Conceptual landslide velocity transition models for a range of landslide behaviour types

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ABSTRACT
The potential variability in velocity of normally slow-moving landslides has important implications for risk assessment, design, monitoring, and maintenance of infrastructure. A conceptual approach to predict landslide velocity probability distributions using landslide observations, engineering judgment and Markov models is reviewed. Landslide behaviour types that link historical evidence of landslide displacement and mechanisms of movement to probabilistic predictions of future velocity are proposed. Tentative velocity transition matrices are proposed for five landslide behaviour types which yield limiting state probability vectors corresponding to long-term average annual landslide displacements ranging from 1 cm/yr to 1 m/yr. Typical model outputs are provided and potential model applications are discussed.

RÉSUMÉ
La variabilité potentielle de la vitesse des glissements de terrain normalement lents a des implications importantes pour l'évaluation des risques, la conception, la surveillance et l'entretien des infrastructures. Une approche conceptuelle pour prédire les distributions de probabilité de vitesse de glissement de terrain à l'aide d'observations de glissement de terrain, d'un jugement d'ingénierie et de modèles de Markov est examinée. Des types de comportement de glissement de terrain qui relient les preuves historiques du déplacement des glissements de terrain et des mécanismes de mouvement aux prédictions probabilistes de la vitesse future sont proposés. Des matrices de transition de vitesse provisoires sont proposées pour cinq types de comportement de glissement de terrain qui produisent des vecteurs de probabilité d'état limite correspondant aux déplacements annuels moyens à long terme des glissements de terrain allant de 1 cm/an à 1 m/an. Des sorties de modèles typiques sont fournies et des applications potentielles de modèles sont discutées.

1 INTRODUCTION

The velocity of normally slow-moving landslides (those that typically move on the order of millimetres to metres per year) in clays and flat-lying mudstones and shales will often vary seasonally and from year to year in response to a range of factors that can alter the forces resisting and promoting movement.

In a large inventory of landslides, some may reside in an inactive or extremely slow-moving state for decades or centuries until weathering, erosion, changes in groundwater conditions or human activity triggers a reactivation. Others may almost always be active and may accelerate or decelerate quickly in response to relatively modest changes in environmental conditions. Some landslides may exhibit geomorphic evidence of past episodes of higher mobility via earth flows and shallow translational slides, while others may appear to have always moved as relatively deep-seated intact blocks, likely at slow rates except during rare periods of retrogression. Others still may have only moved a few tens of metres over the entire Holocene and may in fact be relict. This geomorphic interpretation of landslide behaviour over geologic time, coupled with an understanding of current landslide movement rates and factors controlling stability, can provide useful insight to future behaviour.

The potential variability in velocity of normally slow-moving landslides has important implications for risk assessment, design, monitoring, maintenance, and rehabilitation of infrastructure. For example, Porter et al. (2019) described how pre-existing and normally slow-moving landslides within the Western Canada Sedimentary Basin (WCSB) cause damage to infrastructure with estimated economic impacts likely exceeding $281 to $450 million per year. Landslides in the WCSB typically occur on gentle to moderate slopes in glaciolacustrine sediments, tills, and underlying clay shale, are often deep-seated, and are most often dormant or slow-moving. Occasionally, in response to progressive failure, changes in the natural environment, or human activity, they reactivate or 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 a real-world challenge to engineers and geoscientists practicing in this area.

The timing and significance of changes in most of the factors contributing to a change in landslide velocity cannot be predicted with certainty. Even following considerable investigative effort, landslides subject to environmental factors, human activity, and time are often poorly understood and are perhaps best thought of as dynamic probabilistic systems.

Porter (2020) proposed that treating landslide velocity classes as condition states, and velocity class transitions as a Markov process, might yield useful insight to the probability of these transitions. Porter (2021) expanded on this idea by introducing a proposed range of landslide behaviour types applicable to pre-existing slow-moving clay landslides. Each landslide behaviour type was associated with a defined long-term average annual movement rate. An approach to developing velocity class transition matrices for each behaviour type was proposed such that the long-term distribution of landslide velocity class probabilities, as determined through a Markov chain analysis, multiplied by the assumed mean annual displacement associated with each velocity class, would yield the specified long-term average annual movement rate.

This paper continues to build on that earlier work. Proposed landslide velocity classes and annual displacement criteria are updated. Some basic characteristics of Markov models are briefly reviewed. The proposed five landslide behaviour types are described in greater detail and updated velocity class probability transition matrices are presented for each behaviour type. Two approaches to modelling are discussed: Markov chain analysis using matrix operations, and Monte Carlo Simulation. Example model outputs are presented, and potential model applications are discussed.

