Landslide susceptibility assessment for engineered slopes using statistical and deterministic approaches

Martinović, Karlo; Gavin, Kenneth; Reale, Cormac

Publication date
2016

Document Version
Final published version

Published in
Proceedings of Civil Engineering Research in Ireland 2016

Landslide susceptibility assessment for engineered slopes using statistical and deterministic approaches

Karlo Martinović[1,2], Kenneth Gavin[2,3], Cormac Reale[1]
[1]School of Civil Engineering, University College Dublin, Newstead, Dublin, Ireland
[2] Gavin & Doherty Geosolutions Ltd., Beech Hill Office Campus, Dublin, Ireland
[3]Faculty of Civil Engineering and Geosciences, TU Delft, Stevinweg 1, 2628 CN Delft, Netherlands
email: kmartinovic@gdgeo.com, kgavin@gdgeo.com, cormac.reale@ucd.ie

ABSTRACT: Landslides cause hundreds of deaths and billions euros of damage to infrastructure and the environment each year. The field of landslide hazard and risk assessment has gone through a massive development in the last twenty years by introducing a wealth of statistical and geotechnical landslide susceptibility models. However, these efforts have been largely restricted to landslides occurring in natural terrain. Current risk assessment approaches for earthworks on large transportation networks still largely take form of subjective risk matrices with inputs gathered by visual walkover surveys. This paper shows the application of two distinctive objective landslide susceptibility approaches on a case study of Irish rail. The first is a 'statistical', or 'data-driven' approach, which uses logistic regression as a statistical tool to establish the influence of slope-describing variables that have led to landslide occurrence. In 'geotechnical' or 'deterministic' approach, geometrical and geotechnical properties of each slope are used to carry out probabilistic slope stability analysis, resulting in probability of failure for each slope. Both approaches result in susceptibility zoning for earthwork assets across the network, effectively ranking them in the criticality terms. This study compares the requirements, applicability and outcomes of each approach, and discusses the methods needed for developing each of them into hazard and risk assessments.

KEY WORDS: Landslide susceptibility; Engineered slopes; Risk assessment; Transport network.

1 INTRODUCTION

Landslides represent a serious geohazard across the world, resulting in hundreds of billions euros in damage and thousands of injuries and deaths each year [1]. To respond to this, much research over the past 20 years has gone into developing and enhancing the prediction of landslides' spatial and temporal distributions and consequences. All these procedures follow a general landslide risk assessment framework. Risk assessment is derived by combining hazard assessment (probability of occurrence of a landslide of certain size in a certain time period) and consequence assessment (impact of that landslide on elements at risk which can be people, structures, environment etc.) [2], outlined in Figure 1. Hazard assessment further consists of susceptibility analysis, obtaining the spatial distribution of landslide likelihood; and temporal analysis evaluating its frequency, often combined with consideration of landslide size (magnitude). Consequence assessment incorporates the identification of elements at risk and their vulnerability assessment.

A large variety of methods for calculating and mapping landslide susceptibility, hazard and risk have been developed and applied to different areas up to date [3], [4], [5]. Landslide susceptibility methods are usually subdivided into qualitative and quantitative methods. Qualitative methods are subjective as they are based on expert opinion and engineering judgment, either directly or indirectly through subjective determination of factor weightings. Examples of qualitative methods include geomorphological mapping, analytic hierarchy process and weighted linear combination.

