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Landslide Risk Assessment of Onshore Pipelines Integrating Bayesian Networks and GIS

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Abstract

Landslides constitute a significant threat for linear infrastructure systems, such as roads, pipelines, and transmission lines. Because of the variation on site conditions landslide risk assessment becomes a challenging task that has been traditionally undertaken through heuristic methods, physical modelling, or machine learning methodologies, including the use of spatial datasets and Geographic Information Systems (GIS). In this study, a Bayesian Network model is developed to assess the economic risk of pipelines due to landslide processes. This model follows an innovative risk assessment framework, which consists in identifying the relevant threats, the systems vulnerable to these threats, and their corresponding consequences. To illustrate the applicability of the proposed methodology, a case study of a pipeline in Colombia subjected to strong geological and geotechnical variations, shows the governing variables and their relationships as established by available evidence (i.e. physical observations, model predictions and expert's knowledge). These variables are subsequently mapped with the aid of GIS to serve as input to a Bayesian Network capable of the spatial assessment of the state of economic risk in the pipeline. Preliminary results show that the model adequately represents the state of risk in the infrastructure and that it can be extended to risk management with the inclusion of active and passive countermeasures.

1 INTRODUCTION

Landslides are major geological hazards with a widespread impact on urban areas as well as in transportation networks, and are responsible for significant losses in terms of fatalities and property damage (Froude & Petley, 2018). Given the linear nature of hydrocarbon transportation lines, their alignments often traverse areas of complex topographic, geological, and climatological conditions with varying degrees of landslide susceptibility (Baum et al., 2008). Sweeney et al. (2005) states that the incident frequency in mountainous terrains can be between 40 and 100 times greater than in less challenging environments. Even though, on average, landslide-related events correspond to 8%-10% of the global pipeline incidents behind other hazards, landslide incidents often cause larger ruptures that translate into greater environmental damage and longer periods of service interruption (Lee et al., 2016).

Several landslide hazard and risk assessment methods have been proposed and/or adopted by operators following industry standards. For example, the Canadian standard CSA Z662-15 lists four possible approaches to risk estimation: (i) Risk matrix; (ii a) Semi quantitative Risk Index; (ii b) Quantitative Risk Index; and (iii) Probabilistic Risk Analysis (CSA, 2015). Examples of models following these methodologies can be found in Porter et al. (2004) for risk matrices, Read & Riskalla (2015) for semi-quantitative indexes, Baumgard et al. (2016) for quantitative indexes, and Alvarado et al. (2017) for probabilistic hazard and risk analysis.

Given the length of pipelines and the various environments they traverse, the use of Geographic Information Systems (GIS) has become a valuable tool for implementing hazard and risk assessment models. According to Jaboyedoff et al. (2012), the rise of publicly available spatial datasets, the improvement of remote sensing technologies, and the progress made in both software and hardware improvement, have helped researchers in developing new models applicable to several spatial problems. The works of Henschel et al. (2012) and Borfecchia et al. (2015) use remote sensing data sets and GIS to map landslide susceptibility and pipeline failure probability given the occurrence of earthquake-triggered landslides

The objective of this work is to develop a model for the risk assessment of pipelines due to landslide processes by integrating sources of spatial information in a Bayesian Network that represent the causal relationships between them. With the aid of GIS, prior probability distributions for relevant spatial variables are obtained and inputted into the BN for analysis. This approach, referred to as BN+GIS (Varela 2013), offers the opportunity of model updating as new evidence becomes available. Finally, in order to illustrate the capabilities of the model, a pipeline in Colombia is used as a case study.

2 BAYESIAN NETWORKS AND RISK

2.1 Bayesian Networks

A Bayesian Network (BN) is a graphical representation of the joint probability distribution of a set of random variables, and is a combination of a graphical and a probabilistic model. Nodes and arcs compose a BN, where the nodes represent the random variables in the model, while the arcs illustrate the conditional probability relationships between variables (Korb and Nicholson, 2004). A node is referred to as a parent node if it has one or more arcs directed to another node, called the child node.

