Sequence in the central Coast Ranges	3.32	0.94	31.0	11.0	0.88	1.37	3.37
		3.01	0.82	33.4	8.4	3.79	4.19	8.77
KJf	Franciscan complex rock such as melange, sandstone, shale, chert, and greenstone	3.32	0.84	32.0	11.7	0.78	1.37	2.54
		not present in southern California						
crystalline	Crystalline rocks	3.27	0.92	32.0	12.0	0.81	1.5	2.68
		2.85	1.00	36.9	6.2	1.67	2.72	6.12

*Values in black represent northern California data while values in blue represent southern California data.

borehole datasets indicates that c' in northern California is higher than values obtained in southern California at the same confining pressure. The reverse is the case for ϕ'.

Logic Tree for Displacement Calculation

The logic tree analysis is used to capture different combinations of shear strength parameters, slope properties and displacement models, with each input parameter represented at a node with a range of values on the branches. Weights are assigned to each branch of the logic tree to reflect the degree of confidence in each input parameter. The weighting factor uses the 3-point distribution described in [17] for ϕ', c', t and m. These input parameter combinations result in 81 values of k_y computed from Eqs. 1 and 2 which are then re-sampled into a 5-point distribution using [17]. The logic tree shown in Fig. 2 displays the parameters for a single 10-m grid cell within the Tertiary shale (Tsh) geologic unit in northern California. For this study, three displacement models are considered – two of the models [3, 7] use a combination of magnitude (M) and peak ground acceleration (PGA) and are each given weights of 0.3. The third model uses a combination of PGA and peak ground velocity (PGV) [7] and is given a weight of 0.4.

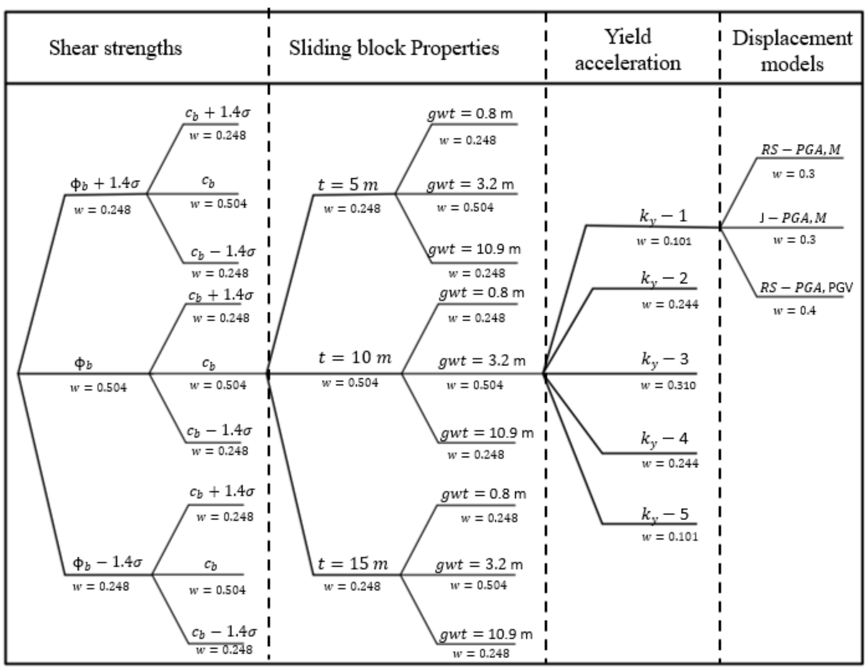

Figure 2. Illustrative logic tree for geologic unit Tsh in northern California

Conclusions

This paper outlined a logic tree approach for seismic landslide assessment that can be applied state-wide in California. The logic tree approach allows for the analysis to account for the epistemic uncertainty in the various input parameters. Best estimates and uncertainty in the shear strength parameters for different geologic units were derived from statistical analysis of borehole and geologic data. Similar analyses and judgment were used to develop logic tree branches for the other input parameters (t and m). The methodology presented above is applied to individual 10-m grid cells but can be expanded to develop probabilistic distributions of the amount of displacement and size of seismic deformation zones for risk assessments of spatially distributed infrastructure as described in companion papers [18, 19].

Acknowledgments

This work is made possible by a research contract from the California Energy Commission to the Natural Hazard Risk and Resiliency Research Center at the B. John Garrick Risk Institute at UCLA. The DEM and geotechnical borehole database were provided by the California Geological Survey. Discussions with Tim McCrink, Randy Jibson, Chris Wills, Alan Kropp and other engineering/geology consultants were very helpful to provide additional perspective to characterize the shear strengths for geologic units in the study area. The views and conclusions expressed in this document are those of the authors.