2 LANDSLIDE VELOCITY AND ANNUAL DISPLACEMENT CRITERIA

Landslide velocity influences several of the factors used to quantify landslide risk and to model the deterioration of infrastructure crossing or proximal to pre-existing landslides. Faster landslides:

- often have greater mobility and potential for retrogression, increasing the spatial probability that nearby infrastructure will be physically impacted by landslide movement;
- develop potentially damaging displacements more quickly and provide less time for avoidance, increasing the temporal probability of impact;
- impose higher impact loads or reduce the time to failure for infrastructure that can accommodate some amount of displacement, increasing infrastructure vulnerability;
- require more intensive, frequent, and costly maintenance interventions to address non-catastrophic, chronic displacements and their effects; and
- complicate efforts to repair infrastructure and restore service following an outage, increasing economic impacts.

Therefore, where infrastructure is exposed to hazard from a pre-existing and normally slow-moving landslide, the probabilities of faster landslide velocities occurring are ideally considered as part of a risk assessment or asset deterioration model.

2.1 Applicable Landslide Mechanisms

Normally slow-moving landslides in clay overburden and flat-lying mudstones and shale are encountered in many regions throughout the world. The work presented herein is heavily influenced by the authors' experience with landslides in the WCSB, river valleys throughout central and southern British Columbia, and in the residual soils and colluvial deposits encountered throughout Appalachia in the eastern United States.

Common landslide mechanisms in the WCSB include deep-seated compound or translational slides along weak bedding planes in shale and glaciolacustrine clay, rotational slides in till and glaciolacustrine sediments, and earth flows of variable thickness in colluvium. Similar landslide mechanisms seated in Tertiary-age mudstones, tills, glaciolacustrine sediments and colluvium are commonly encountered in deep river valleys throughout British Columbia (e.g., Rouse and Mathews, 1979; Evans, 1982). Slow-moving landslides in Appalachia tend to be shallow to moderately deep-seated and occur within residual soils and colluvium derived from shales and mudstones. Most of these landslides move at rates ranging from Extremely Slow to Slow according to the velocity classification of Cruden and Varnes (1996) shown in the second and third columns of Table 1. Rapid to Extremely Rapid slides and flows are rare but can initiate in till, normally and over-consolidated glaciolacustrine sediments and colluvium, and along over-steepened slopes where a cap of stronger rock overlies weaker shale (e.g., Geertsema et al., 2006). First time slides, retrogression events and the formation of active wedges can result in Rapid to Very Rapid movements which may only persist for a few hours or days (e.g., Krahn et al., 1979; Cruden et al., 2003).

Table 1. Modified landslide velocity classification after Cruden and Varnes (1996)

Class	Description	Typical velocity	Proposed annual displacement criteria (m)	Proposed mean annual displacement (m)
7	Extremely rapid	>5 m/sec		
6	Very rapid	>3 m/min		
5	Rapid	>1.8 m/hr		
4+	Moderate	>13 m/mo	>16	64
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

The conceptual approach to modelling the probabilities of landslide velocity transitions outlined below is expected to be applicable in other regions where similar geological conditions and landslide mechanisms are present. As currently formulated the approach is not applicable to many other types of landslides including those in sensitive clays, rock falls, or debris flows. The approach is also not directly applicable to rockslides in folded and faulted sedimentary rock.

2.2 Proposed Velocity Classes

Mansour et al. (2011) compiled examples of damage from slow-moving landslides and demonstrated that the expected degree of damage can be related to the landslide velocity or cumulative displacement. Often minor to no damage is reported for infrastructure impacted by

Extremely Slow landslides unless movements continue to accumulate for decades. Expected damage from Very Slow landslides can vary widely, however, ranging from increased maintenance costs at the lower end of the range to complete loss of serviceability or infrastructure collapse at the high end of the range. Consequently, and as proposed by Porter (2020), we have subdivided the Very Slow velocity class into Class 2a and 2b to provide greater granularity for hazard and risk assessment and asset deterioration modelling. In the work that follows we reference the velocity class numbers listed in the left column of Table 1.

2.3 Reasons for Use of Annual Displacement Criteria

Data and inferences of landslide velocity can come from several sources. Traditionally these included slope inclinometer and survey monument readings, field observations, and comparisons of aerial photographs. These data are typically collected at a frequency of a few times per year or less. Repeat lidar surveys allow for the assessment of topographic change and inferred landslide movement rates over wide geographic areas, though often the time between surveys is still several years, and displacements must be annualized to infer average velocities. Shape acceleration arrays, in-place inclinometers, and satellite-based InSAR and global navigation satellite systems (GNSS) can provide high frequency or near real-time data on landslide velocity, but such tools are typically only deployed on a small fraction of landslides of interest. Consequently, the actual velocity of most landslides of interest is almost never known.

Landslide velocity often varies seasonally. The slower velocity classes (e.g., 1 and 2a) are sometimes maintained year-round, while Velocity Classes 4 and greater rarely persist for more than a few hours or days.

To address ambiguity arising from annual variability in landslide velocity and differing frequencies of displacement observations that might be used to calibrate models of landslide velocity class transition probabilities, we propose that velocity classes be associated with the total measured or inferred annual displacements shown in the fourth column of Table 1. Displacements will typically be as recorded at ground surface near to where infrastructure is (or may potentially be) impacted. In some instances, it may also be practical to consider measured displacements on defined shear surfaces for deeper-seated slides.