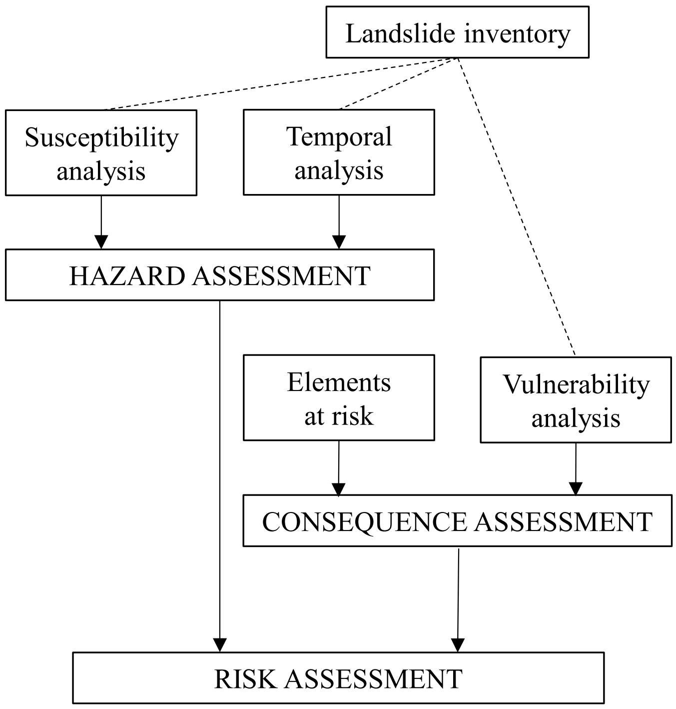

Figure 1. Risk assessment framework

Quantitative methods try to find a numerical correlation between study area's topographical, geotechnical and environmental attributes and landslide occurrence. These methods are generally considered more effective due to their reduced subjectivity, bypassing the need for expert opinion. Quantitative methods are usually carried out using either a deterministic (or 'geotechnical') or a statistical (or 'data-driven') approach. The deterministic approach is based on geotechnical slope stability calculations, while statistical approach is based on statistical evaluation of the influence of slope attributes on landslide-affected slopes by examining past failure data using a variety of statistical techniques. Commonly used statistical methods include frequency ratio analysis, discriminant analysis and logistic regression analysis. Additionally, other data-driven methods such as artificial neural networks are also in use.

While numerous examples of these methods applied to case studies of natural hillslopes can be found, there is relatively little research focused on engineered slopes (cuttings and embankments) on transportation networks. That is somewhat surprising since, due to their location immediately adjacent to transport networks, these landslides can result in drastic consequences such as infrastructure damage, massive transport delays, injuries and even fatalities. Current state of the art of risk assessment methodologies used by asset managers is largely limited to simple subjective risk matrices with data stemming from visual walkover surveys. However, this can be improved by developing quantitative susceptibility, hazard and risk assessment methods that focus on engineered slope specifics.

2 GEOTECHNICAL APPROACH TO LANDSLIDE SUSCEPTIBILITY ANALYSIS FOR IRISH RAIL NETWORK EARTHWORKS

A landslide susceptibility model based on probabilistic slope calculations was developed for cutting and embankments assets on Irish Rail (IR) network as an initial step towards bespoke risk ranking model and decision support tool [6]. A first step included developing a structured database of geometrical, geotechnical and environmental slope characteristics for every asset. This database includes data such as asset location, type, height, slope angle, vegetation cover, soil type, drainage type, and other. Geometrical characteristics were collated following the processing of a detailed digital elevation model (DEM) obtained by aerial LiDAR survey. Soil type was assigned to each asset based on the Geological Survey of Ireland's soil cover maps using a GIS platform. Six main soil types characteristic for IR's assets and surrounding ground were identified: glacial till, granular material (glaciofluvial sands and gravels), soft clays, peat, rock and non-engineered fill. The accuracy of soil type assignment was validated using discrete borehole logs located on the rail network. For each soil type, a typical range of geotechnical parameters was identified from background literature and existing geotechnical reports. This was further complemented by a detailed site investigation for six assets representative of each major soil type.

As the Irish rail network stretches over hundreds of kilometres, large variability in geotechnical parameter values for each soil type can be expected. For that reason, all parameters are described using mean value and standard deviation. This enabled the performance of probabilistic slope stability calculations which give a more accurate representation of stability than standard deterministic approaches.

The 'Hasofer-Lind' first order reliability method (FORM) [7] was used to calculate the probability of failure associated with each asset and its coupled limit state. The 'Hasofer-Lind' approach is an invariant method for calculating the reliability index β, which can then be transformed into a probability of failure Pf.