References

1. Newmark, NM. 1965. Effects of Earthquakes on Dams and Embankments. Geotechnique 15 (2): 139–60. https://doi.org/10.1680/geot.1965.15.2.139.
2. Jibson RW, Harp EL and Michael JA. 2000. A Method for Producing Digital Probabilistic Seismic Landslide Hazard Maps. Engineering Geology. Vol. 58. https://doi.org/10.1016/S0013-7952(00)00039-9.
3. Jibson RW. 2007. Regression Models for Estimating Coseismic Landslide Displacement. Engineering Geology 91 (2–4): 209–18. https://doi.org/10.1016/j.enggeo.2007.01.013.
4. Dreyfus D, Rathje EM and Jibson RW. 2013. The Influence of Different Simplified Sliding-Block Models and Input Parameters on Regional Predictions of Seismic Landslides Triggered by the Northridge Earthquake. Engineering Geology 163 (August): 41–54. https://doi.org/10.1016/j.enggeo.2013.05.015.
5. Wang Y and Rathje EM. 2014. Incorporating Epistemic Uncertainties into Regional Seismic Landslide Maps. In NCEE 2014 - 10th U.S. National Conference on Earthquake Engineering: Frontiers of Earthquake Engineering. https://doi.org/10.4231/D37M04132.
6. Wang Y and Rathje EM. 2018. Application of a Probabilistic Assessment of the Permanent Seismic Displacement of a Slope. Journal of Geotechnical and Geoenvironmental Engineering 144 (6): 04018034. https://doi.org/10.1061/(asce)gt.1943-5606.0001886.
7. Saygili G and Rathje EM. 2009. Probabilistically Based Seismic Landslide Hazard Maps: An Application in Southern California. Engineering Geology 109 (3–4): 183–94. https://doi.org/10.1016/j.enggeo.2009.08.004.
8. Du W, Huang D and Wang G. 2018. Quantification of Model Uncertainty and Variability in Newmark Displacement Analysis. Soil Dynamics and Earthquake Engineering 109 (June): 286–98. https://doi.org/10.1016/j.soildyn.2018.02.037.
9. Rodriguez-Marek A, Bommer JJ, Youngs RR, Crespo MJ, Stafford PJ, and Bahrampouri M. 2021. Capturing Epistemic Uncertainty in Site Response. Earthquake Spectra 37 (2): 921–36. https://doi.org/10.1177/8755293020970975.
10. Wills CJ, Gutierrez CI, Perez FG, and Branum DM. 2015. A Next Generation V_{S30} Map for California Based on Geology and Topography. Bulletin of the Seismological Society of America. 105 (6): 3083–3091, https://doi.org/10.1785/0120150105.
11. Jibson RW and Michael JA. 2009. Maps showing seismic landslide hazards in Anchorage, Alaska: U.S. Geo- logical Survey Scientific Investigations Map 3077, scale 1:25,000, 11-p. pamphlet. http://pubs. usgs.gov/sim/3077.
12. Keefer DK. 2013. Landslides Generated by Earthquakes: Immediate and Long-Term Effects. In Treatise on Geomorphology, 5:250–66. https://doi.org/10.1016/B978-0-12-374739-6.00091-9.
13. California Water Board. 2020. Groundwater Ambient Monitoring and Assessment Program (GAMA). Accessed at: https://gamagroundwater.waterboards.ca.gov/gama/datadownload. Last accessed: March 15th, 2020.
14. Detweiler ST and Wein AM 2017. The HayWired earthquake scenario: U.S. Geological Survey Scientific Investigations Report 2017–5013, https://doi.org/10.3133/sir20175013
15. Fanelli G, Salciarini D, and Tamagnini C. 2015. Reliable Soil Property Maps over Large Areas: A Case Study in Central Italy. Environmental & Engineering Geoscience, no. October 2016: 1078-7275.EEG – 1709. https://doi.org/10.2113/eeg-1709.
16. Zhu H, Zhang LM, and Xiao T. 2019. Evaluating Stability of Anisotropically Deposited Soil Slopes. Canadian Geotechnical Journal. https://doi.org/10.1139/cgj-2018-0210.
17. Miller AC and Rice TR. 1983. Discrete Approximations of Probability Distributions. Management Science, 29, 352-362.
18. Stewart JP, Asimaki D, Rathje EM, Bullock Z, Ojomo O, Wang P, Zimmaro P. 2022. Framework for Analysis of Spatially Distributed Ground Failure Displacement Hazards. Proceedings of the 12th National Conference in Earthquake Engineering, Earthquake Engineering Research Institute, Salt Lake City, UT. 2022.
19. Bullock Z, Zimmaro P, Wang P. 2022. Regional Estimation of Liquefaction-Induced Ground Deformations using a Data-Informed Probabilistic Approach. Proceedings of the 12th National Conference in Earthquake Engineering, Earthquake Engineering Research Institute, Salt Lake City, UT. 2022.