Identifying and Characterizing Rock-Slope Hazards at the Railway Subdivision Scale Using 3D Remote Sensing Data

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ABSTRACT

In this paper, we consider potentially hazardous slopes adjacent to railway corridors, which may not be visible from track-level but could impact the safety and continuity of railway traffic. The study area for this paper, the CN Rail corridor between Hope and Yale, British Columbia, comprises a variety of natural slopes which occasionally produce rockfalls. The objective of the work is to spatially quantify potential rockfall source zones within the study area. We have found that predictive statistical analysis of 3D point cloud data generated from aerial platforms is an effective means for identifying geologic features such as rock outcrops and talus deposits. The spatial positioning of such features relative to each other, as well as physical characteristics of the features themselves and their surroundings are used to quantify slope-scale susceptibility to rockfalls. An inventory of slopes considering the relevant features has been generated and assessed with the ultimate goal of commenting on regional rockfall susceptibility. The methodology proposed shows promise as an effective measure of regional scale susceptibility to rock slope failure.

RÉSUMÉ

Dans le présent document, nous considérons les pentes potentiellement dangereuses adjacentes aux corridors ferroviaires, qui peuvent ne pas être visibles à partir du niveau de la voie, mais qui pourraient avoir une incidence sur la sécurité et la continuité du trafic ferroviaire. La zone d'étude de ce document, le corridor ferroviaire du CN entre Hope et Yale, en Colombie-Britannique, comprend une variété de pentes naturelles qui produisent occasionnellement des éboulements. L'objectif de ce travail est de quantifier spatialement les zones sources potentielles de roches dans la zone d'étude. Nous avons trouvé que l'analyse statistique prédictive des données de nuages de points 3D générés à partir de plates-formes aériennes est un moyen efficace pour identifier les caractéristiques géologiques telles que les affleurements rocheux et les dépôts de talus. Le positionnement spatial de ces caractéristiques les unes par rapport aux autres, ainsi que les caractéristiques physiques des caractéristiques elles-mêmes et de leur environnement, sont utilisés pour quantifier la susceptibilité à l'échelle des pentes aux éboulements. Un inventaire des pentes prenant en compte les caractéristiques pertinentes a été généré et évalué dans le but ultime de commenter la susceptibilité régionale aux éboulements. La méthodologie proposée est prometteuse en tant que mesure efficace de la susceptibilité à l'échelle régionale de la rupture de talus rocheux.

1 INTRODUCTION

Rockfall hazards can cause disruption to the consistent and safe operation of transportation corridors. Therefore, there is interest in identifying, characterizing and quantifying such hazards and the risk associated with them (Kromer et al, 2017; van Veen et al, 2016). CN Rail uses the Railway Hazard Risk Assessment (RHRA) system to assess the risk of a derailment due to rockfall for a given site (Pritchard et al, 2005). The RHRA relies on qualitative and semi-quantitative observations made from track level and is designed with cut slopes immediately adjacent to the track in mind. However, ground-based assessment is insufficient when aiming to assess natural slope conditions, as natural slopes are often not visible from track level due to steep gradient and/or vegetation. Therefore, there is value in utilizing regional-scale remote sensing data to identify potential hazards on natural slopes. This output can, in turn, be used to plan further studies for characterization through more detailed remote sensing (e.g. Lato et al, 2015; Abellan et al, 2016; Eitel et al, 2016; Jaboyedoff, 2010), instrumentation or field inspection, as well as decisions about the need for mitigation of the potential hazard.

In this study, we look at the application of novel analytical techniques using ortho-imagery and 3D point cloud data collected in the area between Miles 21 and 25 in the CN Yale subdivision. Image classification is used to identify areas of exposed rock; this information is fused with airborne LiDAR data, creating a coloured point cloud where each point is classified in terms of its terrain type. Geometrical assessment as per Loye et al (2009) is used to further classify exposed rock as being talus or a potential source for rockfall (a cliff). The classified point cloud data is then assessed using the logic outlined in Figure 1 to qualitatively assess the hazard on a given area of slope. The logic, together with automated terrain classification, allows for the identification of potential rockfall sources, and evidence of rockfall activity, and uses spatial analysis to find the relationships between such features.