The first step using this methodology is to transform all variables into normalised random variables. This is accomplished by means of equation (1).

$$\bar{x}_i = \frac{x_i - E[x_i]}{\sigma[x_i]} \qquad (i = 1,2,\dots,n) \tag{1}$$

After normalising the variables the next step is to express the limit state in terms of the reduced normal random variables, as in eqn. (2)

$$g(\bar{X}) = g(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n) \tag{2}$$

In this reduced variable space the limit state surface describes the boundary between stable and unstable zones. The Hasofer Lind reliability index is then expressed as the minimum distance between the origin (the mean value of the reduced limit state) and the failure zone. Assuming normal random variables, a probability of failure can then be obtained using the following equation (3).

$$p_f = p[g(\bar{X}) < 0] = 1 - \phi(\beta) \tag{3}$$

Where Φ(β) is the standard normal cumulative distribution function.

Three limit states reflect the three failure types for which limit equilibrium slope stability calculations were carried out: (i) shallow translational, (ii) deep rotational slide, and (iii) rock wedge failure (for rock cuttings), see Figure 2.

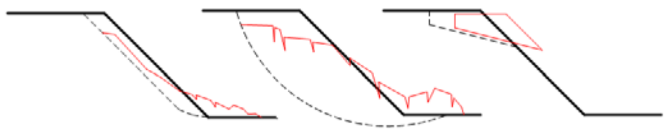

Figure 2. Three failure modes considered in slope stability analyses: (i) shallow translational, (ii) deep rotational slide, and (iii) rock wedge failure

The calculations result in baseline probabilities of failure for each asset. Since these calculations incorporate only simple geometrical and geotechnical data, detailed observations for each asset need to be included in order to account for small differences in landslide-triggering conditions between the assets, controlled by variables which cannot be easily included in limit equilibrium calculations. These variables include data that is usually recorded in a qualitative manner, such as type and condition of drainage, type and density of the vegetation, slope erosion and overall condition, etc. Twenty of these variables, named Degradation Factors (DF), were identified with the help of experienced Irish Rail site inspectors' engineering judgment. Each DF was given the weight based on experience and interrogation of past failures. The total product of DF weights gives the final DF adjustment factor which is combined with baseline reliability indices to obtain final reliability indices and final probabilities of failure. Flowchart of this process is presented in Figure 3. These final probabilities of failure enable to effectively rank and compare all assets across the network.

Baseline reliability index $\beta*$

$\downarrow$

$$DF_{tot} = \sum_{i=1}^{20} DF_i$$

$\downarrow$

$$\beta = \beta* \times DF_{tot}$$

$\downarrow$

$$P_f = 1 - \Phi(\beta)$$

Figure 3. Flowchart of incorporation of degradation factors

3 STATISTICAL APPROACH TO LANDSLIDE SUSCEPTIBILITY ANALYSIS FOR IRISH RAIL NETWORK EARTHWORKS

Another landslide susceptibility analysis on the same network was carried out using a ‘statistical’ (or ‘data-driven’) approach. This approach aims to interrogate the usefulness of past failure records in obtaining conclusions on landslide distribution across the network. The logistic regression statistical technique uses the historical landslide data (some examples in Figure 4) to quantify the influence of topographical, geotechnical and environmental slope characteristics (factors) of slopes on which landslides were recorded. It then uses these results to assess the probability of landslides on all other assets in the network based on their own combinations of these factors.

This approach was tested on the case study area of Athlone Division, a north-western section of Irish Rail network comprising about a third of all earthwork assets (cuttings and embankments). The extent of Irish Rail network (thin lines) and Athlone Division (thick lines) is outlined in Figure 5. A database prepared for the geotechnical approach of susceptibility analysis (described in previous section) was used here to obtain the data on slope characteristics. Since different factors are responsible for initiating different landslide types, it is a common practice to carry out a susceptibility analysis for each landslide type separately [5]. In this example, susceptibility analysis was carried out for shallow translational slides, as they were found to be the most prevalent landslide type across the Irish rail network.