Bayes theorem represents a probabilistic inference between a hypothesis (A) and the evidence (B) to assess the posterior conditional probability P(A|B). This relationship is interpreted as a causal dependency between 'parent' and 'child' nodes, represented with a Conditional Probability Table (CPT), which transmits the message through the network arcs. (Varela & Medina-Cetina, 2017). When the probability is propagated from parent to child node (i.e. cause to effect) a prognostic analysis is performed. In contrast, a diagnostic analysis happens when the probability is propagated from child to parent nodes (i.e. effect to cause).

Figure 1 shows an example of a BN with three independent parent variables (V1, V2, V3) and one child node (V4), for a total of m=4 nodes, with each variable discretized in n=3 classes. Equation 1 describes the message propagation in prognosis ($\pi(Z)$), which produces a list with all the possible combinations of three discrete states of four variables ($m^n = 81$). The diagnosis message ($\lambda(Z)$) is propagated from the child node to the parent nodes and is computed through Equation 2. In this case, the child node is instantiated with a prescribed distribution in order to infer the marginal probabilities of the parent nodes.

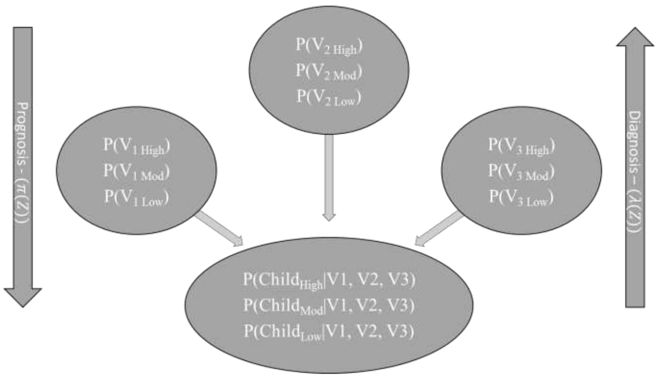

Figure 1. Example of a BN

$$P(\text{Child}_i)=\sum_{j=1}^{27}\pi(Z_i)=$$

$$\sum_{j=1}^{27}P(V_{1i})*P(V_{2i})*P(V_{3i})*P(\text{Child}_i|V_{1i},V_{2i},V_{3i}) \quad (1)$$

$$P(\text{parent}_k)=\sum_{j=1}^{27}\frac{\pi(Z)*\lambda(Z)}{\sum_{j=1}^{81}[\pi(Z)*\lambda(Z)]} \quad (2)$$

2.2 Risk assessment framework

In this work, Risk is defined following the framework of Medina-Cetina et al (2008) as shown in the following equation:

$$R=P[T]*P(C|T)*U(C) \quad (3)$$

Where P[T] is the *Hazard*, or probability of occurrence of a particular threat within a given period of time; P[C|T] is the *Vulnerability*, or the degree of expected loss in an exposed element given the hazard; and U(C) is the loss or utility of a set of *Consequences* C. They can be economical, environmental or social.

To illustrate the definition of Risk, the Figure 2 shows a synthetic case of the economic risk assessment of a pipeline affected by landslides. In this case, the hazard P[T] is the Rainfall **(R)**, the vulnerabilities P[C|T] correspond to the Landslide Intensity **(LI)** and Pipeline damage **(PD)**, and the Economic risk **(ER)** is calculated as the product of the probability of each state of PD and the associated costs. Each variable is discretized in three states or classes (low, moderate, and high) for simplicity.

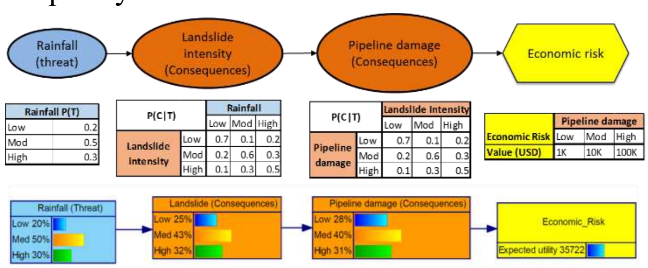

Figure 2. Synthetic case for economic risk assessment

In the figure, a prior probability table is shown for the node **R**, and CPTs for the nodes **LI** and **PD**. For the node **ER**, costs associated to each state of **PD** are specified. The probability propagation is given as follows:

$$P(R)=Bel(R)$$

$$P(LI|R)\leftarrow Bel(LI)=\sum_{i=1}^{3}P(LI|R_i)*Bel(R_i) \quad (4)$$

$$P(PD|LI)\leftarrow Bel(PD)=\sum_{i=1}^{3}P(PD|LI_i)*Bel(LI_i)$$

Where $P(PD|LI_i)$ reflects de definition of *vulnerability*. Finally, the expected risk is given by:

$$E[ER|PD]=\sum_{i=1}^{3}U(O_i|PD_i)*Bel(PD_i) \quad (5)$$

Where $U(O_i|PD_i)$ is the expected economic cost of repair conditioned on Pipeline Damage *i.*