A cone extending laterally +/- 20 degrees from the dip direction of a given source, referred to as the inferred runout cone here, is delineated to bound the extent of the downslope analysis—this is based on the findings of Agliardi & Crosta (2003), which suggest that the majority of rockfall runout is contained within this window. Each cone terminates when it contacts the element at risk, the railway track, in this case. The area within each cone is assessed in terms of evidence of rockfall activity (i.e. presence of talus deposits) as well as the conditions of the potential runout path in terms of slope geometry and vegetation (i.e. would a rock have to traverse a gentle, vegetated slope, or is there a clear near-vertical path between the source and an element at risk).

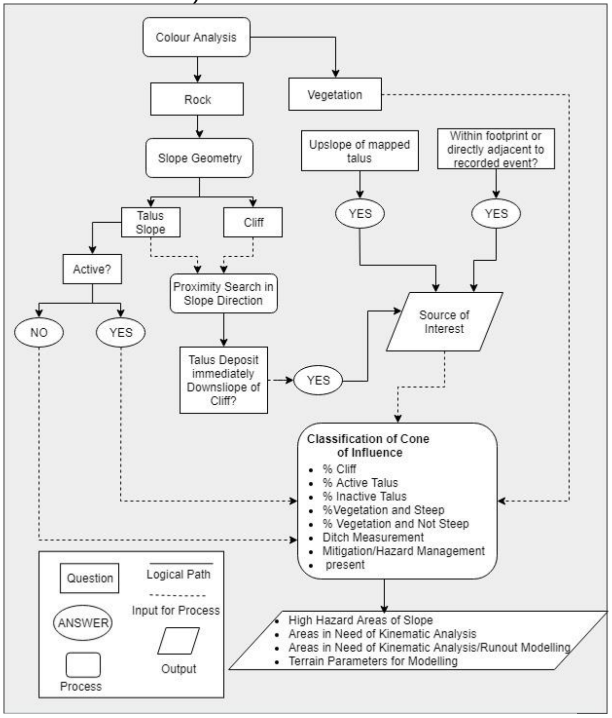

Figure 1: Detailed outline of the logic developed and applied in this study. Broadly, this process can be broken up into terrain classification, identification of talus immediately downslope of a given source and characterization of downslope terrain relative to a given source location.

Gauthier et al (2017) outline a framework for the study of rockfall hazards through remote sensing data collection and analysis, shown in Figure 2. The work carried out in this study fits into the searching phase of that framework—here, we're looking to evaluate slope conditions to identify where rockfalls are possible and to identify evidence of rockfall activity to identify where they are likely. The ideal output of this phase is a reasonable plan to help focus further investigation of slopes with higher hazard potential through remote sensing.

It is important to note that we are not quantifying the probability of a rockfall occurring, or the probability of a rockfall reaching an element at risk, the goal of this approach is to prioritize natural slopes based on qualitative evidence by determining where rockfalls are both possible and likely and guide further investigation through remote sensing or other means, based on that prioritization. Essentially, the aim is to provide an efficient screening process for determining where time and resources will most effectively be used with regards to the management of rock slope hazards.

In the proceeding sections, we will outline the methodology employed, discuss the results and identify potential for continuation and further development of this process.

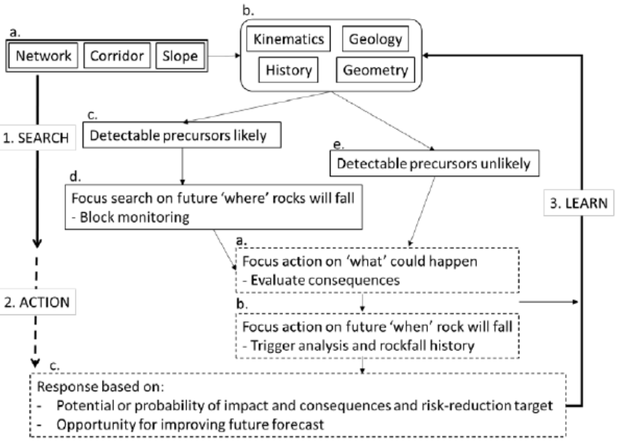

Figure 2: Rockfall forecasting framework taken from Gauthier et al (2017)