Figure 4. Examples of typical landslides on Irish rail network: a) on embankment, b) and c) on cutting

A selection of factors relevant to landslide initiation is a process that depends on landslide type and study area characteristics. Budimir et al. [7] carried out an extensive literature review on the topic of landslide susceptibility analysis using logistic regression, with the aim of determining the frequency and significance of factors used for susceptibility analysis. The review showed that there are no universal criteria established for selecting factors, resulting in the factors selected for analysis varying wildly between studies.

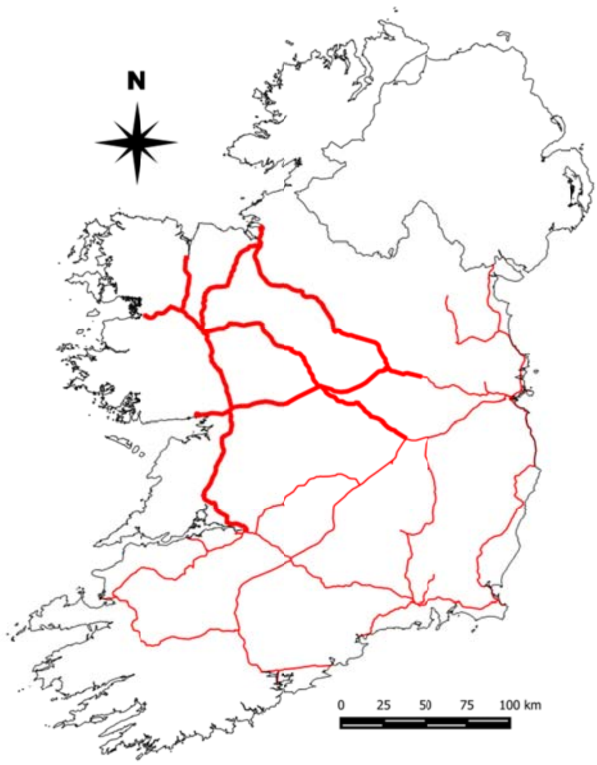

Figure 5. Irish Rail network with rail lines in Athlone divisions (thick lines)

In this study, nine factors describing the asset have been selected, each with a number of possible classes. Factors were selected based on background literature research and the reported causal factors from the available landslide register. The factors selected are slope height (scalar), slope angle (scalar), asset type (cutting or embankment), aspect (classes: N, NE, E, SE, S, SW, W, NW), vegetation type (bare ground, grass, shrubs, trees), adjacent slope (flat terrain, flow towards asset or flow from the asset), soil type (glacial till, granular material, soft clays), annual rainfall (800-1000 mm, 1000-1200 mm, 1200-1400 mm) and slope conditions (1, 2 or 3 based on inspector's observations). Some of these factors such as asset type or slope condition are specific to engineered slopes for transport networks and have not been used in landslide susceptibility studies before.

The goal of logistic regression is to find the best fit model that describes the combined relationship between these factors (independent variables) and the presence or absence of landslides (dependent variable) on all slopes. The final result of this model is a probability p of the landslide occurring, with values ranging from 0 to 1 for each asset, calculated by:

$$p = \frac{1}{1+e^{-Z}} \tag{4}$$

where Z is generated by the coefficients depending on the input data for each factor, obtained by Equation (5):

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{5}$$

where β1, β2,…, βn are the regression coefficients that determine the contribution of the different input factors (independent variables X1, X2,…, Xn), obtained iteratively using maximum likelihood estimation. β_0 is the intercept value of the model.

The asset factor database was divided into training set (70 %) using which the model was set up and the validation set (30 %) against which the model results were verified. The logistic regression was then carried out on the training set. Regression coefficients obtained for each factor class are presented in the Table 1.

