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Predicting Changes in Displacement Probability of Slow-Moving Landslides through Markov Chain and Monte Carlo Simulation

Michael PORTER[1], Mark VESSELY[2], Scott ANDERSON[2]

[1]BGC Engineering, Vancouver, Canada
[2]BGC Engineering, Golden, United States
Corresponding author: Mark Vessely (mvessely@bgcengineering.com)

Abstract

Slow-moving landslides are a form of persistent landsliding with annual movement rates ranging from millimetres to meters that can incur multiple cycles of rapid acceleration or deceleration over decades and centuries. It is often not possible to economically stabilize large slow-moving landslides, resulting in a situation where system owners and users are subject to recurring annual disruption and financial risk for assets crossing these complex slides. When a slow-moving landslide experiences a sudden change to an increased velocity, the risk will likely increase for the exposed system users and owner. Thus, understanding the likelihood of adverse landslide velocity changes is important for infrastructure owners tasked with risk management and resilient planning decisions.

In a changing climate, the resulting variability in slow-moving landslide velocity has important implications for risk assessment, resilient design decisions, and maintenance of transportation and other infrastructure crossing these slides. Markov Chain models offer a systematic, expert-based approach to predict changes in landslide velocity probability distributions over the operational life infrastructure. In many scenarios, infrastructure condition states can be linked to cumulative and/or annual landslide displacement thresholds. Monte Carlo simulation combined with Markov model outputs can be used to estimate the annual probability of landslide displacement threshold exceedances and infrastructure condition state probabilities. In turn, these can facilitate lifecycle cost modelling and risk cost-benefit analysis of landslide stabilization and other management options. With time, the models will benefit from the incorporation of evidence-based ground movement data obtained from rapidly advancing earth observation technology.

Keywords: slow-moving landslide, displacement probability, Markov Chain

1. Introduction

As a broad class, slow moving landslides can be visualized as a form of deep-seated landsliding that is present in gentle to moderate sloping terrain with movement histories that span decades or centuries. When slow moving landslides intersect with portions of an infrastructure system, asset owners are exposed to an elevated level of risk from the persistent slide hazard. The infrastructure disruption caused by slow moving landslides can range from no impacts during periods of dormancy to high frequency maintenance cycles that are needed to repair damaged assets and maintain operations on a daily basis. In a worst-case scenario, slow moving landslides can accelerate to a rate that is greater than can be operationally maintained, resulting in unplanned investments to relocate or rebuild infrastructure at a substantial cost.

Slow moving landslides are often associated with geological environments consisting of weak shale bedrock and the associated overlying clayey soils or areas where deglaciation has destabilized valley slopes or deposited glaciolacustrine sediments. Occasionally, in response human activity, progressive failure sequences, or changes in the climatic patterns, slow-moving landslides will accelerate. It is during these periods of elevated activity and velocity that much of the safety, economic and environmental losses occur. Quantifying the probability of a change from dormant to active, or the potential for changes in landslide velocity class, presents an opportunity for asset owners to forecast where disruptive ground changes are most likely to occur and to manage the resulting life-cycle risk.

The velocity of normally slow-moving landslides will vary seasonally and from year to year in response to numerous factors that can alter the forces resisting and promoting movement. Some factors can be controlled by an asset owner, such as construction details that limit disturbance and maintenance interventions during operations, while other factors related to climate or beyond the boundary works present a threat that must be accepted.

With advances in landslide and infrastructure monitoring it is now possible to dramatically reduce the potential for some types of catastrophic loss such as life loss from train derailments, structure collapse, and pipeline rupture caused by slow-moving landslides. However, landslide monitoring and response is still a relatively reactive approach that typically only proactively manages a small fraction of the total consequence and risk. For example, Porter et al., (2019) described how normally slow-moving landslides within the Western Canada Sedimentary Basin cause damage to infrastructure with estimated economic impacts likely exceeding $450 million per year. Most of the economic impacts were associated with infrastructure maintenance and repair effort and business interruption costs which can only be modestly reduced through monitoring. The authors are familiar with many specific landslides throughout North America where asset owners incur annual costs that exceed $100,000 USD per year to maintain the lowest level of acceptable performance possible.

In certain situations, asset owners will have an opportunity to avoid slow-moving landslides during re-routing projects or to invest in landslide stabilization works and improve stability to the point where the potential for movement is unlikely during the infrastructure design life. However, in most cases neither of these options will be available, particularly across a regional or country scale systems with many slides, and asset owners must accept a recuring annual risk exposure at each slide location.