The proposed boundary between Velocity Class 3 and 4+ is 16 metres per year which, as a matter of convenience, is one order of magnitude greater than the proposed boundary between Velocity Class 2b and 3. In our opinion this criteria is reasonable because landslides that move more than 16 metres in a given year likely moved at an instantaneous rate exceeding 13 metres per month (i.e., Cruden and Varnes' (1996) boundary between Slow and Moderate) for some period of time within that year. Exposure to displacements in excess of 16 m per year are also expected to quickly bring most types of infrastructure to their ultimate limit state, irrespective of whether that displacement occurs over a period of hours, days or weeks.

In the work that follows, we make no attempt to differentiate between the probabilities of occurrence of Velocity Classes 4 to 7, nor their generalized annual displacement criteria. It is expected that other empirical methods (e.g., Glastonbury and Fell, 2008a) and statistical and numerical landslide runout models are much better suited for these types of analysis.

2.4 Proposed Mean Annual Displacements for each Velocity Class

Associating landslide velocity classes with mean annual landslide displacements allows for the estimation of annual and cumulative displacement over time given assumptions of the distribution of velocity class probabilities. Furthermore, if an appropriate probability density function describing the likely distribution of displacements can be assigned to each velocity class, more insight to the probabilities of exceedance of potential landslide displacements can be gained through Monte Carlo Simulation.

In Porter (2021) a uniform distribution of annual displacements associated with each velocity class was assumed. The resulting mean (and median) annual displacements were approximately equated to the midpoint between the minimum and maximum values defining each range.

Since within any given inventory of normally slow-moving landslides there will tend to be many more landslides moving at the slower velocity classes than at the higher classes, it seems reasonable to assume that within each velocity class more landslides will also be moving at the lower end of the range than at the higher end. Several types of probability density functions can be used to generate a distribution with this characteristic, but the simplest is a triangular distribution. The updated proposed mean annual displacement values shown in Table 1 are based on an assumed left triangular distribution. For Velocity Class 4+ the mean annual displacement was calculated based on an assumed range extending from 16 m to 160 m.

Other probability density functions may be more appropriate for some landslide velocity classes and for some landslides with lengthy timeseries observations. For example, a uniform distribution might better describe the range of displacements observed for landslides falling in Velocity Class 1, although the difference between mean and median values for a uniform and left triangular distribution for Class 1 is about 3 mm per year and has little impact on model predictions. Logarithmic density functions may be more appropriate for the higher velocity classes but would add further complexity to the model. This remains an area requiring further review.

3 MARKOV MODELS

3.1 States, Transitions and the Markovian Assumption

The Markov process is a probabilistic model useful in analyzing complex systems (Howard, 2007). In these models, the condition of a physical system can be described by a number of state variables. For the physical system comprising a landslide, velocity (or annual displacement) can be treated as a state variable and the velocity classes listed in Table 1 treated as condition states.

In the course of time a system passes from state to state and thus exhibits dynamic behaviour. For a landslide, factors such as changes in shear strength, porewater pressure or landslide geometry can cause a change in velocity. Velocity is a continuous variable that can change at any time, but in a simplified Markov model changes in velocity can be treated as transitions occurring at discrete timesteps (years) and between a finite number of velocity classes defined in terms of expected total annual landslide displacement.

The probabilities of transitioning between velocity classes (or remaining in the current class) are defined by transition probabilities encapsulated in a transition matrix.

The simplifying Markovian assumption is that only the state presently occupied is relevant in determining the future trajectory of the process. For the conceptual landslide models that follow, the Markovian assumption is that only the velocity class (i.e., displacement) experienced in the prior year is relevant in determining the probabilities of the different velocity classes occurring in future years. While there are few physical systems that we would expect to be so memoryless in a strict sense, the Markov process has proven to be extremely useful for shedding insight on the behaviour of a wide class of complex systems encountered in engineering, economics, medicine, biology and geology; we conjecture that this can be extended to the velocity of slow-moving landslides.

It is tempting to consider shortening the timestep in the conceptual landslide velocity models, using monthly timesteps, for example. However, because the velocity of most slow-moving landslides varies seasonally, this seasonal effect imposes another type of condition state that is difficult to accommodate in a simple Markov model. New condition states would need to be defined based on both the month of the year and each possible velocity class. The number of possible condition states would increase from six (as currently proposed) to 72, and the number of required transition probabilities would increase from 36 to 5,184.

3.2 Transition Diagrams, Event Trees and Transition Matrices

Key elements of a Markov model can be captured in a transition diagram which illustrates the “N” possible condition states and the probabilities of transitioning between states (or remaining in the current state) during each timestep in the model.

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.

A transition diagram can be represented as an event tree. When an initial state vector is worked through the event tree, the resulting probabilities of being in the different possible condition states is referred to as the state vector at timestep 1 (or $\pi(1)$).