3 PROPOSED MODEL

Landslides affect pipeline integrity causing ruptures (or loss of containment) in various ways such as lateral displacement, spanning, loading, or exposure and impact. (Lee & Charman, 2005); Pipelines can present different level of damage (i.e. *vulnerability*) to these failure modes, or load cases, depending on their strength and stiffness properties.

Therefore, the first step for the risk assessment of pipelines is to estimate the probability of landslide occurrence and its intensity. After that, the *vulnerability* of the pipeline in terms of its disposition, strength, and stiffness needs to be characterized. Finally, the economic and environmental *consequences* associated with different levels of damage (i.e. pinhole, buckling, rupture) must be taken into account for a complete risk assessment. The following sections describe and list the relevant variables for each category.

3.1 Landslide's Triggering Events

The probability of a landslide occurrence depends on a set of variables, which go beyond the traditional physically-based models, including environmental and local conditions, but also variables describing evidence of landslide activity.

Regarding environmental conditions, the model considers the variables rainfall and seismicity. These variables induce the slope failure by changing the shear strength and/or the shear stress conditions and correspond to the main triggers of landslides worldwide.

The local conditions include variables such as geology, slope, soil geotechnical and hydraulic properties, and vegetation. Conceptually, the preparatory factors are intrinsic of a slope and create a condition of marginal stability In the model, a combination of slope, geology and land cover is used to define the local conditions.

Finally, the evidence of landslide activity is very important since it gives a confirmation of a landslide process along the ROW. The environmental and local conditions allow for a landslide occurrence prediction, but the evidence of landslide activity is a clear sign of geotechnical instability.

3.2 System's Vulnerable to Landslides: Pipelines and Surface Water

For the purpose of this model, two different vulnerable systems are considered: pipelines and surface water. Pipelines are vulnerable to landslides since the occurrence of ground movements has an impact on pipeline integrity. Consequently, once the pipeline fails, there is a potential spill that can reach surface water bodies, contaminating them, and affecting the environment.

The pipeline *vulnerability* refers to the degree of expected loss or damage in a pipeline given the occurrence of a landslide. In order to assess this factor of the risk equation, an understanding of the pipe-soil interaction is needed. Analytical and numerical approaches for characterizing the pipeline *vulnerability* can be found in the literature (Liu & O'Rourke, 1997; Laing & Young 2017; Islam et al., 2019). The relevant variables for soil-pipe interaction include the relative direction pipe-slope, pipeline thickness and disposition (i.e. aerial or buried), as well as landslide related characteristics such as mechanism and dimensions.

According to Muhlbauer (2015), receptors of pipeline failures include people, property, and environment. Within the environmental receptors are the fauna, flora and water bodies. For this analysis, an environmental sensitivity is considered based on the potential contamination of water bodies.

3.3 Consequences and States of Risk

Economic and environmental *consequences* are considered in the BN network to illustrate its capability of integrating several *threats*, *vulnerabilities*, and *consequences*. The economic *consequence* are given by the pipeline damage level, and the costs associated will give the total economic risk according to Equation 5. In contrast, the environmental risk is not expressed as a cost, but as a Risk Index that goes from 0 to 1, being 1 the highest value of Risk

Figure 3 presents the final structure of the BN, (called informed synthetic case) constructed through literature review and refined via expert knowledge.

4 ILLUSTRATIVE CASE STUDY

This section introduces a case study to illustrate the applicability of the methodology, and it is based on partial information. The results of this exercise are not intended to be actual risk values but to show how the proposed methodology works and its potential to integrate multiple threats, multiple systems vulnerable to these threats, and their corresponding *consequences* or impacts. The purpose of this section is to show the potential applications and advantages of the model through the integration of threats, vulnerabilities and *consequences*, which defined varying States of Risk.

