Report on Assessment of Earthworks
D2.3

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Executive Summary

Shallow landslides induced by infiltrating rainfall are a major hazard along European rail networks. This report describes the development of a probabilistic based framework to analyse this problem. A case study is performed to demonstrate the technique on the Irish Rail network where a set of fragility curves are developed for likely conditions. This methodology can be used for the assessment of both cuttings and embankments on road, rail and water transport networks where the governing failure mechanism is connected to the loss of matric suction in thick soil deposits. The soil conditions and slope geometries present on a specific network will determine the number of different fragility curves needed to accurately assess the vulnerability of the entire network. The work presented in this report fulfils the outputs from Task 2.4 of the Destination Rail project.
1 Introduction

Every year landslides occur on and interfere with rail networks around the world creating serious challenges for rail operators, whose primary concern is the safe and reliable operation of their network, See Figure 1. Failures are increasing in severity and frequency due to undesirable weather patterns brought upon by climate change. Even so, failures are still relatively infrequent but unfortunately when they do occur can carry heavy consequences. Potential consequences are wide-ranging and include passenger fatalities, train derailment, train delays, infrastructure damage, and negative public perception. The obvious solution is to upgrade all aged earthworks and other areas of concern, thus improving the risk profile and making the network less susceptible to landslides. Unfortunately, the monetary cost of implementing such a programme on a network-wide scale is prohibitive. Instead, infrastructure owners must identify areas of particular concern, where budget spending can be prioritised.

Infrastructure asset managers need to be able to identify the most critical earthworks in order to prioritise annual resource allocation. To objectively identify the most critical slopes, the entire asset database needs to be ranked to enable the identification of critical assets. This ranking exercise is a formidable task given the scale of the network and the variable nature of the assets. Procedures to identify critical assets can be aided by risk assessment (RA) procedures such as the one described by Varnes [1], where a hazard (likelihood of failure) and the extent of potential consequences for a particular asset are calculated to determine the associated risk. Current literature studies and anecdotal evidence suggest that there are very few examples of advanced risk assessments currently used on national-scale transport networks. Instead, the ranking of assets for the purpose of budget allocation is typically decided using simple algorithms that quantify subjective opinions in relation to the risk associated with individual assets. The use of such a framework means that the identification of critical assets is generally reactive, whereby deterioration of the asset normally has to have taken place in order to be identified as critical. For that reason, there is a clear need to develop a predictive landslide risk assessment approach which will enable infrastructure managers to quantify the risk across the network. This report focuses on developing a detailed hazard assessment based on a quantitative probabilistic geotechnical slope stability model. The approach allows for the explicit consideration of uncertainties arising from limited site data. This report focuses on hazard determination for three different landslide failure modes, which can affect infrastructure slopes namely rotational slips, shallow translational slips, and rock wedge failure. Furthermore, the report discusses how to determine parameter variability when presented with raw data. Finally, the report provides a methodology for examining how vulnerable transport slopes are to rainfall-induced failure. The methods discussed herein are applied to the Irish Rail network to demonstrate their applicability.
Figure 1 Landslides on Irish Rail network: a) cutting on Cork – Cobh line, b) embankment on Manulla Junction – Ballina line
2 Failure Modes

To attain a meaningful measure of slope safety, we must first consider how the slope in question might fail so we can model it appropriately. In this study, we considered three different types of landslide failure mechanisms. The chosen mechanisms were selected as they represent the most common failure types witnessed on the Irish Rail network. The failures mechanisms considered were a shallow translational failure, rotational failure and rock wedge failure. Shallow translational failure and rotational failure were considered for soil slopes, whilst rotational and rock wedge failure modes were assessed for rock slopes. The critical failure mode for each asset was the failure mechanism with the lowest reliability index. The limit equilibrium method was used to describe all failure modes. Where the factor of safety (FOS) of a slope is defined as the ratio between a slopes capacity and its demand along with a potential slip surface (see Eq. 1).

\[ FOS = \frac{\text{Capacity}}{\text{Demand}} \]  

2.1 Shallow translational failure

The majority of landslides occurring annually on the Irish Rail network are shallow translational slides [2], [3], these landslides fail along planar slip surfaces parallel to the slope surface. These are normally instigated by excessive rainfall infiltration during periods of intense or prolonged precipitation, which lowers soil suction in the near-surface soil, leading to a decrease in soil shear strength [4]. A simplified model of the mechanism shown in Figure 2 assumes the wetting front depth as the failure surface [5].

![Wetting front development in an unsaturated soil slope](image)

Figure 2 Wetting front development in an unsaturated soil slope

These slides are particularly prevalent on steep slopes where the slope angle is in excess of the internal angle of friction, which means that these slopes rely on the beneficial action of soil suction for stability. Unfortunately, steep cuttings and embankments are relatively
abundant across Western Europe’s rail network as the majority of the network was constructed prior to the advent of design codes and mainly constructed using tipping techniques. As a result, there is a significant discrepancy between exacting modern slope designs and those inherited from a previous era. Unfortunately, in Northern Europe, the stability of such slopes is likely to become increasingly questionable if current projected rainfall trends hold true.