Following the Markovian assumption, the procedure for calculating condition state probabilities at timestep 2 would involve replacing the initial state vector with the state vector at timestep 1 and working it through the event tree again. The process can be repeated for as many timesteps as desired, but it is tedious to do it this way. For efficiency and ease of computation, the transition probabilities in a Markov model are usually encapsulated in a “Transition Matrix” (P) with N rows and N columns. The state probability vector at any timestep can be calculated by post-multiplying the state probability vector at the preceding timestep by the transition matrix P [Equation 1], or alternatively, the n^{th} state probability vector can be calculated by post-multiplying the initial state vector by the transition matrix raised to the n^{th} power [Equation 2]. These calculations are easily completed using a computer spreadsheet or code for as many timesteps as required.

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

$$\pi(n) = \pi(0)P^n \qquad [2]$$

3.3 Limiting State Probability Vectors

The changing values of the state vector calculated for various timesteps following an observation of the process reflect our changing state of knowledge in the absence of observation (Howard, 2007). If at any time we were able to observe the process, our probability assignment would change so as to assign a probability of 1 to occupying the state actually observed.

A characteristic of these types of Markov models is that after many timesteps without observation, our knowledge of the state of the system diminishes to a constant value referred to as the limiting state probability vector, irrespective of the value of the initial state vector. In the case of landslide velocity, the limiting state probability vector can be thought of as the distribution of velocity classes that might be realized over a very long period of observation (i.e., thousands of years). Alternatively, if one was able to observe the distribution of velocity classes from a large inventory of landslides of a certain type and within a certain geography over a period of a few decades, for example, that distribution also ought to resemble the limiting state probability vector for that type of landslide operating in that type of environment. We make use of this limiting state behaviour in the section that follows to develop conceptual Markov models for a range of proposed landslide behaviour types.

4 CONCEPTUAL MODELS FOR VELOCITY CLASS TRANSITION PROBABILITIES FOR FIVE LANDSLIDE BEHAVIOUR TYPES

4.1 Premise

Markov models have been developed for five example landslide behaviour types to help estimate velocity class transition probabilities for the range of normally slow-moving landslides often encountered in some areas of our practice. The models have been ‘tuned’ to yield specified long-term average outputs including velocity class distributions and mean annual displacements which can be used by a landslide practitioner to help guide the assignment of an appropriate behaviour type to each landslide of interest. The underlying premise is that if the models yield appropriate long-term average velocity class distributions and displacements, they might also generate useful insight to potential near-term conditions (over periods of years to decades) which will tend to be of interest to asset managers and other decision makers.

The models developed for each proposed landslide behaviour type incorporate several important assumptions that have tentatively been assigned based on literature review (e.g., Glastonbury and Fell, 2008b), our experience and judgment, and supported by trial and error. They continue to be tested and will be improved upon as more data for model calibration become available.

The intent is that for a particular landslide, the most applicable behaviour type (or types) would be selected based on a review of geomorphic evidence obtained through lidar, aerial photographs, field mapping, and potentially radiometric dating or dendrochronology. This evidence would be used to estimate the dominant mechanisms of movement, the age of landslide features such as scarps, sag ponds and debris deposits, and the past occurrence and approximate frequency of more rapid surges of movement (e.g., Dyke et al., 2011). For landslide complexes containing multiple landslides a unique behaviour type and initial velocity would be assigned to each individual slide within the landslide complex.

4.2 Proposed Landslide Behaviour Types

The five general landslide behaviour types and their typical characteristics are shown in Table 2.

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 geology	Relatively intact shales, mudstones	Relatively intact shales, mudstones, residual soils, overconsolidated glacial deposits	Relatively intact glacial deposits, colluvium derived from shales, mudstones, residual soil and glacial deposits	Colluvium derived from shales, mudstones, residual soil and glacial deposits	Colluvium derived from shales, mudstones, residual soil and glacial deposits
Typical failure mechanism	Translational block slides and spreads	Translational block slides and spreads	Translational block slides and spreads, rotational slides, complex earth slides-earth flows	Translational slides, rotational slides, earth flows, complex earth slides-earth flows	Translational slides, rotational slides, earth flows, complex earth slides-earth flows
Typical inclination of basal shear surface	Sub-horizontal (0 to 5 degrees)	Sub-horizontal (0 to 5 degrees)	Similar to the residual friction angle	Similar to the residual friction angle	Sub-parallel to the ground surface
Typical toe condition	No toe erosion	Toe erosion usually absent	Toe erosion may be active	Toe erosion often active	Toe erosion almost always active
Long-term annual probability of Class 4+ velocities	1 in 20,000	1 in 6,500	1 in 2,000	1 in 650	1 in 200
Assumed limiting state velocity class distribution; (assumed average annual displacement for each velocity class in brackets)					
0 (0 m)	70%	50%	30%	10%	0.5%
1 (0.005 m)	28.5%	45.5%	55.0%	44.9%	3.0%
2a (0.064 m)	1.1%	3.2%	10.8%	32.4%	54%
2b (0.64 m)	0.4%	1.1%	3.6%	10.8%	36%
3 (6.4 m)	0.06%	0.18%	0.60%	1.8%	6.0%
4+ (64 m)	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