Decisions on how best to reduce economic risk where existing or planned infrastructure crosses slow-moving landslides are ideally informed by trade-off studies that estimate the risk costs to asset owners and system users. Quantification of this risk in the context of whole-life asset modelling requires tools to estimate the probabilities of landslide velocities that are non-stationary when viewed over a several decade investment period.

Since early 2020, the author and several colleagues have been working on methods to estimate the probabilities of landslide velocity transitions and total annual displacements using Markov Chain models which offer a systematic, expert-based approach to predict annual displacement probability distributions for certain types of landslides (Porter et al., 2022a).

2. Landslide Velocity Modelling

2.1 Modified Landslide Velocity Classification System

The proposed approach involves treating landslide velocity as a state variable and velocity classes as condition states. Some modifications to the Cruden and Varnes (1996) classification system for landsliding are required to allow for compatibility with the modelling approach. These modifications include creating a Velocity Class 0 for dormant landslides, subdivision of the Very Slow category into two classes, equating the velocity classes to expected total annual displacements (as opposed to instantaneous velocities), and assignment of an assumed left-triangular probability density function to the expected displacements associated with each velocity class range. The modified landslide velocity classification system is shown in Table 1, and additional detail is provided in Porter et al. (2022a).

Table 1: Modified Landslide Velocity Classification after Cruden and Varnes (1996).

Class	Description	Typical velocity	Annual displacement criteria (m)	Mean annual displacement based on assumed left-triangular distribution (m)
4+	Moderate	>13 m/mo	>16	64 (for the range between 16-160 m/yr)
3	Slow	>1.6 m/yr	>1.6	6.4
2b	Very slow	>160 mm/yr	>0.16	0.64
2a	Very slow	>16 mm/yr	>0.016	0.064
1	Extremely slow	<16 mm/yr	>0.0016	0.005
0	Dormant	0 mm/yr	<0.0016	0

Note: Class 4+ refers to all velocity classes Moderate or greater (i.e., Rapid, Very rapid and Extremely rapid)

Within the description for Moderate landslide velocity, the Rapid, Very Rapid, and Extremely Rapid velocities are included in an undifferentiated category, resulting in a broad class that includes any annual displacement exceeding 16 m (Class 4+). If such velocities are deemed credible for a specific landslide and delineation of a subset of greater movement rates is required, other approaches (e.g., Glastonbury and Fell, 2008) can be deployed to further estimate the respective conditional probabilities in the case that Class 4+ velocities are realized.

2.2 Predicting the Annual Displacement of Slow-moving Landslides

Many normally slow-moving landslides have a credible potential to produce the annual displacements associated with Velocity Classes 0 to 4+ in Table 1. The challenge is to efficiently estimate the probability distribution for each landslide velocity class of interest over the whole life of infrastructure or other assets of value, and with sufficient accuracy to improve decision-making. With time, the prediction of landslide velocity class probabilities will be informed by evidence-based and data-driven statistical conclusions developed through long-term measurement of landslide movements, particularly with the adoption of remote earth observation methods. However, the temporal nature of such data collection may limit evidence-based conclusions to be informed at the start of the proposed approach. In the interim, the framework can begin using expert elicitation or subjective assessments to inform the initial risk management decisions. To do so, we leverage the Theory of Uniformitarianism – over the long-term, future velocity distributions ought to resemble past distributions, acknowledging that non-stationary climate conditions may challenge this assumption; and the hypothesis that current annual velocity is a useful predictor of velocity in the near-term.

3. Forecasting Landslide Velocity Change

3.1 Markov Chains

Markov Chains offer an approach to capture the change in state of knowledge between a known velocity today and an assumed velocity class probability distribution many years into the future. Markov Chains are probabilistic models useful in the analysis of change in dynamic systems (Howard, 2007). In these models, the condition of a physical system can be described by state variables. For the physical system comprising a landslide, the annual displacement can be treated as a state variable and the velocity classes listed in Table 1 treated as condition states. Key elements of a Markov model can be encapsulated in a “Transition Matrix” (P) with N rows and N columns which illustrates the “N” possible condition states and the probabilities of transitioning between states (or remaining in the current state) during each model timestep. To predict the probabilities of being in a particular condition state after a certain number of timesteps, one needs to know the state of the system at timestep n = 0. This is referred to as the initial state vector. The initial state vector ($\pi(0)$) is a 1-row matrix listing the probabilities of being in each possible state at n = 0. The state vector at any timestep can be calculated by post-multiplying the state vector at the preceding timestep by the transition matrix P [Equation 1].

$$\pi(n+1) = \pi(n)P \qquad (1)$$

After many timesteps without observation, our knowledge of the state of the system diminishes to a constant value represented by a limiting state probability vector, irrespective of the value of the initial state vector. In the case of landslide velocity, the limiting state vector can be thought of as the distribution of velocity classes that would be realized over a very long period of observation (e.g., hundreds or thousands of years). Alternatively, the observed distribution of velocity classes from a large inventory of landslides of a certain type over a period encompassing decadal-scale climate cycles also ought to resemble the limiting state vector for that type of landslide in that environment.

