Methods comparison to predict debris avalanche and debris flow susceptibility in the Capilano Watershed, British Columbia, Canada

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Abstract

Landslide susceptibility can be assessed by statistical and empirical methods. Statistical methods often require landslide conditioning factors and inventories of events to predict the occurrence probability for regional scales. In contrast, empirical methods compute susceptibility values based on theorical concepts and compare them with observations. Both approaches were followed to evaluate debris avalanche and debris flow susceptibility in the Capilano Watershed in southwestern B.C. This was accomplished through Random Forest (RF) and Flow-R models. The RF model resulted in predictive accuracies of 76% and 83% for debris avalanche and debris flow models, respectively, and 45% and 28% of the total watershed area were classified as high susceptibility for these landslide types, respectively. Flow-R spreading algorithms were tested to reproduce similar results to observed debris flows. The high debris flow susceptibility class (>0.5) covers 4.5% of the Capilano Watershed according to the Flow-R results.

Keywords: debris flow, debris avalanche, landslide susceptibility, Random Forest, Flow-R, statistical, empirical.

1 INTRODUCTION

Landslides are recognized as substantial natural hazards worldwide due to their destructive impact (Samia et al., 2017). In Canada, an estimated 200 people have lost their lives due to this phenomenon between 1880 and 2007, resulting in an average of two persons per year (Hungr, 2004), and economic losses are estimated to be in the range of $200 to $400 million in direct and indirect costs annually (Clague and Bobrowsky, 2010).

To minimize these impacts, it is desirable to predict locations where landslides could occur and then avoid placing infrastructure in their path. Several methods exist for spatial landslide prediction (e.g. Aleotti and Chowdburry, 1999; van Westen et al., 2006) and include heuristic (based on human judgement or expert opinion to produce an output), statistical, empirical, and deterministic. At a regional scale, the first three methods are often tested due to the efficiency of remotely sensed data collection compared to deterministic frameworks, which are commonly limited to analyze specific sites or slopes due to the detailed geotechnical and hydrological data needed as input. Morphometric, lithological, hydrological features such as drainages, and inventories of past events comprise databases used for statistical and empirical models. Since the development and implementation of Geographic Information Systems (GIS), data are now easier to manage, analyze and present. Software such as Flow-R has created more interactive and understandable graphic representations for the public, enhancing risk communication and decision-making processes (Dragićević et al., 2014). In this paper, we assess landslide susceptibility in the Capilano watershed in British Columbia via Flow-R and the Random Forest statistical model.

2 STUDY AREA

The Capilano River watershed spans 195.4 km^2 and is located northwest of Vancouver in southern British Columbia, Canada. It borders to the south with the North Vancouver urban area, east with the Seymour River watershed and west with the Howe Sound crest, with peak elevations of 1741 m at Mount Brunswick. Considered one of the three Greater Vancouver watersheds, it supplies a third of the region's drinking water. Capilano River runs north to south through the North Shore mountains (Figure 1).

3 DATA

Various geospatial data were collected to create a geospatial database comprising morphological, lithological, surficial processes and other features to use as training and predicting datasets in the statistical model, and as source areas in Flow-R. An event inventory was built with 1:5000 scale aerial photos and previous databases. Air photos from 1992 to 2016 allowed classification by landslide type (debris avalanches and debris flows) and type of slope (open slope and gully). A debris flow is considered as a very rapid to extremely rapid (>3m/min) flow of saturated non-plastic debris in a steep channel, whereas, a debris avalanche is defined as a very rapid to extremely rapid shallow flow of partially or fully saturated debris on a steep slope, without confinement in an established channel (Jakob and Hungr, 2005). In total, 595 debris avalanche and 336 debris flow initiation points were identified, the latter associated with zero-order gullies.