1.1 Scope

The overarching goal of this study is to generate a logical process which allows for the assessment of terrain and slope conditions at a regional scale with minimal user input—we do so using a combination of conventional GIS based tools as well as custom built tools using Python or MATLAB. Wherever possible, the tools aim to utilize 3D point cloud information as opposed to rasterizing 3D data and working in a 2.5D environment. The reasoning for this is twofold. First, the vertical geometry of the area is extremely complex, consisting of many cliffs and overhanging features which cannot be fully captured in 2.5D. Second, advances in computational capability have made it more practical to deal with the highly dense 3D point cloud data over large areas—this is a relatively recent development. Therefore, in the interest of progressing the state of practice, analysis is carried out in 3D, whenever possible. In addition, the proven ability to effectively merge datasets at different scales, data density and accuracy, and, different vantage points, permits analysis of more complex geometry.

2 STUDY AREA

The study area for this paper, outlined in Figure 3**,** is roughly Mile 21 to Mile 25 of the CN Yale subdivision, which runs through the Fraser canyon between Yale and Boston Bar, British Columbia. The canyon is oriented North/South within this reach and is largely characterized by steep scarp-like rock slopes, talus deposits and vegetated slopes. There is unmistakable evidence of geohazard activity in the area such as landslides, rock avalanches, rockfall and debris flows. Steep cliffs, oriented near parallel