3.2 Example Landslide Behaviour Types and Landslide Velocity Markov Models

An expert-based geomorphic assessment of the past behaviour of a landslide can be used to define a subjective limiting state vector for that behaviour type. This is accomplished by assessing or the displacement over a historical period of time as a product of the proportion of years spent in each velocity class, and evidence of episodes of faster movement. Porter et al. (2022a) proposed five different behaviour types with limiting state vectors yielding long-term average annual displacements ranging from 0.01 to 1.0 m/yr (Table 2). A transition matrix that would generate the desired limiting state vector was established for each landslide behaviour type (e.g., Figure 1).

Table 2: Proposed landslide behaviour types and characteristics for pre-existing slow-moving landslides.

Behaviour Type	**Type A**	**Type B**	**Type C**	**Type D**	**Type E**
Typical failure mechanism	Translational block slides and spreads	Translational block slides and spreads	Translational block slides and spreads, rotational slides	Translational and rotational slides, earth flows, complex slides	Translational and rotational slides, earth flows, complex slides
Assumed limiting state velocity class distribution					
0	70%	50%	30%	10%	0.5%
1	28.5%	45.5%	55.0%	44.9%	3.0%
2a	1.1%	3.2%	10.8%	32.4%	54%
2b	0.4%	1.1%	3.6%	10.8%	36%
3	0.06%	0.18%	0.60%	1.8%	6.0%
4+	0.005%	0.015%	0.050%	0.15%	0.50%
Mean annual displacement	0.01 m	0.03 m	0.1 m	0.3 m	1.0 m
Probability of Class 4+	1:20,000 (or not credible)	1:6,700	1:2,000	1:670	1:200

From/To	0	1	2a	2b	3	4+
0	0.99620	0.00342	0.00034	0.00003	0.000003	0.000000
1	0.00387	0.99376	0.00213	0.00021	0.00002	0.000002
2a	0.00332	0.02991	0.95320	0.01221	0.00122	0.00014
2b	0.00052	0.00467	0.04666	0.92800	0.01814	0.00202
3	0.00015	0.00134	0.01345	0.13446	0.82000	0.03060
4+	0.00007	0.00062	0.03381	0.34500	0.31050	0.31000
Target	**0.50**	**0.455**	**0.032**	**0.011**	**0.0018**	**0.00015**

Figure 1: Velocity class transition matrix for Landslide Behaviour Type B and target limiting state vector.

4. Applying Landslide Velocity Change Forecasting in Practice

4.1 Linking Landslide Velocity Forecasts and Asset Condition States

The output of the Markov modelling process produces probability distributions for the landslide velocity classes that are possible for each annual timestep. As the these are subjective probability values, judgment should be applied as a check on the model findings. In many scenarios, measured conditional state of an infrastructure asset can be linked to cumulative and/or annual landslide displacement thresholds. Monte Carlo simulation can be used to combine the Markov model velocity class probability distributions with the assumed left-triangular displacement probability density function for each velocity class to estimate the annual probability of landslide displacement threshold exceedances and infrastructure condition state probabilities (Porter et al., 2022b; Porter et al., 2022c). In turn, these can facilitate lifecycle cost and risk cost-benefit analysis of landslide treatment options and other risk management strategies.

4.2 Calibration and Model Improvement

The emergence of regional scale earth observation technologies for measuring temporal ground changes enables the uncertainty within a landslide velocity model to improve through calibration to actual ground movements. For instance, global satellite InSAR data and/or rapid, regional lidar change detection methods allow an owner to develop an improved understanding of the rate and amount of ground change over time. In many cases, data for baseline data have already been obtained and subsequent collection efforts can inform an owner of with quantification of several years ground movements (Lato, et al., 2019). Combining these historical findings, if available, and initiating future remote sensing change programs will reduce uncertainty in landslide classification as well as providing a known time ranges in the given class(es), producing a model that is more evidence-based with time.

4.3 Prioritization Tool

Owners with risk exposure from several landslides across a network of infrastructure assets likely have considerably more investment needs than funds available for investment. Modelling the probability of landslide velocity changes provides an additional tool for asset owners to manage risk and prioritize sites on the likelihood for future changes. For instance – given two landslides with a similar risk exposure in a constrained investment scenario, an asset owner can reduce the likelihood of whole life cost escalation by identifying the landslide with the greater probability of velocity increase to receive treatment funds when available.