The landslide behaviour types and their associated transition matrices have been designed to satisfy two main criteria:

1. The models yield the long-term mean annual displacements specified at the bottom of Table 2 for each landslide behaviour type. These range from 1 cm per year (Type A) to 1 m per year (Type E), increasing by approximately one-half order of magnitude for each of the behaviour types. Because of the skew in the assumed velocity class probability distributions for each behaviour type and assumed average displacements by velocity class, the long-term mean annual displacements are greater than the median or modal annual displacements. Long-term mean annual displacements are strongly influenced by the relatively small percentage of years that landslides of each behaviour type are expected to experience the higher velocity classes.
2. Over the long-term, the specified annual probability of surges of landslide movement achieving Velocity Class 4+ also vary by about one-half order of magnitude between each behaviour type. These range from a 1 in 20,000 chance per year (and

perhaps not credible) for Type A, to a 1 in 200 chance per year for Type E. Again, care is required in interpreting these criteria. For example, not every Type C Landslide is expected to have a 1 in 2,000 chance per year of achieving Velocity Class 4+ in the near-term: those currently dormant or moving at Velocity Class 1 would be expected to have a much lower chance than those currently moving at Velocity Class 2b or 3.

Additional guidance is provided in Table 2 about typical geological conditions, landslide mechanisms, and other factors that might help with selection of the most appropriate landslide behaviour type, but careful review of the two main criteria listed above should take precedence over all others in selecting which model to use.

The Markov models satisfy the above criteria because the associated transition matrices have been 'tuned' such that their limiting state vectors are equivalent to the long-term average velocity class distributions specified for each behaviour type in Table 2. It should be acknowledged, however, that these velocity class distributions are not unique; other limiting state vectors could also yield the specified mean annual displacement criteria.

The transition probabilities have also been adjusted to accommodate other general criteria including:

- "hold-time" probabilities (probabilities of remaining in the current velocity class) along the diagonal of the transition matrix decrease with increasing velocity class, for most landslide types
- "hold-time" probabilities for Velocity Class 0 are greatest for Type A landslides and smallest for Type E landslides
- the conditional probabilities of transitioning to a higher velocity class if a transition occurs decrease with increasing velocity class
- at lower initial velocity classes (e.g., 0, 1), the mean annual displacement of Type E landslides increases most rapidly, while Type A increases most slowly
- at higher current velocity classes (e.g., 3 and 4+), the mean annual displacement of Type E landslides decreases most slowly, while Type A decreases most rapidly
- limiting state vectors are typically achieved within 100 to 200 years depending on the initial state vector and landslide behaviour type.

4.3 Transition Matrices for each Landslide Type

Updated transition matrices describing probability transitions between velocity classes for each landslide behaviour type and are presented below in Figures 1 to 5. The general approach used to develop each matrix is described in Porter (2021).

From/To	0	1	2a	2b	3	4+
0	0.99766	0.00211	0.00021	0.00002	0.000002	0.000000
1	0.00551	0.99266	0.00165	0.00017	0.00002	0.00000
2a	0.00506	0.04550	0.93600	0.01210	0.00121	0.00013
2b	0.00067	0.00607	0.06070	0.91570	0.01517	0.00169
3	0.00015	0.00138	0.01377	0.13770	0.82000	0.02700
4+	0.00007	0.00063	0.03430	0.35000	0.31500	0.30000
Target	**0.70**	**0.28**	**0.01**	**0.004**	**0.0006**	**0.00005**

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

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 2. Velocity class transition matrix for Landslide Behaviour Type B and target limiting state vector

From/To	0	1	2a	2b	3	4+
0	0.99070	0.00837	0.00084	0.00008	0.00001	0.000001
1	0.00455	0.99090	0.00410	0.00041	0.00004	0.000005
2a	0.00233	0.02098	0.96300	0.01232	0.00123	0.00014
2b	0.00043	0.00386	0.03859	0.93600	0.01901	0.00211
3	0.00015	0.00133	0.01328	0.13284	0.82000	0.03240
4+	0.00007	0.00060	0.03283	0.33500	0.30150	0.33000
Target	**0.30**	**0.55**	**0.108**	**0.036**	**0.006**	**0.0005**

Figure 3. Velocity class transition matrix for Landslide Behaviour Type C and target limiting state vector

From/To	0	1	2a	2b	3	4+
0	0.96200	0.03420	0.00342	0.00034	0.00003	0.00000
1	0.00724	0.98190	0.00977	0.00098	0.00010	0.00001
2a	0.00153	0.01379	0.97110	0.01222	0.00122	0.00014
2b	0.00037	0.00337	0.03370	0.94150	0.01895	0.00211
3	0.00013	0.00118	0.01178	0.11781	0.83000	0.03910
4+	0.00007	0.00059	0.03234	0.33000	0.29700	0.34000
Target	**0.10**	**0.449**	**0.324**	**0.108**	**0.0180**	**0.0015**