The proposed region of analysis is hypothesized to be 10km long, located in the Colombian piedmont. The zone is characterized by gentle slopes, and sedimentary rocks such as sandstone of average mechanical properties compose the lithology formation. The rainfall exhibits a monomodal pattern with marked peaks between the months of April and August. The seismic hazard is high given the localization of relevant fault systems that conform the Andes Cordillera. Figure 4 presents both sections with the slope over hillshade.

4.1 Model Variables

The following is a description of each variable considered, along with its source of information. All the variables are discretized in three states: Low, Moderate, and High unless stated otherwise.

Rainfall. The source for this variable is a climatic zoning of the transportation systems that characterize the rainfall patterns in terms of quantity (mm) and number of days with rain in monthly and annually basis (Chaves et al., 2019). The prior distribution for both sections is shown in table 1.

Table 1. Distribution of Rainfall variable

State	P()
Low	0.42
Med	0.58
High	0.00

Seismicity. The seismicity is considered as high, consistent with the pipeline location close to a principal fault system.

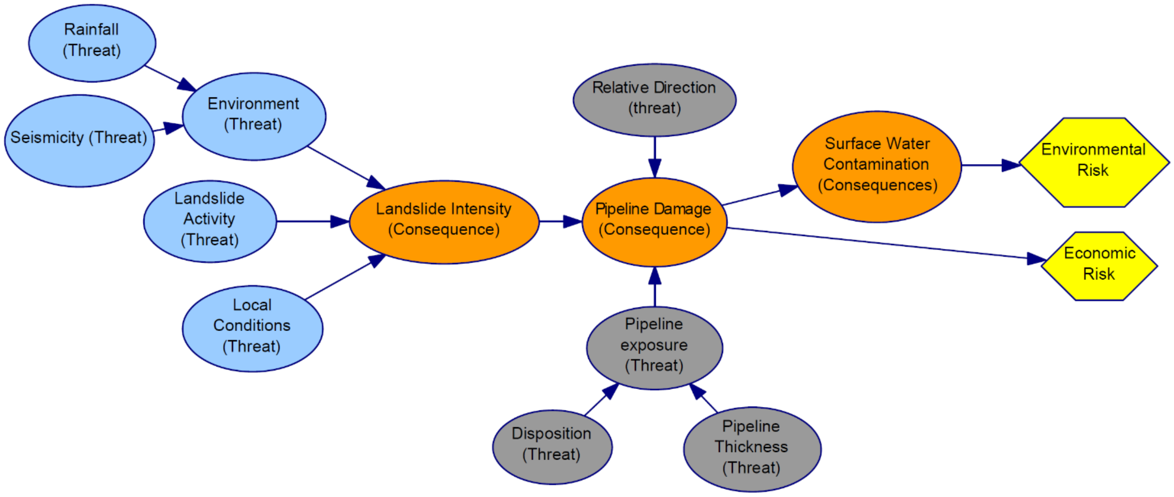

Figure 3. Synthetic informed case.

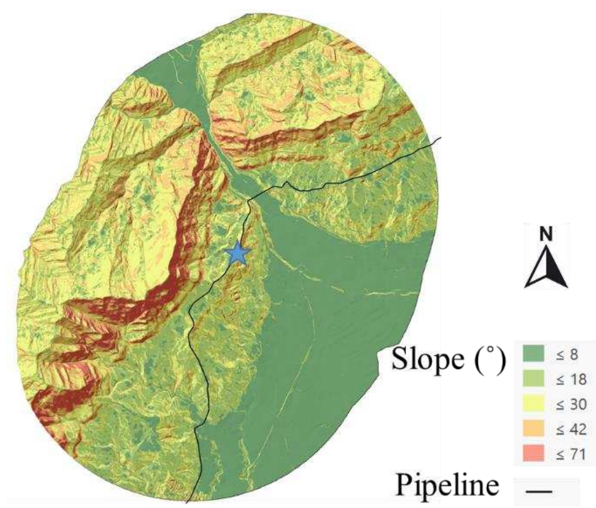

Figure 4. Section of analysis with slope angle over topo-hillshade.

Landslide Activity. This variable has four states: None, Low, Moderate, and High. It measures the intensity (i.e. landslide mechanism, volume) of an existent landslide on the Right of Way (ROW). For the analysis, no existent landslides were considered.