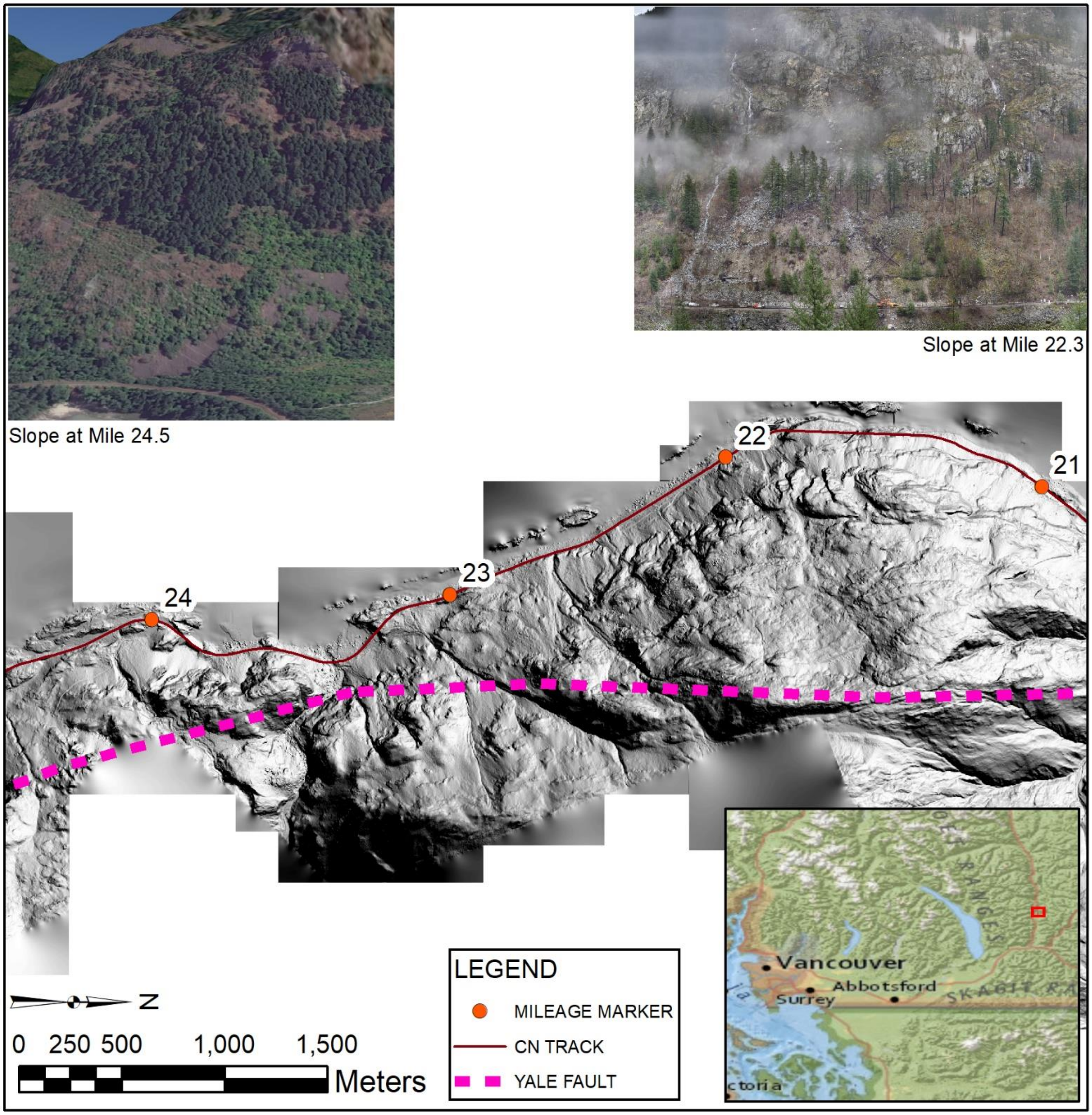

Figure 3: Plan map of Miles 21 to 25 within the CN Yale Subdivision in Southwestern British Columbia. Above are photos of the sites used to test the analysis procedure developed, on the left at Mile 24.5 and on the right Mile 22.5.

to the Fraser and Yale faults, produce talus benches in many locations. Rockfall activity in the area is predominantly sourced from these features. Vegetation acts as an indicator of recent rockfall activity on such benches—benches below recently-active slopes consist of sparse vegetation, whereas benches below inactive slopes are covered in moss, shrubs and sporadic tree growth. Figure 4 shows the clear difference between recently active and recently dormant talus benches characteristic of the region. It is within reason to suggest that this difference in the colour signatures of talus deposits could be used to further inform decision making based on evidence of activity or lack thereof within a talus deposit. This is not to say that vegetated talus deposits are not hazardous—merely that vegetative cover is one potential data input which can be used to determine how frequently and recently rockfalls have occurred within a given reach of slope.

Figure 4: In the box on the left, a talus deposit which has clearly been recently active as noted by the disturbed surficial material. In the box on the right, another deposit immediately adjacent which is covered in vegetative growth, and does not contain disturbed terrain, both of which are indications of a lack of recent activity.

Piteau (1977) identified several massive post-glacial slide scars in the area between Boston Bar and Yale, specifically between Miles 24 and 26, directly adjacent to the town of Yale. He also noted that the entire area is characterized by a pronounced faulting zone which trends roughly parallel to the Fraser River and is marked by an abundance of heavily fractured rock along the two dominant faults in the area—the Fraser and Yale faults. From a geomorphological standpoint, the physiography of the Fraser Canyon points to post-glacial landslides as being the most influential process in the area. This observation is furthered by the prominence of steep rock cliffs on the upper reaches of many of the slopes which are likely scarps of major slides. Rockfall activity in the area is dominated by these features and are thus largely controlled by faulting.

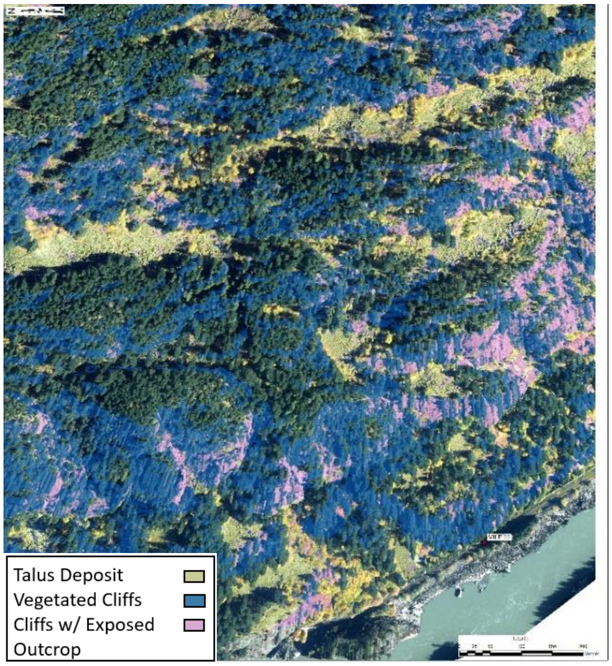

Figure 5: Results of terrain classification using colour

3 METHODOLOGY

The methodology employed here is outlined in Figure 1 and is described in detail in this section. At a high level, the process can be broken up into the following components:

- **Identification of evidence of previous rockfall or related geohazard activity** through literature review and field investigation.
- **Terrain classification** through statistical analysis of imagery and geometrical assessment of 3D point cloud data: identifying areas of talus, vegetation and outcrop
- **Identification of evidence of rockfall activity** by assessing whether or not talus exists immediately downslope of a given source zone
- **Assessment of potential runout area** by assessing the proportion of the area belonging to each terrain class as well as the slope geometry within the area. A qualitative evaluation of the slope between a given source and an element at risk can be formulated based on the geometry of the slope within the inferred-runout cone as well as the amount of vegetative cover.

Statistical analysis of the ortho-imagery is used to identify terrain material—specifically, the images are classified into exposed rock and vegetation—this process, developed by Carter et al (2016), uses a maximum likelihood classification on the RGB value of each pixel within the image to place it into one classification bin or the other.

Convention is to use slope geometry alone to classify data into cliffs and talus deposits within 3D data. However, adding colour classification to the process allows for a more precise identification of relevant geomorphic features, and more importantly, eliminates a great deal of false positives prevalent in the conventional approach. The classes are then superimposed onto the 3D point cloud using a GIS overlay; therefore, each point within the cloud includes its 3D location in space as well as a scalar field denoting its terrain type identified through image analysis. Figure 5 contains the results of this stage of the process for the study site at Yale Mile 22—one limitation of the process is that the vertical geometry of the slopes within the study area are difficult to capture in 2D space, from a downward looking point of view. Therefore, many cliffs would go unclassified using just this methodology—therefore, each geometry from the LiDAR point cloud is used to identify cliffs, and the colour analysis is supplementary.

Once terrain classification is established, further classification can be carried out based on geometric parameters according to the methods noted above outlined in Loye et al (2009), which use slope angle to infer terrain type. Here, the points classified as being exposed rock are further classified into talus deposits or potential rockfall source zones. The next portion of the process looks at the relationship between a given feature and its surroundings. This is done using the runout cone described above.

The first logical step in the process is to look for unmistakable evidence that a potential source is actively releasing rocks downslope. It is noted by Piteau (1977) that active rockfall sources within the region are marked by talus benches at their base. Therefore, in this study for a given source, immediately adjacent, downslope talus deposits are identified. A talus slope that is immediately downslope of a given source is defined here as being between a given source and the next down-slope cliff in the dip direction of the source. Put simply, for a given cliff, is there a talus deposit between it and the next downslope cliff? This is a binary, yes/no classification, if it’s satisfied, the source is flagged as such and the process moves on to the next component, which is the downslope characterization.

The runout cone for each source is broken down in terms of the proportion of area belonging to each terrain classification type (cliffs, talus deposits, vegetation). The average slope angle of vegetated area within a cone is also calculated—this provides insight as to how likely a rockfall would be to propagate through a given area of vegetation—here we’re asking, is the vegetated area of low gradient, or is it steep and therefore is it likely that a rock will pass through the vegetation?

The next step is to assess the slope geometry between the source and the element at risk. This is done by assessing the 3D profile of the inferred runout cone to determine if the topography of the slope within the boundaries of the inferred runout cone is likely to prohibit rocks from reaching the element at risk, or if it is entirely steep and therefore prone to rockfall events which reach the track.

The process outlined above was built using Python and automated wherever possible. The inputs include a classified LiDAR pointcloud, input source points (a random sample of points belonging to the cliff classification), and the runout cones, which are created in ArcGIS. The output is a table with a column for each parameter extracted throughout the process.

The process outlined here was applied to the region and analyzed in detail for two hand picked sites—one above Mile 22.3 and one above Mile 24.5. These slopes were selected on the basis that they are both active in producing rockfalls, but each has distinctive characteristics in terms of vegetative cover, slope geometry and evidence of rockfall. The slope at Mile 22.3 is a known hazard and has been the location of several notable rockfall events. It is very steep, sparsely vegetated and shows obvious signs of rockfall activity. Mile 24.5 on the other hand is heavily vegetated and has a much gentler slope profile than Mile 22.3. From a hazard management perspective, Mile 22.3 is a slope that should be prioritized ahead of the slope above Mile 24.5.