Figure 4. Velocity class transition matrix for Landslide Behaviour Type D and target limiting state vector

From/To	0	1	2a	2b	3	4+
0	0.52000	0.43200	0.04320	0.00432	0.00043	0.00005
1	0.06000	0.80000	0.12600	0.01260	0.00126	0.00014
2a	0.00076	0.00682	0.97835	0.01267	0.00127	0.00014
2b	0.00021	0.00185	0.01845	0.95900	0.01845	0.00205
3	0.00010	0.00093	0.00932	0.09324	0.85200	0.04440
4+	0.00007	0.00059	0.03185	0.29250	0.32500	0.35000
Target	**0.005**	**0.030**	**0.540**	**0.360**	**0.060**	**0.005**

Figure 5. Velocity class transition matrix for Landslide Behaviour Type E and target limiting state vector

5 EXAMPLE MODEL OUTPUTS

The transition matrices outlined above, combined with assignment of an initial velocity class, can be used to generate several useful outputs including:

- the estimated probabilities of a landslide being in each velocity class each year for the next several years;
- the estimated cumulative probability of realizing a specific velocity class (or expected number of

years of being in that class) over a certain period of time; and,

- expected mean annual and mean cumulative displacements.

These outputs can be generated by spreadsheet through simple matrix operations. For example, Figure 6 provides modelled velocity class distribution probabilities for a 50-year period for Landslide Behaviour Type C, with an initial velocity of Class 2b.

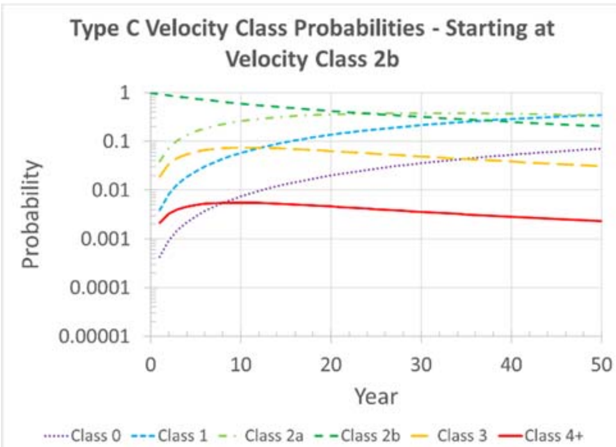

Figure 6. Modelled velocity class distribution probabilities for Landslide Behaviour Type C starting at Class 2b.

Figures 7 through 10 provide modelled mean annual displacements for a 50-year period for all landslide behaviour types starting at Velocity Classes 0 to 2b. These were generated using the assumed mean annual displacements assigned to each velocity class in Table 1.

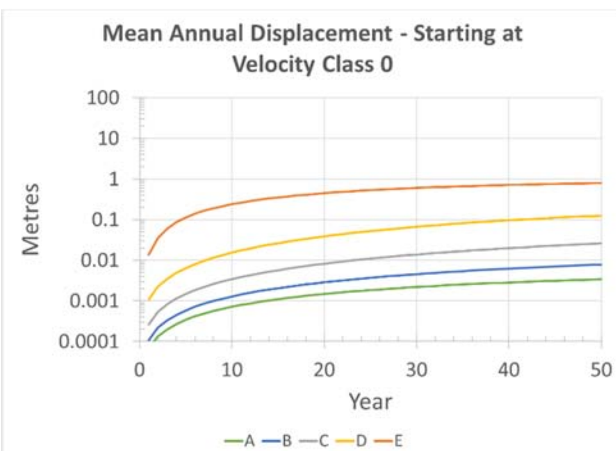

Figure 7. Mean annual displacements starting at Class 0.

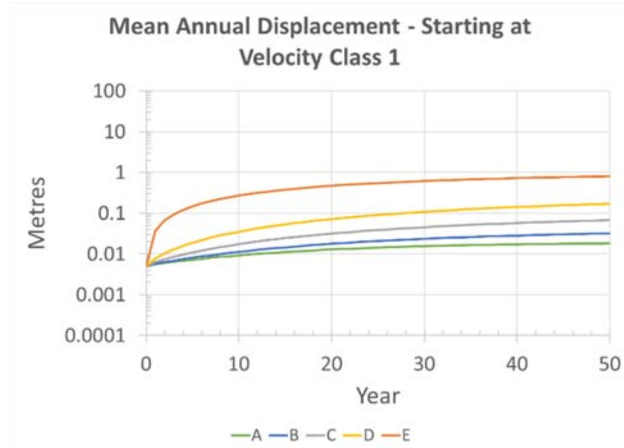

Figure 8. Mean annual displacements starting at Class 1.