Table 1. Regression coefficients

Factor	Class	β
Object type	Embankment	0
	Cutting	1.327
Aspect	E	0
	N	0.312
	NE	-0.405
	NW	-0.236
	S	-0.540
	SE	0.832
	SW	-0.636
	W	1.110
Adjacent slope	-1	-0.797
	0	0
	1	1.704
	2	1.410
Asset height	*Height [m]*	0.135
Asset slope angle	*Angle [°]*	0.078
Vegetation type	Bare	1.383
	Grass	0.932
	Shrubs	0.394
	Trees	0
Soil type	Granular till	0
	Granular material	-0.542
	Soft clays	-21.393
Rainfall	800-1000 mm	0
	1000-1200 mm	0.239
	1200-1400 mm	0.959
Condition	1	0
	2	2.000
	3	3.284
Constant	β_0	-8.54

In general, results identified the slope angle as the most important driver for the shallow instability, complementing similar conclusions made for natural slopes [8]. Cuttings were found to be more susceptible to failure than embankments, attributed among other things to influence of groundwater level which was generally at shallower depth for cuttings. Slope condition was found to exert a significant influence on landslide occurrence, highlighting the role of small localized defects in landslide initiation.

These results were also used to infer quantitative comparison of the relative influence between classes of the same factors to landslides occurrence. Some of the results are graphically presented in the Figure 6. These results for example show that bare slopes are 4 times more likely to fail than densely vegetated ones, and that west facing slopes are 3 times more likely to fail than the east facing ones.

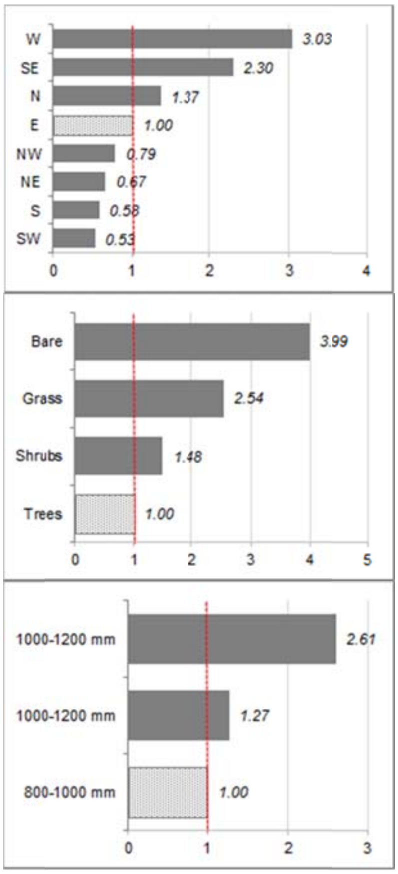

Figure 6. Odds-ratios for a) aspect, b) vegetation type and c) annual rainfall

The performance of the model was interrogated using several statistical measurements such as chi-square test and McFadden's and Nagelkerke's R^2 tests. These results indicated a very good fit of the model. The model was then validated using the validation dataset. Probabilities of failure of assets in validation dataset were obtained by applying regression coefficients acquired through training model. Assets with $p>0.5$ were regarded to be predicting the landslides. They were then compared to the actual state of assets (presence/absence of landslides). Comparison was carried out with the help of confusion matrix [9], classifying assets into true positives, true negatives, false positives and false negatives. The confusion matrix showed the overall accuracy of the model to be 92.3%, but slightly overpredicting the absence of landslides. That was attributed to a small sample size of landslide-affected assets in both training and validation datasets. Model was additionally validated using Receiver Operating Curve (ROC), shown in Figure 7. The ROC curve presents the relationship between the model's sensitivity and specificity, expressions inferred from the values from the validation confusion matrices with varying cut-off levels. ROC confirmed a very good fit of the model, with area under curve (AUC) of 0.902 for validation dataset (AUC=0.5 representing a random fit and AUC=1 indicating a perfect fit).