The failure surface was modelled using an infinite slope model extended to account for unsaturated soil [6] (see Equation 2).

\[
FOS = \frac{c' + (u_a - u_w) \tan \phi^b + \gamma h \cos^2 \alpha \tan \phi}{\gamma h \cos \alpha \sin \alpha} \tag{2}
\]

where \( \gamma \) is the unit weight of soil, \( h \) is the wetting front depth and \( \alpha \) is the slope angle, \( c' \) is the effective cohesion, \( u_a \) is the pore-air pressure, \( \phi' \) is the angle of internal friction associated with the normal stress state variable \( \sigma_n - u_a \), \( u_w \) is the positive pore water pressure, \( u_a - u_w \) is the matric suction and \( \phi^b \) is the angle which describes the rate of increase in shear strength due to matric suction.

### 2.2 Rotational slide

Rotational landslides are landslides which move downward as a solid block along a curved slip surface. The failure surface tends to be deep in the soil. While large landslides in natural terrain are frequently rotational, they’re less commonly found on cuttings and embankments and typically occur on embankments founded upon weak bearing layers such as soft clays or peat. O’Donohue et al. [7] noted that anthropogenic activity on slopes and their immediate surroundings has often been the instigating factor for this type of landslide. Numerous different limit states exist which could be used to model such a failure, most of which are based on the method of slices. This study uses Bishop’s method for circular failures. For the slope shown in Figure 2, using the simplified Bishop’s method of slices [8], the factor of safety of a slope can be defined according to Equation 3.

\[
FOS = \frac{\sum_{i=1}^{n}[c_i \Delta x_i + (W_i - u_i \Delta x_i) \tan \phi_i]}{\sum_{i=1}^{n} W_i \sin \alpha_i} \tag{3}
\]

where \( W_i \) is the weight (kN) of the \( i^{th} \) slice, \( \alpha_i \) is the inclination angle of the base of the \( i^{th} \) slice, \( \Delta x_i \) (m) is the \( i^{th} \) slice width, \( c_i \) (kPa) is the cohesion of the soil on the base of the \( i^{th} \) slice, \( u_i \) (kPa) is the pore water pressure at the base of the \( i^{th} \) slice, and \( \phi \) is the friction angle of the soil at the base of the \( i^{th} \) slice. It is important to note however that any Limit Equilibrium Method (LEM) model can be adapted for probabilistic analysis and the methods discussed in this section are equally applicable to other LEM models. An extensive review of LEMs suitable for slope stability analysis can be found in Fredlund & Krahn [9] and Nash [10]. To obtain the minimum FOS of a rotational slip either a trial and error or an optimisation technique must be implemented to search for the critical slip surface. In this study, the critical probabilistic slip surface and associated reliability index were calculated.
2.3 Rock wedge

A 2D planar failure of a rock block along a discontinuity was modelled, with block geometry being dependent on actual slope geometry. This mechanism was used for rock cuttings only. The observed rock slope failures across the network were typically complex and involved a combination of mechanical weathering, erosion, and rock falls, slides and topples of small magnitude in the highly jointed rock mass. However, this complex interaction is difficult to model in LEM methods, so a Rock Wedge failure mechanism (see Figure 4) was used according to Equation 4.

\[
FOS = \frac{c' + N' \tan \phi}{W(\sin \psi_p + \alpha \cos \psi_p) + V \cos \psi_p - T \sin \theta'}
\]  

[4]

where

\[
A = (H - z)/\sin \psi_p
\]  

[5]

and 

\[
z = H\left(1 - \sqrt{\cot \psi_p \tan \psi_p}\right)
\]  

[6]

and 

\[
N' = W(\cos \psi_p - \alpha \sin \psi_p) - U - V \sin \psi_p + T \cos \theta
\]  

[7]
\[ W = 0.5 \gamma H^2 \left( 1 - \left( \frac{Z}{H} \right)^2 \right) \cot \psi_p - \cot \psi_f \] \hspace{1cm} [8]

\[ U = 0.5 \gamma_w z_w A \] \hspace{1cm} [9]

\[ V = 0.5 \gamma_w z_w^2 \] \hspace{1cm} [10]

**Figure 4** Sketches of the assumed Rock Wedge failure mechanisms used in the risk model. Adapted from Low [13]
3 Reliability Analysis

Reliability analysis is a probability based methodology that allows designers to integrate uncertainty into their stability calculations, therefore, providing a more meaningful interpretation of safety than deterministic calculations [14]. The performance function \( g(X) \) also known as the limit state function is defined as the difference between a slopes capacity (C) and its demand (D), see Equation 11.