In a non-stationary climate where changes in temperature and precipitation trends are possible, prioritization of mitigation work on the basis of highest likelihood for adverse velocity change is an important step towards stewardship of limited public or private investment funds. To illustrate this concept with two landslides with similar present risk exposures but in different changing climate scenarios, such as a site that will be warmer and drier compared to a site that may receive greater precipitation, selecting the site that will be wetter in the future could represent the more favourable investment approach for the network owner.

4.4 Application Example

Application of this framework has begun for mitigation studies on large slides in British Columbia and the United States. The results of this ongoing work are not yet available for publication. To illustrate the use of the framework in a project setting, a post-action review of a prior treatment selection was completed, providing an assessment of the success of the chosen alternative.

The assessment was performed a prior risk project completed by the Colorado Department of Transportation (CDOT) on Interstate 70 (I-70) near the Eisenhower-Johnson Memorial Tunnel. For over 20 years and shortly after the original highway construction, a large landslide (Landslide Behaviour Type C as per Table 2) at mile marker 212 on I-70 caused several centimetres of annual settlement to adversely impact the I-70 pavement. This annual landslide displacement (upper end of Velocity Class 2a as per Table 1) generally occurred in the spring and summer months, resulting in an estimated owner cost of around \$130,000 per year (current dollars) for pavement overlays and other roadway maintenance. The ongoing landslide displacements and maintenance activities resulted in a section of roadway that routinely alternated between acceptable and unacceptable condition states for CDOT. Geotechnical investigations and studies of the landslide generated mitigation options to improve the landslide to above a factor of safety of 1.3; however, the preliminary cost of these options was over \$30M (current dollars). This amount of mitigation cost is approximately three times more than the typical annual CDOT budget for all geohazards and thus not feasible for investment without re-allocating funds from elsewhere in the agency.

As an alternative to full stabilization, CDOT developed a partial mitigation plan that was directed at reducing pavement deformation and the resulting annual maintenance expenses. It was well accepted that the mitigation plan would not change the factor of safety by more than a few percent; however, the opportunity to reduce pavement distress was desirable regardless of the level of improvement in stability. In 2010, CDOT completed a the partial mitigation project involving 135 drilled shafts installed to a maximum depth of 20 feet below the westbound I-70 lanes, with the shafts backfilled with lightweight cellular concrete to reduce driving loads. A drilled groundwater drain system was also installed at the base of the slide. Based on observed performance improvements, a similar project was performed in 2011 for the eastbound lanes. The cost of these two projects was about 10 to 15 percent of the estimated costs for full stabilization.

The performance data for this slide over a ten-year period suggest the landslide velocity has decreased by approximately a factor of 20 on the slide plane (more than 50 mm per year to approximately 2.5 mm per year, or Velocity Class 1 as per Table 1) (D. Thomas CDOT Geotechnical Program, 2022). The benefit to CDOT of this velocity change is landslide maintenance expenses over the last decade have reduced to near zero because there have been no further recurring pavement overlays efforts and the slide is viewed as “stable” by management and maintenance teams. Note, geotechnically the landslide is still at a factor of safety of near unity and thus not geotechnically “stable.” By employing this strategy, CDOT was able to reduce landslide velocity, improve roadway performance, and transition the management approach to an optimized life-cycle cost strategy. From an investment perspective, CDOT avoided the need to move over \$25M in funds from elsewhere in the department to fund full mitigation or the need to reactively respond to a sudden disruption to the system that impacted user mobility and the resiliency of the CDOT system. The graph in Figure 2 presents a conceptual life-cycle cost curve for this landslide and estimated options for full stabilization, continuing a do minimum approach, and the selected approach to reduce landslide velocity. As illustrated on the figure, the selected mitigation strategy is approaching parity with the historical annual pavement maintenance approach and is well below the amount needed for full stabilization.