4 RESULTS

The results of the analysis on the two hand-picked sites are summarized in Table 1, and Figure 6 is a spatial representation of the results for these sites. As hypothesized, the classification of the slope at Mile 22.3 indicates a slope with a higher probability of rockfall than does Mile 24.5. When comparing these two sites, a rail operator could clearly see where resources would be used most efficiently. However, at a regional scale, this conclusion becomes less clear. At this point in the research, the priority classification criterion is being developed, the prioritization is merely an example of how this information can be applied en masse.

Figure 7 shows the results applied at a regional scale. Points are coloured based on specific criteria, which can be altered at the discretion of the expert making decisions regarding hazard management or monitoring. As an example, the criteria chosen at this point in the research are as follows. As further analysis of other slopes is conducted, the parameter combinations are likely to be refined: High Priority: Sources with talus located immediately below, >10% talus within runout cone and <60 vegetative cover within runout cone. Medium Priority: Sources with talus located below, <10% talus within runout cone and >60% vegetative cover within runout cone, Low priority: Sources without talus located below, <10% talus within cone and >60% vegetative cover within cone.

This classification is illustrated in Figure 7. In general, the classification seems to be consistent with visual interpretation of the imagery. An important thing to note is that the criteria which looks at the location of a potential rockfall source relative to the runout path of a previous failure, included in Figure 1, is not considered here due to a lack of such information within the study area. A detailed geohazard database which stores the spatial extents of rockfall runout paths does not exist.

Once fully developed and validated, the prioritization ratings can be used by operators to determine where they need to focus their efforts. A high priority rating indicates that a hazard is likely, and that, based on evidence within the inferred runout cone, runout is likely to expand beyond the talus deposit directly below the source. A medium rating indicates that hazards are likely, but that, based on the evidence in the inferred runout cone, the majority of rockfalls are captured by the talus deposit immediately below the source. Low priority sources show no indication of rockfall immediately below and have a large proportion of vegetation within the inferred runout cone.

5 DISCUSSION

The airborne LiDAR data was classified using statistical classification of ortho-imagery and a geometric assessment of 3D point cloud data within each classification. We then applied the logic outlined in Section 3 to all cliffs within the study area between Miles 21 and 25 of the Yale subdivision. The results of the runout cones were analyzed in detail and demonstrated the value of a qualitative approach to hazard identification using remote sensing data.

in a logical way to prioritize such hazards. The workflow designed for this study can be used to identify areas of slope which are likely to benefit from further investigation through remote sensing, kinematic assessment and/or runout modelling. Moreover, classified inferred runout cone can be used to inform modelling parameters, however, kinematic assessment of structures would be necessary to identify potential failure volumes. This information can be used to quantify both the probability of a hazard occurring and the vulnerability of the element at risk.

This work could also be used in combination with the ideas proposed in Bonneau and Hutchinson (this conference) which involve the detailed characterization of debris flow hazards using high density remote sensing. The terrain classification and geometrical assessment employed here could be used to identify potential debris flow hazards and inform the more detailed remote sensing data collection required to carry out that type of analysis.

Table 1. Summary of results of downslope analysis of two potential sources

Site Mileage	Talus Directly Below Source	Percentage Talus	Percentage Cliff	Percentage Vegetated	Profile Slope (m/m)
22.3	YES	32	8	40	0.87
24.5	NO	16	5	70	0.65