\[
g(X) = (C - D)
\]

\[
\begin{align*}
g(X) &> 0, \text{ safe state} \\
g(X) &= 0, \text{ limit state} \\
g(X) &< 0, \text{ failure state}
\end{align*}
\]

where \( X \) is the vector of the different random variables \( (x_i) \) in the problem. A reliability analysis outputs two equivalent measures of safety: a reliability index, \( \beta \), and a probability of failure, \( P_f \). The probability of failure is defined as the probability of the performance function being less than zero (see Equation 12).

\[
P_f = P[g(X) \leq 0]
\]

The reliability index is defined as the distance in standard deviations from the mean of the performance function to the design point, Equation 13.

\[
\beta = \frac{E[g(X)]}{\sigma[g(X)]}
\]

where \( E[g(X)] \) is the mean of the performance function at the design point (critical slip surface) and \( \sigma[g(X)] \) is its standard deviation (see Figure 5).

![Figure 5 Relationship between the reliability index, probability of failure, and the performance function.](image)
3.1 Hasofer-Lind Method

Hasofer & Lind [15] developed a method, which assumes a first order tangent to the limit state function at the design point, giving an exact solution for linear performance functions and a close approximation for nonlinear functions. This method assumes normally distributed random variables and is used in many engineering fields. It requires the vector of correlated random variables (X) to be transformed into a vector of uncorrelated standardised normal variables ($\bar{X}$) prior to minimisation. Equation 14 is used to transform random variables into the standard space.

$$\bar{x}_i = \frac{x_i - \mu_i}{\sigma_i} \text{ for } i = [1, 2, ..., n]$$  \[14\]

As a result, the performance function is transformed as follows, with $g(\bar{X}) = 0$ separating the safe and the unsafe zones.

$$g(\bar{X}) = g(\bar{x}_1, \bar{x}_2, ..., \bar{x}_n)$$  \[15\]

The reliability index is then defined as the minimum distance from the origin to the limit state surface in the normalised Gaussian space (see Equation 16).

$$\beta = \min_{\bar{X} \in \psi} \{(\bar{X} \bar{X}^T)^{1/2}\}$$  \[16\]

where the limit state surface $\psi$ is defined by $g(\bar{X}) = 0$.

3.2 First Order Reliability Method

Rackwitz and Fiessler [16] proposed a method known as First Order Reliability Method (FORM) which transforms the moments of non-normal random variables into approximately equivalent normal moments (mean and standard deviation). This method solved one of the major inadequacies of the Hasofer-Lind method and allowed a wide array of different distributions to be considered. However, it is important to note that these equations merely provide an approximation at a specific point along the distribution in question and are not an exact solution, see Equations 17 and 18.

$$\sigma_i^N = \frac{\Phi^{-1}[F(x_i)]]}{f(x_i)}$$  \[17\]

$$\mu^N = x_i - \sigma_i^N\Phi^{-1}[F(x_i)]$$  \[18\]

where $x_i$ is the design point, $\Phi^{-1}$ is the inverse of the standard normal distribution CDF, $F(x_i)$ is the original non-normal CDF evaluated at the design point, while $\phi$ is the PDF of the standard normal distribution.

Similarly, parameter correlation can be incorporated into FORM analyses through the addition of a correlation matrix (C) into Equation 17 as shown in Equation 19.

$$\beta = \min_{\bar{X} \in \psi} \{(\bar{X} \bar{C} \bar{X}^T)^{1/2}\}$$  \[19\]
### 3.3 Target Values of Reliability Index

When new slopes are designed using probabilistic methods, the design is required to meet or exceed certain predefined minimum target reliabilities [17]. Depending on the potential consequences of a failure, the design life of the slope, and other social, economic, and political concerns, the required target reliability will differ. For infrastructure assets that have high consequences associated with their failure, higher target reliabilities are required. When upgrading existing transportation infrastructure all new designs should be in line with the recommended target reliability. Target reliability indices should be chosen taking account of all potential consequences arising from the failure of an element [18]. The Transportation Research Board [19] and the US Army [20] have both published tables of recommended target reliabilities and/or target probabilities of failure for engineered slopes. The transportation research board compiled their target reliabilities based on the intended use of the asset and how achievable it was to achieve large safety margins in that domain.
4 Application of Reliability Hazard Assessment to the Irish Rail Network

As is common practice with most large infrastructure networks, Irish Rail maintains a cuttings and embankments asset database, which has extensive information on every network asset. The type of data available for each asset includes the slope location, geometry (height, slope angle, clearance, adjacent land angle, etc.), geotechnical data (soil type), physical characteristics (drainage type and condition, presence of retaining wall, etc.), environmental characteristics (vegetation cover) and others. Most of the inputs are populated through detailed visual walkover surveys which are repeated at regular intervals, thus continuously updating the database. This database is used to develop individual slope models for every asset on the network and before a detailed hazard assessment is carried out.