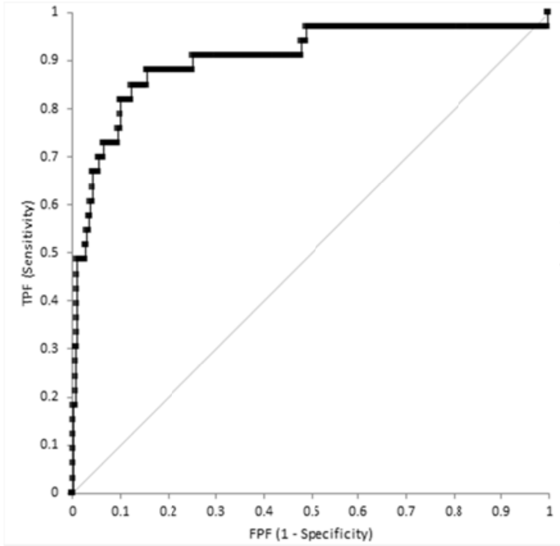

Figure 7. ROC curve for validation dataset

Using the calculated probabilities, assets were classified into five susceptibility classes: very low (79.4% of all assets), low (13.0%), moderate (3.9%), high (2.3%) and very high (1.4%); effectively identifying and ranking the top critical assets. A large percentage of assets in a 'very low' class is indicative of engineered slopes, which are designed to satisfy stability.

4 STEPS TO RISK ASSESSMENT

Landslide susceptibility analysis presents the spatial distribution of landslide occurrence likelihood. However it does not provide information on the frequency of occurrences or the impacts landslides can cause.

The temporal occurrence of landslide can be expressed in terms of frequency, return period, or exceedance probability. It is often obtained through statistical empirical analysis of past failures in the study area in a discrete time interval. For landslide hazard assessment on transport networks, it is common to look at joint temporal aspects of landslide event and traffic features, such as temporal probability that a vehicle (car or train) will be at the debris path. Similar approach can also be used to obtain magnitude-frequency curves, jointly assessing landslides' size and temporal aspect.

Another way of obtaining the temporal patterns of landslide occurrence is by analysing the frequencies and return periods of the triggering factors that initiate the landslides, rather than the landslides themselves. For rainfall triggered landslides, the influence of rainfall is typically interrogated using either physical model or rainfall thresholds. Physical models couple the hydrological and slope stability models to assess the response of the slopes in study area to the applied rainfall [10]. Rainfall thresholds represent the lower bound of a combination of some rainfall characteristics such as intensity, duration or accumulation necessary to induce landslides [11]. They are obtained in an analytical way by collating the data on rainfall characteristics in place during and before the known historical landslides.

Another major subcomponent of a risk assessment is the consequence assessment. Consequence assessment aims to quantify the impact that a specific landslide has on the surrounding built and natural environment. The first step here is to define the elements at risk that can be potentially affected by landslides and for which risk assessment is being carried out. The examples of elements at risk are people, buildings, infrastructure, and other. The next step involves obtaining the vulnerability of each element at risk to the landslide. Vulnerability is defined as the degree of potential damage, or loss a given element may experience as a result of a landslide of a particular type and intensity [4]. The vulnerability of an element depends on the element at risk observed, the type of landslide, relative position of element at risk to the landslide, and the magnitude and run-out distance of the landslide. For example, vulnerability of people in vehicles to slow moving deep rotational landslide is extremely low, while the vulnerability of a road or rail element positioned at the crest or toe of the same landslide is extremely high. Conversely, vulnerability to shallow rapid moving debris flow is much higher for people than for reinforced concrete buildings or road/rail elements. Vulnerability is typically expressed using vulnerability factors with values ranging between 0 and 1, quantified through expert judgment or by using statistical methods to analyse the consequences of historical landslides. The alternative way of obtaining the vulnerability values is by developing the fragility curves, which express the conditional probability of exceedance of a pre-defined damage level for various values of landslide intensity [12].

The final risk value is obtained as a product of hazard and consequence assessment results. The last step in risk assessment typically involves evaluating the risk against existing risk criteria. Risk criteria depend on the perception of risk in the society exposed to hazard, and as a result they vary from country to country and between infrastructure management organisations. Further actions towards risk acceptance or mitigation are covered in detail through risk management frameworks.

5 CONCLUSIONS

Two approaches to landslide susceptibility assessment for engineered slopes on transport infrastructure are outlined in this study. Both approaches were applied on the earthworks on the rail network in Ireland. The first, 'geotechnical' approach is based on slope stability calculations for each of the cutting and embankment on the network. Slope stability calculations were carried out in a probabilistic fashion to accommodate the large uncertainty in soil parameter values expected across the network. The resulting probabilities of failure were then fine-tuned using engineering experience to include the detailed asset-specific observations. The second, 'statistical' approach is based on interrogating the past landslide records to quantify the influence of geotechnical and environmental attributes of those slopes on landslide occurrence. It was carried out using a statistical multivariate method of logistic regression. Statistical model was trained on the training dataset and resulted in probability of the landslide occurrence for all geotechnical assets in the study area.