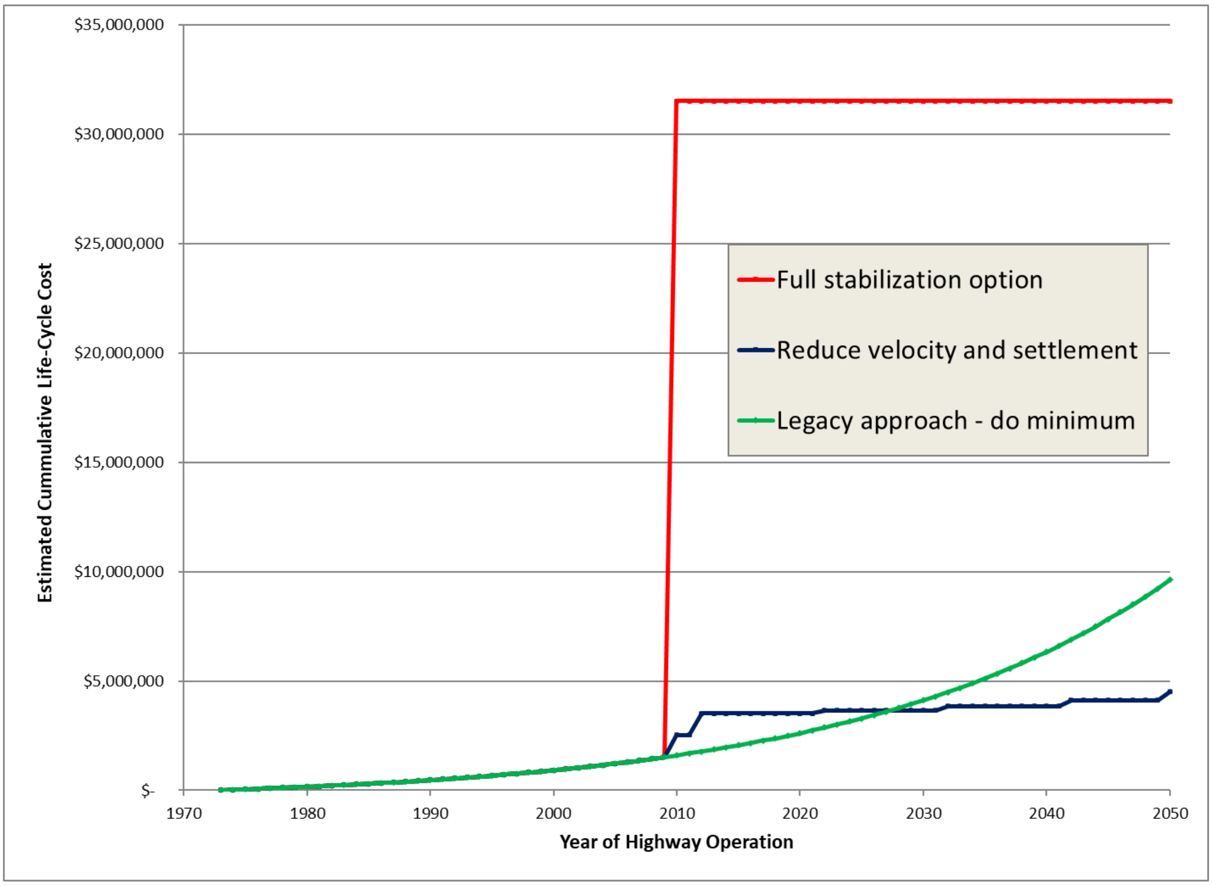

Figure 2: Cost-benefit example illustrating the value in reducing velocity on a large landside.

One of the authors of this paper was involved with the CDOT project over several years, including geological explorations, engineer of record, and resident engineering positions on the project. While the Markov model approach to probabilistic landslide velocity and road condition states presented in this paper was not yet developed for use, the mitigation selection process would have benefited from using this approach in the following ways.

- The uncertainties and risks associated with a potential increase in landslide velocity prior to mitigation could have been more effectively quantified and communicated. For example, the approach proposed here would have estimated the probability of approaching a failed condition state over a 10-year period has a probability range 0.35 and 0.09, in the absence of some form of slide mitigation.
- Subject matter expert input would be considered in a probabilistic approach rather than subjective opinion.
- The likelihood of success in terms of total life-cycle cost can be presented to executives charged with approving the project investment. Model outputs for un-mitigated and mitigated scenarios, can be incorporated into life-cycle cost models (similar to Figure 2) and risk-based cost benefit analyses.

5. Conclusions

A Markov Chain, Monte Carlo Simulation approach has been developed to support estimates of velocity class probability distributions for normally slow-moving landslides which are useful inputs to landslide hazard and risk assessment and can inform management options. Regional landslide databases and velocity timeseries data are being assembled to improve the statistical basis for the approach. The resulting model approaches can be used by asset owners to prioritize risk treatment investments on the basis of increased likelihood for future adverse movement rates. In a changing climate, the limiting state vectors of the velocity classes for different landslide types are further expected to change. The approach offers the possibility of accounting for climate change by compiling limiting state vectors for similar landslide types in climatic regions that are representative of a region-of-interest's future climate or prioritizing climatic regions where adverse velocity increases are more likely.

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