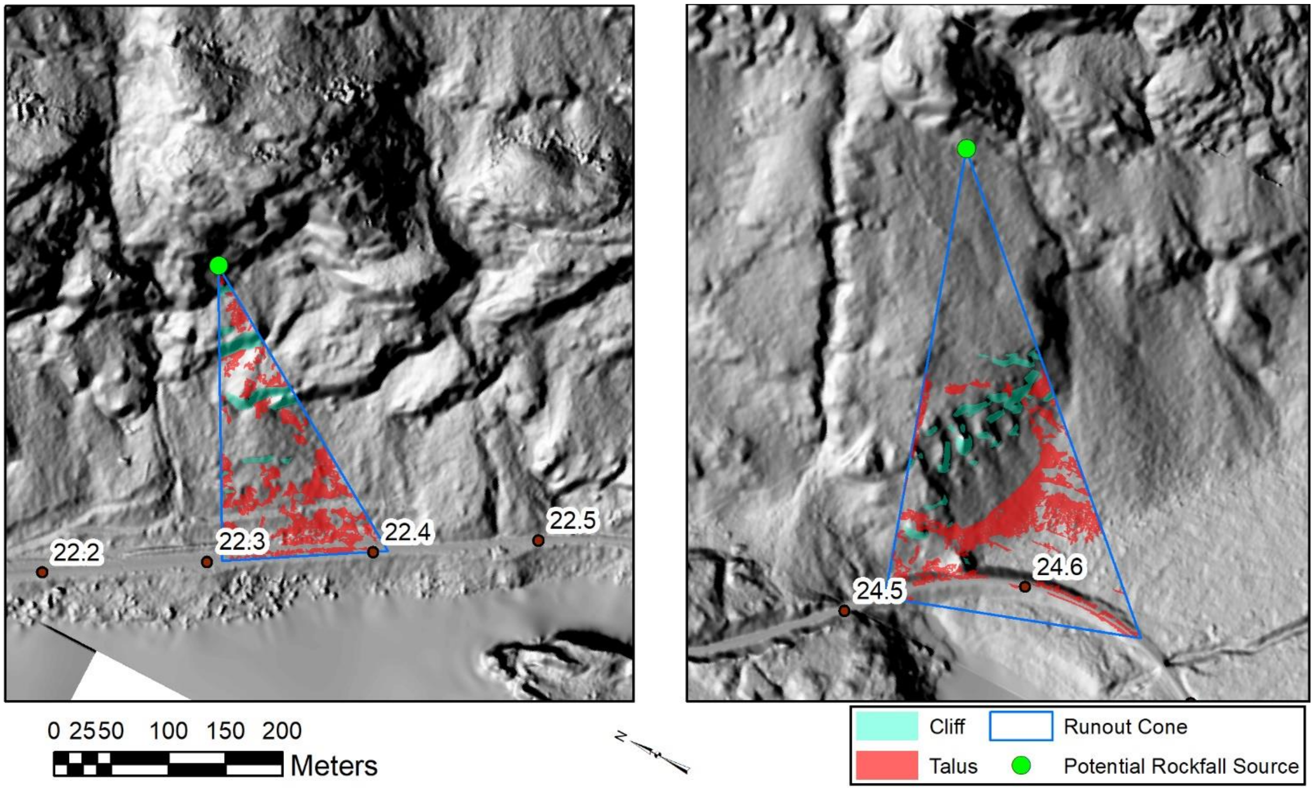

Figure 6: Results of runout cone analysis for slopes at Mile 22.3 and 24.5

Remote Sensing is a useful tool in the identification and prioritization of potential hazards on natural rock slopes in railway corridors. Novel analytical techniques can be used

It would also be plausible to use similar processes to identify large isolated blocks within an inferred runout cone to account for less frequent, higher magnitude events which may not be identified using the current system. Similarly, the logic could be expanded to include a calculation of the capacity of a ditch at the base of an inferred runout cone or to identify how much of the track is covered by other types of hazard management (eg rock sheds, or lock blocks).