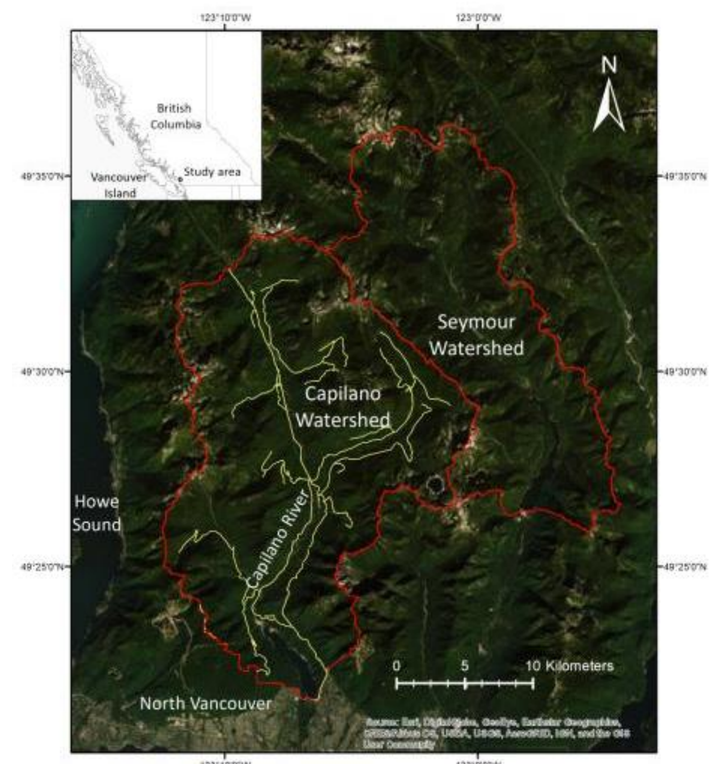

Figure 1. Location of the study area

Morphological variables for the Capilano Watershed such as slope angle, slope aspect, and profile and plan curvature were extracted from LiDAR information provided by Metro Vancouver, which comprises 243 tiles of 1km x 1km. Slope angle has a direct relationship with landslide occurrence because it controls the stress regime in hillslopes. Profile and plan curvature relate to erosion and runoff processes. Profile curvature describes convex (negative values), linear (0 value) or concave slopes (positive values) and influences flow acceleration, while plan curvature is associated with dispersion or convergence of the flow (Kimerling et al., 2016; Moore et al., 1991). Aspect refers to the surface direction and is measured in angles from 0 to 360°; values of -1 are given to flat areas (Kienzle, 2004). Distance to features such as drainages and roads are considered conditioning factors because: 1) they are associated with changes in the water table and anomalous groundwater conditions, and 2) forest roads in British Columbia are mostly cut-fill construction with fill being placed loosely on the downhill side. This may lead to unstable fills on steep slopes, which are exacerbated by inadequate drainage control and inspection (Jordan et al., 2010).

4 METHODS

4.1 Random Forest

Random Forest is a machine learning method that achieves classification through the creation of structures called "trees", which are a subset of the observations or training data used to build a model (Breiman, 2001). A random selection of the predictor variables is used to split each node or "branch" of the tree (Criminisi et al., 2012). Each of the trees is developed like so and combined with others (therefore, the name "forest") to minimize errors and improve stability of the model (Catani et al., 2013).

This statistical approach was applied to various landslide conditioning factors and an inventory of landslide events as predictor and response variables, respectively. Landslide events were reclassified from categorical or quantitative values to discrete values for easier handling. Pixels that included the events, which represented 10% of the pixels of the study area, were given a value of 1 in the database; other pixels were given a value of 0. Training and testing datasets were selected from the database; the first combining 70% of the landslide pixels with the same number of non-landslide pixels. The other 30% was utilised as the testing dataset.

4.2 Flow - R

Flow-R is a spatially distributed empirical model that uses a Digital Elevation Model (DEM) to identify landslide source areas by means of morphological and user-defined criteria, as well as travel paths on the basis of frictional laws and flow direction algorithms (Horton et al., 2013). It has been used not only to produce regional debris flow susceptibility maps with satisfying accuracy, but also to assess other natural hazards such as rockfalls (Michoud et al., 2012), snow avalanches and flooding (Jaboyedoff et al., 2012).