While some of the data is easily obtainable from visual surveys, other vital characteristics such as slope geometry and soil mechanical properties require more precise measurement. In order to improve the precision and reliability, LiDAR techniques were used to collect the data on slope geometry (slope height and angle). While soil type was assigned to each asset based on the Geological Survey of Ireland’s subsoil cover maps integrated into a GIS platform. One soil type input was recorded for cuttings, while two separate soil type inputs were recorded for embankments: embankment body (fill) and natural ground (below embankment). For the purpose of hazard assessment, subsoil types were reclassified into six major soil categories representative of the Irish Rail network: glacial till, granular material (glaciofluvial sands and gravels), soft clays, peat, rock and non-engineered fill. The appropriate category or categories were assigned to each cutting and embankment. If otherwise unknown, Glacial Till was assumed to be the soil type for all embankment bodies (fills) as many of the embankment records had no information on soil type. The accuracy of the soil type assignment was then validated using existing geotechnical investigative reports, containing borehole logs from discrete locations on the Irish Rail network.

As the Irish Rail network includes hundreds of kilometres of track, large variability in geotechnical parameter values can be expected. Furthermore, the level of uncertainty varies based on the amount of available information, i.e. between assets on which some kind of soil investigation was conducted and assets where all geotechnical data was inferred from soil maps. By taking account of the various sources of uncertainty, probabilistic calculations give a more accurate description of slope instability as opposed to traditional deterministic calculations. In this study, all geotechnical parameters were described using a mean value and coefficient of variation (COV) and normal distributions were assumed throughout. The COV represents the estimated total variability of the parameter, and in this study, it was set to vary depending on the data source, i.e. more accurate data was assigned a lower COV and therefore less uncertainty.

The default mean values (for assets with no available ground investigation) were assigned based on expert judgement and a review of existing literature for all six soil types [21]–[25]. A specific ground investigation programme was carried out on six representative assets from the Irish Rail network to validate the mean values and COVs employed for the wider network. This ground investigation programme is described in detail in Martinović [26]. The ground investigation included geophysical tests (seismic refraction, MASW and electric
tomography) for an initial screening of the area and determination of spatial variability, followed by a performance of a number of Cone Penetration Tests (CPT) at the test site. The results were further validated using relevant geotechnical reports held by Irish Rail and through the Irish National Geotechnical Borehole Database. COVs were assigned based on the recommendations from Phoon and Kulhawy [27] and the results from the study-specific ground investigation. For sites with existing ground investigation reports, the asset-specific mean values overwrite the default values, and COV is reduced accordingly. This enables the continuous update and improvement in network-wide results in future following each new ground investigation (GI) results being stored in the database.
5 Establishing Parameter Values and Variability from Site Data

Phoon and Kulhawy [27] identified three primary causes of uncertainty in soil property estimates. The first is inherent variability, arising from the geological heterogeneity of soil. The second one is measurement error, jointly caused by equipment and sampling error resulting from the limited amount of data available. These two primary sources are commonly described as data scatter. The third source of uncertainty is introduced by transformation of measured values into design soil properties using correlations.

A statistical analysis of variability was carried out on the CPT data for each soil type. The data from all CPTs pertaining to a certain soil layer was amalgamated and the isolated outliers removed. The trend was then established (and the extreme outliers were removed). The standard deviation of the dataset was then found using the sum of the squared residuals (differences between the actual measure and the trend at a given depth) (Equation 20).

\[
SD = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} w(z_i)^2}
\]  

[20]

where SD is standard deviation, \( n \) is a number of data points, \( w \) is the residual value and \( z \) is the depth.

The coefficient of variation (COV), the measure utilised to account for variability in this study was obtained using Equation 21.

\[
COV = \frac{SD}{X_m}
\]  

[21]

where \( X_m \) is the mean value of the soil parameter.

This procedure was repeated for each relevant parameter of each tested soil: effective peak friction angle for glacial till, granular material and fill; and undrained shear strength for soft clays. These values serve as a basis for determining the overall soil parameter variability on Irish Rail slopes.

According to Phoon and Kulhawy’s definition, this procedure covers the inherent variability. It can be further argued that the procedure covers the entire data scatter variability (i.e. inherent and measurement variability) since the tests were done in a controlled manner with certified equipment and operator, and a large amount of data was taken for a relatively small area. A summary of the COVs from this SI is presented in Table 1. It is further compared with the typical COVs for inherent variability from Phoon and Kulhawy.
Table 1 Coefficients of variation (COV) from GI

<table>
<thead>
<tr>
<th>Soil type</th>
<th>Parameter</th>
<th>COV from SI [%]</th>
<th>Mean COV from literature [%]</th>
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<tr>
<td>Glacial Till</td>
<td>Effective friction angle</td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td>Granular material</td>
<td>Effective friction angle</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td>Soft clays</td>
<td>Undrained shear strength</td>
<td>40</td>
<td>22-33*</td>
</tr>
<tr>
<td>Non-engineered fill</td>
<td>Effective friction angle</td>
<td>7</td>
<td>9</td>
</tr>
</tbody>
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* Values for all clays (not only soft clays)

It can be seen that the measured COVs match those reported in literature very well. The apparent overestimation of COV of soft clay is attributed to the well-known trend that as the mean value of the parameter decreases, the COV increases. The reported range from literature was obtained from tests on all clays and not just soft (with undrained shear strength values up to 600 kPa). When only soft clays (undrained shear strength values from 0 to 100 kPa) from that dataset are taken into account, the data ranges from 10 to 65 kPa, with a mean value around 35 kPa, providing an excellent match with the COV from GI.