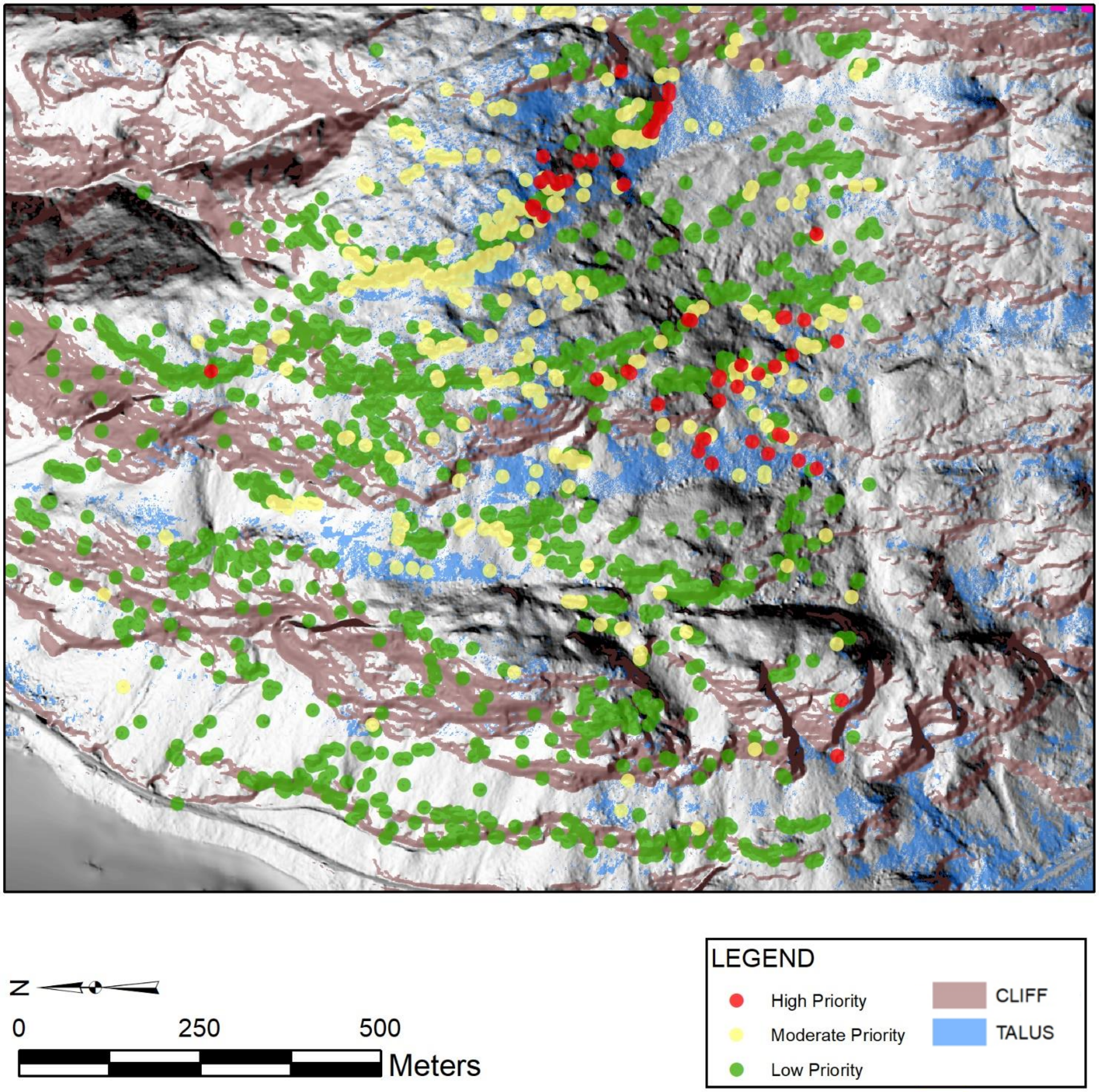

Figure 7: Preliminary results of the slope prioritization logic at this point in the research. Red points are high priority, yellow are medium and green are low priority.

The value of colour in terrain classification of LiDAR point clouds is clearly demonstrated here. This could be extended to identify the level of vegetative cover present for a given talus deposit. This would add one more tangible channel of information to be used by experts in determining whether or not a given area of slope is of interest from a hazard management perspective. Moreover, digging deeper into the properties of slope vegetation, namely density, would allow for parametrization of this information for use in runout modelling, for example Dupire et al (2016) look at the protective capabilities of vegetation against rockfall. The methodology provided here could be useful for deriving inputs to such modelling.

6 CONCLUSIONS

Airborne LiDAR data and airborne imagery can be used as inputs into the analytical procedure outlined above, which aims to prioritize slopes based on the likelihood of rock slope failure. Colour analysis added a useful layer of information to add the process developed by Loye et al (2009) in order to accurately classify terrain in LiDAR point clouds. Spatial analysis is a powerful tool for identifying the relationship between a potential rockfall source and it's surroundings; it can be used to identify where a downslope talus deposit exists, and whether or not there are any potential rock fall sources in between. The prioritization criteria applied here are preliminary, but demonstrate how this methodology can be used to inform stakeholders on how their time and resources can most effectively be used for the management of rockfall hazards.

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