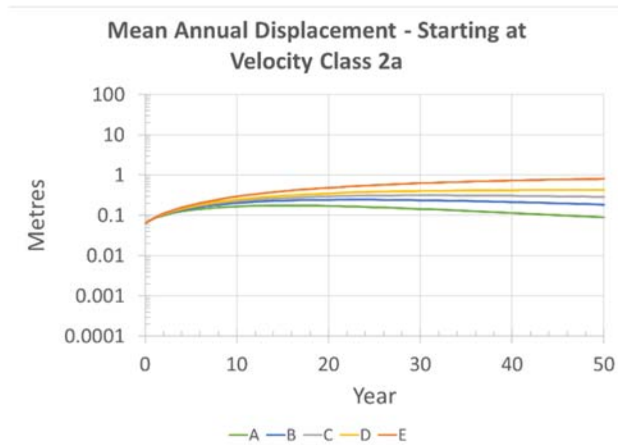

Figure 9. Mean annual displacements starting at Class 2a.

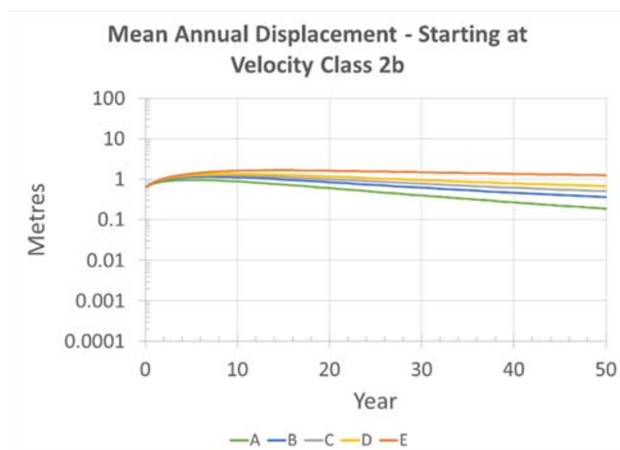

Figure 10. Mean annual displacements starting at Class 2b.

More advanced, and potentially more useful outputs can be generated using the same transition matrices by way of Monte Carlo Simulation (MCS). The velocity class state vectors from each timestep modelled through matrix operations can be treated as tables of cutoff values that can be compared to randomly generated numbers between

0 and 1. These comparisons are used to assign a trial velocity class at each timestep. The process is repeated over thousands of trials to simulate the probabilistic nature of the process. MCS also allows for use of probability density functions for the annual displacements associated with each velocity class, and for generation of statistics such as the probability of exceedance of specified annual and cumulative displacements which can be fed into risk assessments or asset deterioration models.

As an example, Figure 11 provides modelled mean, median and percentile annual displacements for Years 1, 2, 5 and 10 for all landslide behaviour types, starting at Velocity Classes 1 and 2a. Figure 11 was generated through MCS using a left triangular distribution for each velocity class probability density function and 50,000 trials for each modelled timestep. Mean annual displacements derived from Markov Chain matrix operations are provided for comparison with the mean values obtained from MCS. Markov Chain and MCS results in Figure 11 are typically within +/-5% of each other, suggesting the number of trials used in the MCS approach did a reasonable job of simulating the dynamic process.

Type A	Annual Displacement Starting at Class 1 (m)				Type A	Annual Displacement Starting at Class 2a (m)			
	Year 1	Year 2	Year 5	Year 10		Year 1	Year 2	Year 5	Year 10
Markov Mean	0.006	0.006	0.007	0.01	Markov Mean	0.08	0.10	0.14	0.17
MCS Mean	0.006	0.006	0.007	0.01	MCS Mean	0.09	0.11	0.14	0.17
50%	0.005	0.005	0.005	0.004	50%	0.06	0.05	0.05	0.03
90%	0.01	0.01	0.01	0.01	90%	0.12	0.12	0.12	0.13
99%	0.01	0.01	0.02	0.04	99%	0.35	0.75	1.2	1.4
99.9%	0.07	0.10	0.31	0.84	99.9%	4.7	9	11	13

Type B	Annual Displacement Starting at Class 1 (m)				Type B	Annual Displacement Starting at Class 2a (m)			
	Year 1	Year 2	Year 5	Year 10		Year 1	Year 2	Year 5	Year 10
Markov Mean	0.006	0.006	0.008	0.01	Markov Mean	0.09	0.10	0.15	0.20
MCS Mean	0.006	0.006	0.008	0.01	MCS Mean	0.09	0.11	0.15	0.21
50%	0.005	0.005	0.005	0.005	50%	0.06	0.06	0.05	0.04
90%	0.01	0.01	0.01	0.01	90%	0.12	0.12	0.13	0.14
99%	0.01	0.01	0.02	0.07	99%	0.36	0.77	1.2	2.1
99.9%	0.09	0.12	0.47	0.96	99.9%	4.9	9	12	14