While both approaches were proven to be highly useful for determining landslide susceptibility for engineered slopes, the approaches differ in some features. In comparison, statistical method requires less computing power and explicitly takes past experience into account. It also results in the quantitative recommendations of influence of each factor class to failure occurrence. However, it is very sensitive to the completeness of past failure dataset and the variations in dataset size and training/validation ratios. It also needs to be carried out for every landslide type individually. Unlike statistical approach, the geotechnical approach takes account of soil mechanics principles and geotechnical characterisation of each asset. That makes results progressively more precise as the available asset data is being widened following site investigation across the network. It is also able to readily include the effect of any observation through the use of degradation factors.

Landslide susceptibility assessments like the two described in this study require temporal analysis and vulnerability assessment to be developed into the full risk assessment. This study finally gives a short overview of the typical methods used to carry out these steps.

ACKNOWLEDGMENTS

This work is partly funded by the Horizon 2020 DESTination RAIL Project (Decision Support Tool for Rail Infrastructure Managers) EU Project No. 636285. This research is supported by the Irish Research Council Employment Based Postgraduate Programme scholarship fund.

REFERENCES

[1] Aleotti, P., & Chowdhury, R. (1999), 'Landslide hazard assessment: summary review and new perspectives', *Bulletin of Engineering Geology and the environment*, 58(1), 21-44.

[2] Varnes, D. (1984) Landslide hazard zonation: a review of principles and practice. No. 3.

[3] Guzzetti, F., Carrara, A., Cardinali, M., & Reichenbach, P. (1999), 'Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy', *Geomorphology*, 31(1), 181-216.

[4] Fell, R., Ken KS Ho, S. Lacasse, E. Leroi.(2005), 'A framework for landslide risk assessment and management', *Landslide risk management*, pp. 3-25.

[5] Corominas, J., Van Westen, C., Frattini, P., Cascini, L., Malet, J. P., Fotopoulou, S., ... & Pitilakis, K. (2014), 'Recommendations for the quantitative analysis of landslide risk', *Bulletin of engineering geology and the environment*, 73(2), 209-263.

[6] Doherty, P., Gavin K., Martinović K., and Reale, C. (2014), 'GEORISK–A Risk Model and Decision Support Tool for Rail and Road Slope Infrastructure', *Proceedings of the International Conference on Road and Rail Infrastructure CETRA2014*., pp 573-579

[7] Budimir, M. E. A., Atkinson, P. M., & Lewis, H. G. (2015), 'A systematic review of landslide probability mapping using logistic regression', *Landslides*, 12(3), 419-436.

[8] Dai, F. C., Lee, C. F., Li, J., & Xu, Z. W. (2001), 'Assessment of landslide susceptibility on the natural terrain of Lantau Island, Hong Kong', *Environmental Geology*, 40(3), 381-391.

[9] Mancini, F., Ceppi, C., & Ritrovato, G. (2010) GIS and statistical analysis for landslide susceptibility mapping in the Daunia area, Italy. Natural Hazards and Earth System Sciences, 10(9), 1851-1864.

[10] Godt, J. W., R. L. Baum, W. Z. Savage, D. Salciarini, W. H. Schulz, and E. L. Harp. (2008) 'Transient deterministic shallow landslide modeling: requirements for susceptibility and hazard assessments in a GIS framework', *Engineering Geology* 102, no. 3: 214-226.

[11] Aleotti, P. (2004) 'A warning system for rainfall-induced shallow failures', *Engineering Geology* 73, no. 3: 247-265.

[12] Fotopoulou, S. D., Pitilakis, K. D. (2013). 'Fragility curves for reinforced concrete buildings to seismically triggered slow-moving slides', *Soil Dynamics and Earthquake Engineering*, 48, 143-161.