According to Rickenmann and Zimmermann (1993) and Takahashi (1981), three criteria in a critical combination are relevant for the initiation of a debris flow: terrain slope, water input and sediment availability. The spreading is implemented through several flow direction algorithms: Holmgren (1994), D8, D∞, Rho8, multiple flow direction and Quinn et al. (1991), which differentiate themselves in the methods used to compute flow directions and spreading proportions. The persistence or inertial functions, for instance Gamma (2000) or the Cosines approach, aim to reproduce the behaviour of inertia and weight the flow direction based on the change in direction with respect to the previous one. Finally, the runout distance assessment uses simple frictional laws and the friction loss is assessed by two algorithms: the Perla et al. (1980) model and the Simplified Friction-Limited Model (SFLM), where the minimum travel angle or angle of reach determines the result of this component.

To assess susceptibility by the empirical approach, several inputs were tested. First, the 1m LiDAR DEM information was converted to a 10 m DEM (Horton et al., 2013); this size is considered appropriate to balance processing time and quality of results. To recognize the source areas, several parameters were set, including elevation, slope angle, plan curvature and flow accumulation, determined based on the values where landslide events occurred (Table 1). A trial-and-error approach was applied with combinations of direction and persistence algorithms while the friction loss function remained constant by using the calculated mean travel angle and velocity of the events for the Capilano watershed.

Table 1. Parameters values for modeling in Flow-R.

Parameter	Value	Source
Elevation	>200 m	Inventory
Slope angle	>14°	Inventory
Plan curvature	-3/100 m-1 to 2.6/100 m-1	Inventory
Flow accumulation	0.01 km^2	Horton et al. (2013)
Mean travel angle	24°	Inventory
Velocity	< 10 m/s	Inventory

One of the debris flow specific preprocessing options is river identification, since this type of landslide usually happens in or close to gullies, creeks or water drainages. To model susceptibility for debris avalanches, which can occur on open slopes and in gullies, river identification was not used. The best susceptibility map predicting the occurrence of debris flows in the watershed was determined by calculating the difference of pixels between observed and predicted landslides.

5 RESULTS

In general, landslides are triggered on slopes between 30° and 60°, 27% of them in the 30-40° class, 29% in the 40 -50° and 17% in the 50 - 60°. 16% of the remaining occurred on slopes lower than 30°, usually close to lakes while 11% were identified in values higher than 60°. The relationship between geology and landslides can be described as 84% of the identified events occurred in Mid Cretaceous dioritic intrusive rocks and 10% in metamorphic and sedimentary formations (Lower Cretaceous Gambier and Jurassic Bowen Island Group). Regarding land cover, 93% of the events were found in forest/trees class, 4% in non-vegetated land and 2% in shrublands. Since Capilano is a protected watershed, it has minimal human influence.

5.1 Random Forest

In order to improve model performance, a correlation matrix was examined, which showed that the plan curvature variable was highly correlated to the profile curvature; therefore, the plan curvature variable was not used for the model. The importance of the landslide conditioning factors is one of the outputs of RF, calculated from the Mean Decrease Gini coefficient, a measure of how, on average, a record at a given node from a determined variable is correctly classified when compared to leaves. (Hong et al., 2017). For debris avalanches, the most important factors are the slope (20%), followed by the distance to roads (18%) and land cover (16%). For debris flows, slope (25%), geology (18%) and distance to drainages were the most significant.

The model was validated with the testing dataset and shown on a Receiver Operator Characteristic (ROC) curve (Figure 2). The closer to the upper left corner, the higher the overall model accuracy. In this case, a higher and better Area Under the Curve (AUC) was obtained for debris flows than for debris avalanches. The value predicted for each pixel in the statistical model can be interpreted as the likelihood of a landslide to happen in that area.