The presented work describes how to obtain precise COVs for each asset based on a site specific ground investigation which is currently the most precise and preferred option for the hazard model. However, this method is only currently available for a very small number of assets. Therefore, there is a need to establish COV values for the assets which have been assigned with the default soil types due to the lack of more specific soil investigation data. These ‘default’ COVs will rely on the COVs obtained through GI, but will be upwardly adjusted to accommodate larger uncertainty due to the spatial scatter of the assets and soil conditions unique for each asset. Total variability values derived from CPT testing were used as a further guidance. Values from the upper part of that range have been taken instead of the mean value to account for large network wide variability. The final COV values for each of the Irish Rail soil types are presented in Table 2.

Table 2 Final COVs for soil in hazard model

<table>
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<tr>
<th>Soil type</th>
<th>COV [%] for c'</th>
<th>COV [%] for (\phi')</th>
<th>COV [%] for (s_u)</th>
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<tr>
<td>Glacial till</td>
<td>0</td>
<td>12</td>
<td>-</td>
</tr>
<tr>
<td>Granular material</td>
<td>0</td>
<td>12</td>
<td>-</td>
</tr>
<tr>
<td>Soft clays</td>
<td>-</td>
<td>-</td>
<td>40</td>
</tr>
<tr>
<td>Peat</td>
<td>-</td>
<td>-</td>
<td>40</td>
</tr>
<tr>
<td>Non-engineered fill</td>
<td>0</td>
<td>20</td>
<td>-</td>
</tr>
<tr>
<td>Rock</td>
<td>20</td>
<td>20</td>
<td>-</td>
</tr>
</tbody>
</table>
6 Results from Hazard Assessment

After applying the hazard assessment framework to the entire network, the results were compared to the existing ‘hotspot register’ of problematic assets for model validation purposes. The ‘hotspot’ list was created by Irish Rail personnel during the last round of inspection process, prior to the development of this model. Hotspot assets were noticed to exhibit rapidly deteriorating conditions or having exceptionally strong preconditions for landslide triggering. Thirty such assets were identified as exhibiting high risk and marked for priority maintenance, see Figure 6. Following the model calculations for the entire network, 18 out of 30 hotspot assets were positioned in the top 115 (top 3%) of ranked assets, validating the appropriateness of the Hazard model. Furthermore, the model also correctly predicted the actual expected failure mechanism, such as assigning deep rotational failure as the critical mechanism for gently sloping embankments built on peat.

Hazard values calculated in this approach present a meaningful value that allows earthwork assets to be ranked and compared. The ranking presents an objective input that helps to inform asset manager’s decisions on work action prioritisation and budget distribution. As all factors necessary for calculation are stored in the asset database, every data update (such as after a new round of inspections or mitigation and remediation works) automatically provides new hazard profile for the network.
Figure 6 The locations of the assets most likely to fail occurring to the model in blue, yellow dots signify the location of an asset which is both on the hotspot list and predicted by the model.
7 Hazard Assessment Conclusions

A framework was developed for the analysis of landslide hazard based on reliability methods across a transport infrastructure network on a national scale. The aim of this relative hazard assessment was to enable asset ranking for prioritisation of budget allocation in order to increase the efficiency of asset management for slopes. The framework introduced several novel features in relative risk assessment for engineered slopes. The approach relies on quantitative physically-based susceptibility analysis based on probabilistic slope stability calculations. The calculations enable simultaneous analysis of multiple failure limit states and explicitly take account of spatial variability and data uncertainty. An extensive data collation exercise was conducted to obtain geotechnical data needed for these calculations, which included the use of geological maps, a review of scientific literature and existing geotechnical reports, and a tailor-made ground investigation programme. The resultant values, enable an objective ranking and thus aid asset managers to make informed decisions on asset prioritisation and maintenance budget allocation.