Local Conditions. This variable relates to the preparatory factors for landslides. The source of information was a Geotechnical Susceptibility Zoning described in Chaves et al., (2019) which classifies the ROW in five different classes of susceptibility according to values of slope, structural geology, lithology, and land cover. The susceptibility classes were mapped to the variable states as follows: Low (Very Low and Low), Moderate (Moderate), High (High and Very High). In order to obtain the prior distribution for both sites, a buffer of 30m was used to clip the Susceptibility Zoning layer. The probability of each state corresponds to the percentage in area for each class inside the buffer. Figure 5 presents an example for the calculation. The prior distribution is presented in Table 2.

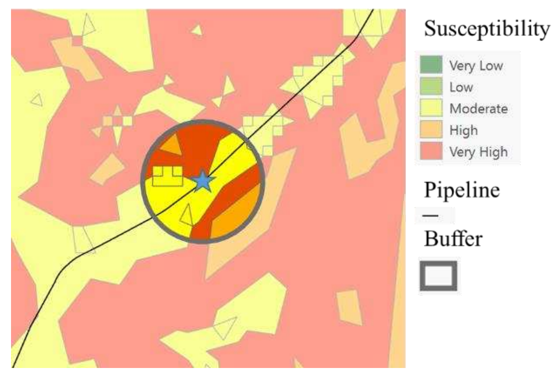

Figure 5. Sampling buffer

Table 2. Distribution of Local Conditions variable

State	P()
Low	0.00
Mod	0.46
High	0.54

Landslide Intensity. In similar fashion to Existent Landslide, this variable has four states: None, Low, Moderate, and High. It gives information of both the probability of landslide occurrence and it intensity. The CPT was built with expert knowledge and literature review. It was considered that the distribution of *Existent Landslide* has a strong influence on the conditional probability.

Disposition. This variable represents the disposition of the pipeline, being it aerial or buried. It is a relevant variable since it influence the *vulnerability* of pipelines facing landslide hazards. The pipeline is considered as buried for the analysis.

Thickness. The pipeline thickness is below 1/8 inches. Thus, the thickness is Low for both sections.

Pipeline Exposure. This variable summarizes the *vulnerability* parameters that are intrinsic of the pipeline, independent of the characteristics of the ROW. Similar to the other variables, the CPT was built with expert knowledge and literature review. In this case, an aerial disposition and high thickness are the most favorable conditions while buried pipelines with low thickness will present higher strains when impacted by landslides.

Relative direction. This variable has three states: Longitudinal, Diagonal, and Transversal. The relative direction at both points is Diagonal. The information was obtained through a comparison of the pipeline azimuth and the slope aspect of a raster dataset in a GIS application.

Pipeline Damage. This variable has three parent nodes, Landslide Intensity, Relative Direction, and Pipeline Exposure. For the CPT, higher levels of landslide intensity will increase the probability of pipeline damage, similarly to smaller thickness and a buried disposition. The lowest conditional probability of pipeline damage occurs when there is no landslide intensity, the thickness is high and the pipeline is aerial.

Surface Water Contamination. This variable represents the contamination of water bodies given a pipeline failure. The characteristics of water bodies were analyzed for the entirety of the section. For the analysis region, there is a relevant drainage in proximity of the pipeline. Thus, the conditional probability of contamination is deemed important even for a low state of Pipeline Damage.

Economic Risk. Table 3 shows the costs associated to each state of Pipeline Damage in dollars. The costs were obtained from a database and selected according to the complexity for each level of damage expected. For example, for low damage level, geotechnical and mechanical works related with stress relief and ROW maintenance were considered. For the case of high level of damage, the cost of major maintenance activities such as complex geotechnical works, realignments, and complete replacement of the pipeline were used.

Table 3. Cost associated with Pipeline damage levels

Pipeline damage	Cost	
Low	$	130,000.00
Mod	$	320,000.00
High	$	650,000.00

Environmental Risk Index. Table 4 presents the value of the risk index for each state of the parent node.

Table 4. Risk index values

Surf. Water Cont.	Risk index
Low	0.0
Mod	0.5
High	1.0

5 RESULTS

Figure 6 shows the results in prognosis. For this case the Environmental Risk is 0.67 and the Economic Risk is $406.368, meaning that the section has a moderate-to-high risk under the conditions analyzed.