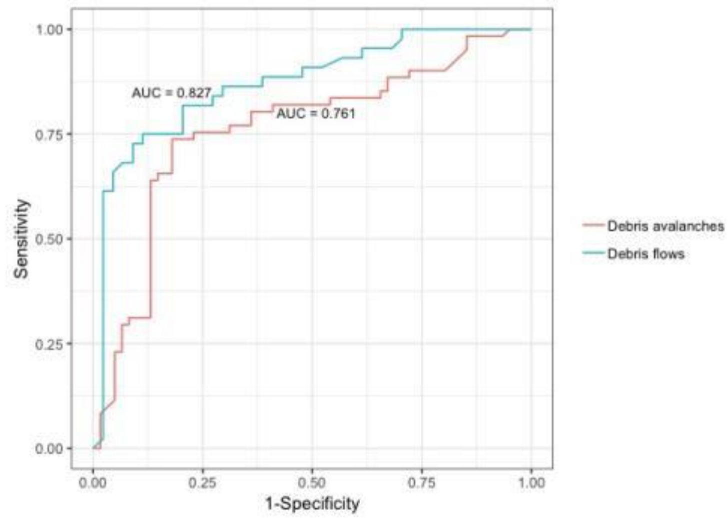

Figure 2. Receiver Operator Characteristic (ROC) curves for predicted debris avalanche and debris flow RF models (AUC = Area Under the Curve).

According to Figure 3, 45% and 27.5% of the watershed is highly susceptible to experience debris avalanches and debris flows, respectively. A higher value for debris avalanches could be related to the fact that these can start on unconfined slopes, unlike debris flows, which are limited to channels or gullies.

5.2 Flow - R

Susceptibility for debris avalanches and debris flows were assessed in Flow-R using the input parameters described in the last section. From the attempt to model susceptibility of debris avalanches, the results show that 51% of the observed events coincide with the locations modeled in Flow R, however, 77% of the cases underestimated the paths with respect to propagation extent.

Debris flow susceptibility was modeled with a minimal flow accumulation for triggering of 0.01 km^2 and, overall, 73% of the observed events were predicted, with differences attributed to underestimation at the source or not being completely connected along the path. The outputs from Flow-R are the sources and the maximum probability of the event to happen along the path, where values closer to 1 imply the most probable runout extent of an event.

Due to the fact that several methods were tried for propagation modeling, results varied, increasing or decreasing the difference between the observed and predicted landslides. More pixels were matched by Quinn et al. (1981) - Cosinus, which predicted 87% of the total pixels, followed by Rho8 – Cosinus and Rho8 - Default, in which 83% of the pixels coincided. Because these