The proposed approach is a robust framework that could be implemented on any significant infrastructure network. However, the usefulness of the resulting outputs is highly dependent on how the procedures are tailored for the network being considered. With the correct application of this approach, infrastructure managers can move from reactive remediation towards predictive maintenance of their slope networks. This may aid in reducing the risk and enhancing the reliability and safety of the network.
8 Development of Fragility Curves

Fragility curves are a visual representation of the conditional probability of reaching or exceeding a pre-defined damage state for a range of intensity measures, see Equation 22. The intensity measure is a metric which can be directly related to the intensity of event it causes. In this report, we examine the probability of reaching or exceeding shallow failure for a given intensity measure, rainfall loading. As the total rainfall applied to the slope can result from numerous combinations of rainfall intensity and duration, the resultant infiltration will differ accordingly. Rainfall duration is considered on the x-axis and the rainfall intensity is kept constant at 5mm/h unless specified otherwise. This approach still allows one to calculate the total rainfall applied at any point by simply multiplying the rainfall intensity by the duration at the specific point in question. Damage states are considered in the form of target reliabilities where the exceedance of a damage state represents a loss in performance of the slope. The chosen target reliability indices, see Table 3, represent the minimum limits acceptable which characterise a slopes performance into the following conditions, “poor”, “unsatisfactory”, and “hazardous”. When a slope exhibits a particular performance level (e.g. hazardous) it does not mean that it has experienced failure, but instead means there is a significant likelihood of failure. Knowing that the performance level of the slope has deteriorated to a certain point may inform the infrastructure manager’s decision to take proactive safety measures such as inspecting the slope, reducing the line speed, temporary closure of the road/rail segment if a slope, slope regrading etc. if certain damage states are exceeded.

\[ V = P(D \geq DS) \]  \[22\]

where \( V \) is vulnerability, \( D \) is the damage resulting from a certain intensity measure and \( DS \) is the damage state considered.

**Table 3: Definition of damage states for fragility curves**

<table>
<thead>
<tr>
<th>Damage state</th>
<th>Performance level</th>
<th>( \beta_T )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Poor</td>
<td>2.0</td>
</tr>
<tr>
<td>Medium</td>
<td>Unsatisfactory</td>
<td>1.5</td>
</tr>
<tr>
<td>High</td>
<td>Hazardous</td>
<td>1.0</td>
</tr>
</tbody>
</table>

8.1 Rainfall infiltration analysis

The seepage of rainwater into the case study slope was modelled using the finite element software, Geostudio SEEP/W 2007. Saturated and unsaturated flow were calculated using Richard’s equation [28] for unsaturated flow, see Equation 23.

\[ \frac{\delta}{\delta x} \left( k_x \frac{\delta H}{\delta x} \right) + \frac{\delta}{\delta y} \left( k_y \frac{\delta H}{\delta y} \right) + Q = \frac{\delta \theta}{\delta t} \]  \[23\]

where \( H \) is the total head, \( k_x \) is the hydraulic conductivity in x (horizontal) direction, \( k_y \) is the hydraulic conductivity in the y (vertical) direction, \( Q \) is the applied boundary flux, \( \theta \) is the volumetric water content and \( t \) is time.
8.2 Case study: typical slope on Irish rail network

One of the defining characteristics of cuttings and embankments on the Irish rail network is their steep slope angles. The embankments were constructed in the 1800s using simple end-tipping methods and as a result are under compacted. Figure 7 presents the frequency distribution and cumulative distribution of slope angles of soil slopes on the network. An approximately normal distribution can be observed with a mean slope angle value of 40° and a median value of 38°. For demonstrative purposes, a 45° slope has been chosen for the analysis herein. Almost 25% of the soil assets on the network have a slope angle equal to or above this value.

![Figure 7 Frequency and cumulative distribution of soil slope angles on Irish rail network](image)

Glacial tills (boulder clays) cover almost 50% of the ground surface in the Republic of Ireland [29] and are the most commonly encountered soil type on the Irish Rail network. Irish glacial tills have been extensively characterised [21], [23]. Typical material parameter values needed for rainfall infiltration and slope stability calculations have been inferred from the literature, the values used are presented in Table 4. Coefficients of variations (COV) were also assigned, where applicable, for probabilistic calculations based on the recommendations of Phoon and Kulhawy [30] (see Table 4).

The angle of internal friction selected is a conservative estimation of the constant volume friction angle, which roughly corresponds to the large strain value for this non strain-softening soil. A φb value equal to the internal angle of friction is used, following recommendations by Gan et al. [31] for soils approaching saturation. The effective cohesion of Irish glacial tills is close to zero (as the material is largely comprised of crushed rock with an absence of clay minerals) and a minimum value of 1 kN/m² is used in order to investigate the effect of the cohesion magnitude in a subsequent sensitivity analysis. The selected value of saturated permeability is inferred from values reported for near-surface layers of an Irish glacial till engineered slope affected by fracturing and weathering [32]. Because of a dearth of information about the unsaturated behaviour for Irish glacial tills, a soil water characteristic
curve (SWCC) of a well-characterised Canadian glacial till [33], [34] was adopted in this study. This SWCC was also used to obtain the unsaturated hydraulic conductivity curve.