Notably, the probability distribution of the **Landslide Intensity** node shows that the most probable state is *Moderate* with only a 0.13 probability of it being *High*. Given that the pipeline is buried and has a low thickness, the **Exposure** is *High*, increasing the overall *vulnerability* of the pipeline. The results show that this factor drives both the economic and environmental risks.

Figure 7 and Figure 8 presents the result of the diagnosis analysis for lower and upper bounds scenarios. This means, that the diagnosis scenarios set both risks at its lowest values for the lower bound, and both risks at its higher values for the upper bound.

For the lower bound scenario, there is a marked change in the probability distribution of the **Landslide Intensity** node, where it shifts from the *Moderate* and *High* states to the *None* and *Low* states. On the other hand, the posterior distribution of **Pipeline Exposure** is closer to the prior distribution. This diagnostic analysis shows that in order to reduce the risk states, the geotechnical stability of the ROW is very important if the disposition and thickness of the pipeline cannot be changed.

The upper bound scenario shows that the Exposure node has probability of almost 1 of being in a *High* state, while the posterior distribution of **Landslide Intensity** is very similar to the prognosis case. This means that the higher states of risk are controlled, or heavy influenced, by the pipeline *vulnerability*.

The diagnostic analyses help to identify the required threshold in the threats and vulnerabilities that will lead to the stated consequences and risks. It is useful since it gives information about the combination of states of threat intensities and vulnerabilities that produce undesirable states of risk. By introducing actions or measures (i.e. nodes into the network) aimed to reduce the states of risk that cannot be exceeded, the model is expanded from risk assessment to risk management.

6 CONCLUSIONS

This paper presents a methodology for the risk assessment of onshore pipelines exposed to landslides using BN, and an integration with GIS.

This model follows a risk assessment framework, which consists in identifying the relevant *threats*, the systems vulnerable to these *threats*, and their corresponding *consequences*.

An illustrative case study was carried out in order to demonstrate the applicability and advantages of the developed model. The prognosis result showed a high state of risk for the conditions considered, while the diagnostic analyses highlighted the importance of the geotechnical stability of the ROW for achieving a low state of risk and the relevance of pipeline *vulnerability* for higher risk states.

The illustrative case study is a first approximation to the integration of BN and GIS and serves as a preliminary result in the implementation of the risk assessment model for landslides affecting pipelines.