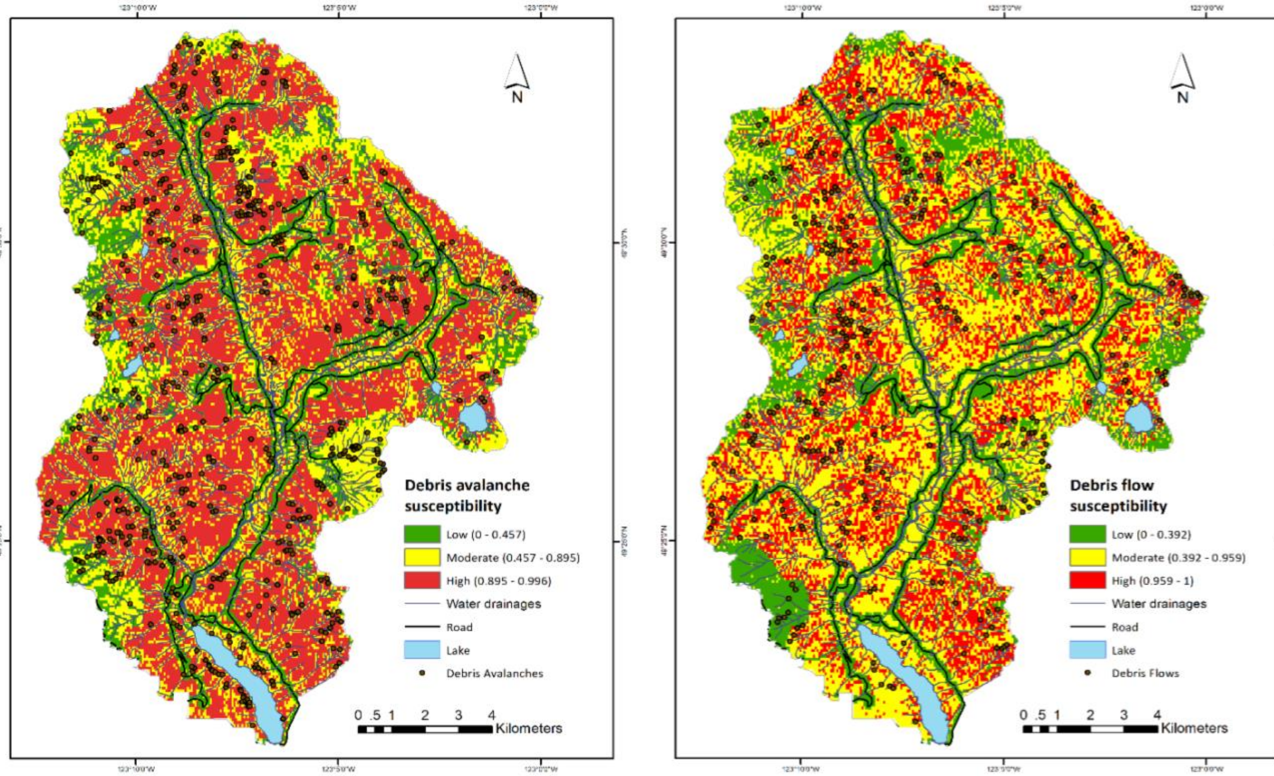

Figure 3. Susceptibility maps for debris avalanches (left) and debris flows (right) in the Capilano Watershed using Random Forest.

methods overestimated the spreading, as shown in Figure 4, especially on the sides of the observed events, it is believed that the number of pixels matched was higher.

The accuracy of propagation results was computed similarly but using only predicted pixels with a probability value of 1, obtaining the highest with a probability value of 1. Figure 5 shows that this approach results in a better match between the model and the actual paths of the events. Assuming a high susceptibility class above a probability value of 0.5, 4.5% of the watershed area is susceptible to debris flows.

6 DISCUSSION

Overall, both methods are associated with prediction errors. Among them, while it is expected that high susceptibility areas would be found at higher elevations, the RF debris avalanche map (Figure 3, left) shows a higher probability of these events in low elevation areas (e.g. close to Capilano lake). With respect to the RF debris flow map (Figure 3, right), for this study, it was assumed that these kinds of landslides were related to gullies, however, areas with this feature and with high elevations (north west of the watershed) were predicted as low susceptibility. Flow-R spreading results underestimated true runout when the river identification option is not activated for modelling, which could affect the correct prediction of debris avalanches, considering they are not related to water drainages. Furthermore, depending on the algorithm, runout extent and width of the events can be overestimated, thus increasing the uncertainty when classifying the susceptibility.

Higher accuracy values could have been achieved with the two approaches if surficial geology of the study area was included. Surficial geology information would exclude bedrock outcrops and identify areas with enough soil cover for debris avalanches to be triggered. Similarly, according to Kang and Lee (2018), considering types of soil texture or geological conditions when using the Flow-R model contributes to increased accuracy of debris flow susceptibility assessment.