**Table 4** Glacial till geotechnical parameters used in the case study slope

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit weight γ [kN/m³]</th>
<th>Angle of internal friction φ' [°]</th>
<th>Effective cohesion c' [kN/m²]</th>
<th>Saturated permeability Ks [m/s]</th>
<th>Initial suction [kN/m²]</th>
<th>Residual suction [kN/m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean value</td>
<td>19</td>
<td>36</td>
<td>36</td>
<td>1</td>
<td>1 x 10⁻⁶</td>
<td>20</td>
</tr>
<tr>
<td>COV</td>
<td>0.02</td>
<td>0.1</td>
<td>0.1</td>
<td>0.2</td>
<td>-</td>
<td>3</td>
</tr>
</tbody>
</table>

* angle indicating the rate of increase of the shear strength due to matric suction

The case study slope was modelled with an impervious lower boundary running parallel to the slope surface at a depth of 6 m. Both vertical boundaries were also set as impervious (zero flux) boundaries. Infinite elements were assumed on the lower (right) vertical boundary to avoid modelling an impermeable obstacle. The slope section was then divided into a dense quadrilateral element mesh with vertical sides. A relatively small element size of 0.2 m was used in order to obtain a clear picture of the wetting front progression with depth. The four layers closest to the surface had a refined mesh, with a combined height of 0.1 m, in order to more accurately capture the early wetting front progression. The model mesh is presented in Figure 8.

![Figure 8 Model mesh](image)

A constant initial suction of 20 kPa was assumed throughout the slope. The Irish Meteorological Service operates a weather warnings system, based on a traffic light system with red representing severe. A red weather warning is issued when total anticipated rainfall is expected to exceed 50 mm in 12 hours (4.17 mm/h) or 70 mm in 24 hours (2.92 mm/h). Current climate predictions for Ireland forecast an increase in intense or prolonged precipitation events (Sweeney et al. 2008). A constant rainfall intensity of 5 mm/h was used in this case study to mirror this and was applied in the model as a unit flux upper boundary.
condition. As this rainfall intensity is greater than the saturated permeability of the soil, the infiltration capacity will continue to reduce with time until positive pore pressures start to appear on the surface of the model, indicating water ponding. Given ponding cannot occur on a steep slope the upper boundary condition is at this point changed to a constant head condition having a pressure head of zero, following the approach suggested by Collins and Znidarcic [35]. The wetting front was defined when the suction reached 3 kPa and the relationship between time and wetting front depth was recorded for the probabilistic analyses.

8.3 Results and discussion

Following the approach described in the preceding sections, fragility curves for low, medium and high damage states were constructed for the test slope, see Table 1. Using the mean geotechnical parameter values and COVs outlined in Table 2, in combination with wetting front depths and corresponding rainfall durations, obtained through the SEEP/W rainfall infiltration analysis, a FORM probabilistic slope stability analysis was performed on the infinite slope limit state function. The resulting fragility curves are presented in Figure 9.

![Figure 9 Fragility curves for case study slope](image)

The curves show that during the first five hours of rainfall the probability of exceeding any of the damage states is virtually zero. For longer rainfall duration, the probability exceedance rises steadily, together with the time differences between the damage states. For example, after 12-hours of rainfall, the probability of exceeding the low damage state ($\beta_T = 2$) is 0.8, while the probability of reaching the high damage state ($\beta_T = 1$) is approximately 0.44. For rainfall durations longer than 18 hours, the probabilities of exceedance from all three damage states are in excess of 0.9 and thereafter increase asymptotically towards 1.
As a relatively large number of inputs are required to construct the fragility curves, the extent of each parameter's influence on the final results should be assessed. This enables end users to identify which data types are of greater importance and therefore resources can be committed to obtaining more accurate distributions of these key inputs. Ultimately this provides recommendations on slope typology, which will determine the number of fragility curves required for complete coverage of the network [36]. A sensitivity analysis was carried out to determine the relative influence of each input parameter. A benchmark reliability index was calculated, assuming a wetting front depth of 1 m that represents the wetting front depth associated with the majority of failures seen on the Irish Rail network. Input parameter values were then adjusted by ± 10% and the resultant reliability indices plotted in a tornado plot (see Figure 10). The results unsurprisingly show that slope angle and soil friction angle are the major drivers of slope reliability, with the effective cohesion and residual suction having significantly less influence. Naturally, this is a point variation and hence cannot capture the relative importance of various parameters over their entire range. Nevertheless, the results are meaningful as they capture the relative importance of parameters over the ranges typically encountered on Irish Rail earthworks, for a typical failure depth. Changing the COVs of the parameters was shown to have a much less significant effect when compared to changes in mean values. However, it should be noted that some sites will have significantly higher variations, at which point the relative importance of COVs will become more important. The results indicate that when creating a typology classification for glacial till slopes, slopes should be classified into a large number of sub-groups based on relatively small slope angle increments, with each group attributed a family of fragility curves.