Type C	Annual Displacement Starting at Class 1 (m)				Type C	Annual Displacement Starting at Class 2a (m)			
	Year 1	Year 2	Year 5	Year 10		Year 1	Year 2	Year 5	Year 10
Markov Mean	0.006	0.007	0.01	0.02	Markov Mean	0.09	0.11	0.16	0.23
MCS Mean	0.006	0.007	0.01	0.02	MCS Mean	0.09	0.11	0.16	0.23
50%	0.005	0.005	0.005	0.005	50%	0.06	0.06	0.06	0.05
90%	0.01	0.01	0.01	0.01	90%	0.12	0.12	0.13	0.15
99%	0.01	0.02	0.07	0.11	99%	0.37	0.78	1.2	2.7
99.9%	0.11	0.20	0.93	1.4	99.9%	4.9	9.3	12	16

Type D	Annual Displacement Starting at Class 1 (m)				Type D	Annual Displacement Starting at Class 2a (m)			
	Year 1	Year 2	Year 5	Year 10		Year 1	Year 2	Year 5	Year 10
Markov Mean	0.008	0.01	0.02	0.04	Markov Mean	0.09	0.11	0.17	0.25
MCS Mean	0.007	0.01	0.02	0.04	MCS Mean	0.09	0.11	0.17	0.26
50%	0.005	0.005	0.005	0.005	50%	0.06	0.06	0.06	0.06
90%	0.01	0.01	0.01	0.01	90%	0.12	0.12	0.13	0.18
99%	0.02	0.07	0.12	0.37	99%	0.36	0.78	1.2	3.3
99.9%	0.32	0.88	1.4	5.5	99.9%	4.9	9.3	13	31

Type E	Annual Displacement Starting at Class 1 (m)				Type E	Annual Displacement Starting at Class 2a (m)			
	Year 1	Year 2	Year 5	Year 10		Year 1	Year 2	Year 5	Year 10
Markov Mean	0.04	0.07	0.15	0.27	Markov Mean	0.09	0.11	0.18	0.29
MCS Mean	0.04	0.07	0.16	0.28	MCS Mean	0.09	0.12	0.19	0.30
50%	0.005	0.006	0.01	0.05	50%	0.06	0.06	0.06	0.06
90%	0.04	0.08	0.12	0.27	90%	0.12	0.12	0.13	0.30
99%	0.39	0.8	1.3	4.2	99%	0.39	0.81	1.3	4.5
99.9%	5.3	9.3	14	39	99.9%	5.3	9.4	14	40

Figure 11. Mean, median and select percentile annual displacements for all landslide behaviour types, with initial Velocity Classes 1 and 2a.

6 DISCUSSION

Slow-moving landslides are complex, dynamic systems. Their velocities change in response to small changes in factor of safety, often in a non-linear way, and the future fluctuations in factor of safety cannot be predicted with certainty. Linear infrastructure may cross tens, hundreds, or even thousands of slow-moving landslides, and insight to the potential for those landslides to move at different rates is important for hazard and risk assessment, asset deterioration modelling, selection of appropriate monitoring frequencies and technologies, establishment and optimization of maintenance budgets, and evaluation of the potential benefits of slope stabilization. Treating velocity class transitions as a Markov process and modelling transitions as a Markov chain using matrix operations or Monte Carlo Simulation can provide additional insight that can complement more traditional approaches including geomorphic interpretation, subsurface investigation, monitoring, and slope stability analysis.

Leveraging these approaches for dynamic risk assessment and asset deterioration modelling involves several considerations and additional areas for development:

- Approaches are needed to associate asset condition states and risks with outputs that can be generated with support of the landslide velocity transition models. These may include estimated annual displacement rates, cumulative displacements, and the probabilities of exceeding these criteria.
- Approaches to incorporate monitoring observations are required. These may include refinement of current and historical landslide movement rates that help select the initial landslide velocity state vector, adjustment of assumptions about the probability density functions assigned to each landslide velocity class, and mechanisms for re-setting the velocity state vector and cumulative displacement estimates pending the results of monitoring observations.
- Often there will be a need to make estimates of the potential short and long-term benefits of improving slope stability through drainage improvements, toe berms and other means. Small improvements will tend to reduce movement rates and possibly reduce the probability of higher velocity classes being realized in the future, and consistent approaches will be required to link stabilization efforts with estimated initial velocity state vectors following their implementation.
- Because precipitation and soil moisture are often significant controls on slope stability, there will be a need to recognize where within decadal-scale climate cycles observations of landslide velocity are being made. Predictions of future landslide velocity would be expected to improve if better linkages between current and past movement rates, soil moisture trends and precipitation could be established.

A key step to making progress on each of these considerations is continued expansion of databases of landslide velocity timeseries data. Landslide databases classified according to proposed landslide behaviour types, and abundant observations of landslide velocity transitions (or lack thereof) will provide opportunity to refine estimated transition probabilities and to examine the effects of climate and other factors on landslide velocity. It may also allow for the development of transition matrices that could be applied to other landslide mechanisms and geographic environments.

The concepts presented here remain a work in progress and will continue to be updated as they are tested in practice.

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