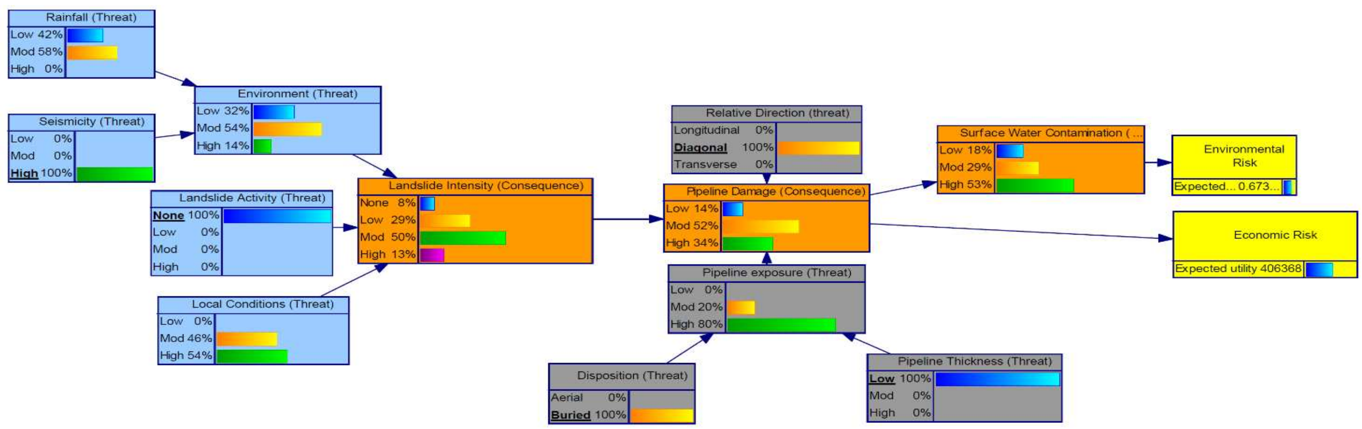

Figure 6. Prognosis results

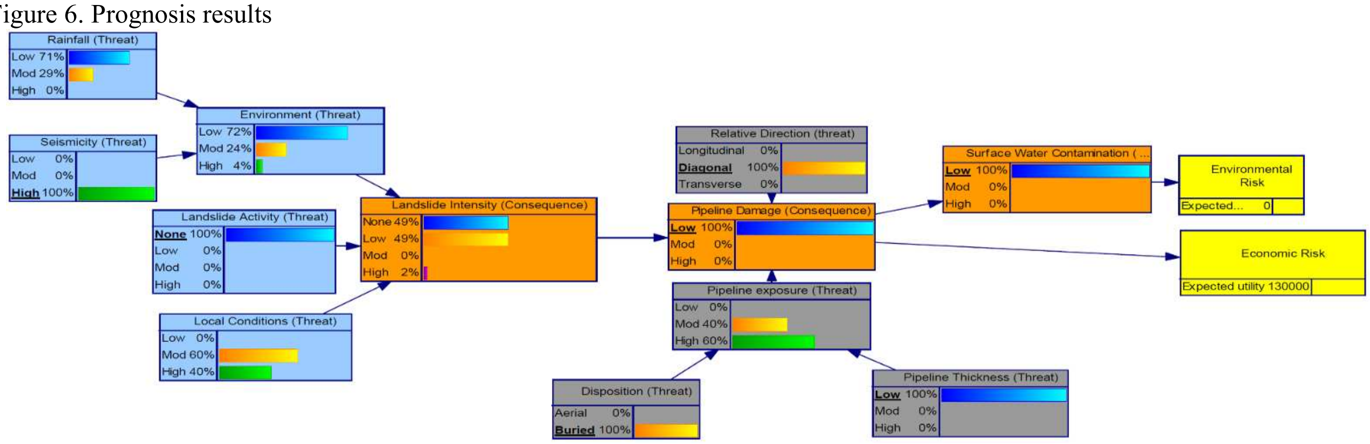

Figure 7. Diagnosis results. Low States of Risk

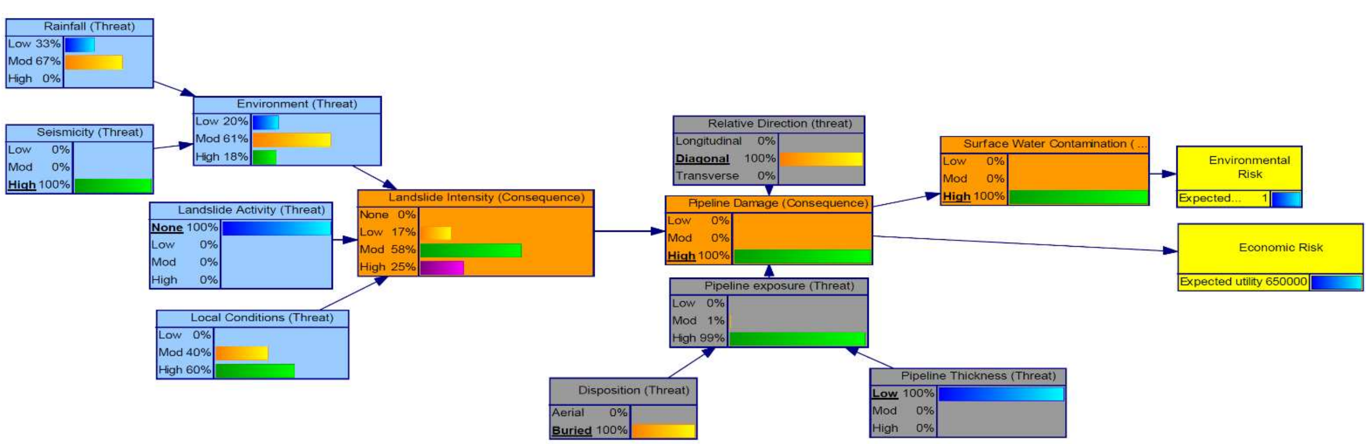

Figure 8. Diagnosis results. High States of Risk

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