**Figure 10** Sensitivity analysis for a selection of input parameters: slope angle (α), internal angle of friction (φ), the angle describing the rate of increase in shear strength due to matric suction (φ_b), residual suction (u_a-u_w), effective cohesion (c') and their respective coefficients of variations (COVs)
While the values of parameter influence in Figure 10 will change substantially depending on the initial mean parameter values, very little variation was found in parameter influence with depth, indicating a linear variation in the performance function with depth.

Developing a full suite of fragility curves by varying input values of a particular parameter will bring more insight into the effects of design point variation on a single parameter. An example of this can be seen in Figure 11 where fragility curves for all three damage states are developed for a slope with the same material parameters but with a slope angle between 40° and 50°. These values represent the lower bound for the steepest 43.9%, and 12.7% soil slopes on Irish Rail network respectively. Interestingly the influence of slope angle on rainfall duration required to develop some probability of failure appears to be non-linear, as the sets of fragility curves appear to be grouped closer together at steeper slope angles and further apart at shallower inclinations. This indicates that the influence that slope angle has on vulnerability increases as the slope angle increases. This is because at steeper slope angles the failure depth (wetting front) is lower, as a smaller volume of soil needs to be mobilised to overcome equilibrium.

![Figure 11 Fragility curves for slope with 40°, 45° and 50°](image)

While a change in infiltration input parameters (saturated permeability, rainfall intensity, initial and residual suctions) will not affect the percent change of reliability index it will change the time of arrival of the wetting front, which subsequently will affect the shape of the fragility curves. To appreciate this, fragility curves for a rainfall intensity of 3 mm/h, akin to the lower bound red warning rainfall intensity, are compared together with the fragility curves for the rainfall intensity of 5 mm/h in Figure 12.
It is clear that the fragility curves for the lower intensity rainfall are displaced significantly to the right, as the wetting front takes a much longer time to develop. However, once the degradation process initiates the curves have a very similar shape, as the infiltration process following wetting front development largely depends on the saturated permeability value. This will hold true only for cases where the rainfall intensity is higher than the saturated permeability.

![Fragility curves for rainfall intensities of 3 mm/h and 5 mm/h](image)

**Figure 12** Fragility curves for rainfall intensities of 3 mm/h and 5 mm/h

Given that the saturated permeability of the soil is one of the most variable and uncertain parameters, the influence of this parameter on the shape of the fragility curve is considered in Figure 13. Values for saturated permeability were taken as 50 % higher and 50 % lower than the initial case study value, amounting to 1.5x10^{-6} m/s and 5x10^{-7} m/s respectively. The values are seen to have a significant impact on the rainfall duration required for a failure to occur. In Figure 13, the lower value causes a slower advance of the wetting front, resulting in lower probabilities of exceeding damage states. Conversely, higher saturated permeability's facilitate downward seepage and as a result fragility curves are much steeper. It should be noted however that this conclusion is not universal as for coarser soils with a different SWCC and high permeability a wetting front might not form at all.
The analyses presented show that fragility curve development depends on both environmental loading and soil parameters. In addition to the parameters considered the shape of fragility curves will also depend on input parameters including initial suction, SWCC and others. This makes the initial evaluation of geotechnical parameters and their expected ranges an important step in the development of fragility curves for a specific network.
9 Conclusion

To accurately assess the risk of landslides on large transport networks there needs to be a methodology for considering the consequence of an event. To date, for rainfall-induced landslides, this has involved simple vulnerability matrices populated with indices based mostly on expert judgement. Fragility curves overcome this shortcoming by providing a rational, logical framework for quantifying the degree of damage an asset, thereby allowing one to understand the impact and hence consequence of certain events.

This report presents a comprehensive methodology for developing fragility curves for soil slopes subject to rainfall-induced shallow landslides. The loading event or intensity measure is a product of rainfall intensity and duration, while damage states are represented by target reliability indices. The assumed failure mode is a translational shallow slide, following shear strength reduction caused by infiltrating rainwater leading to a decrease of soil suction. The fragility curves are modelled using Monte Carlo simulations to determine the change in reliability with rainfall duration. The fragility curves, therefore, monitor the change in slope capacity with rainfall and chart the probability of the slope passing certain critical thresholds which correspond to a loss in performance. These thresholds are target reliabilities and can be viewed as serviceability limit states. While they may not correspond with ultimate failure, they represent the transition between various safety levels. In this fashion, fragility curves can be used by the operators of transport networks in conjunction with detailed weather forecasts to justify reducing speed or closing services when the risk of failure exceeds allowable limits.

This methodology can be used for the assessment of both cuttings and embankments on road, rail and water transport networks where the governing failure mechanism is connected to the loss of matric suction in thick soil deposits. The soil conditions and slope geometries present on a specific network will determine the number of different fragility curves needed to accurately assess the vulnerability of the entire network.
References