The statistical and empirical approaches used in this study allowed regional susceptibility assessment for debris avalanches and debris flows for initiation points and propagation, especially for channelized landslide types. Depending on the method applied, input data will vary, from datasets containing several landslide conditioning factors to only morphometric parameters. The databases used comprise morphometric variables (slope, aspect, curvature, elevation), distance to faults, roads and drainages, lithological data, and triggering factors

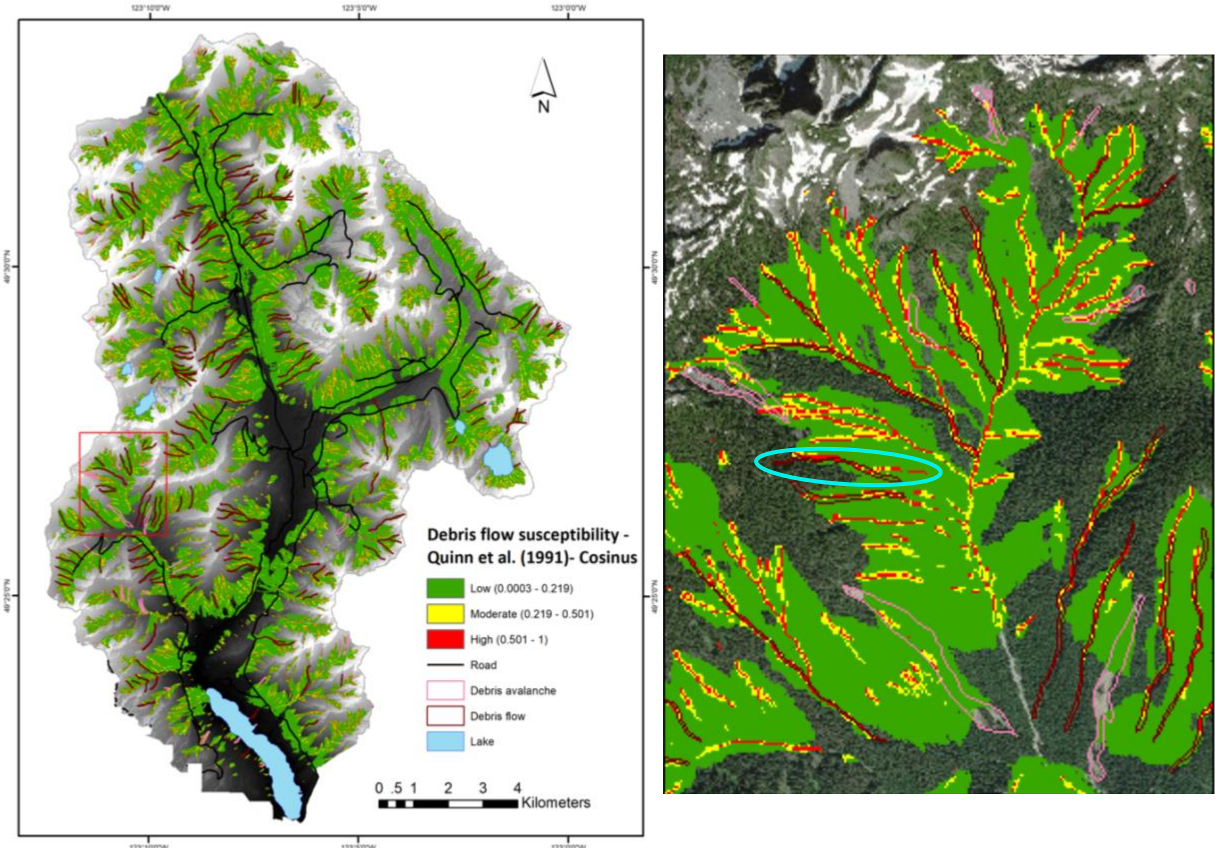

Figure 4. Susceptibility map modeled using Quinn et al. (1991)-Cosinus combination in Flow-R. The figure on the right is an enlargement of the left-hand figure's red box area. The light blue circle is an example of how the predicted path is not triggered at the same location as the observed debris flow and is not fully connected along the path.

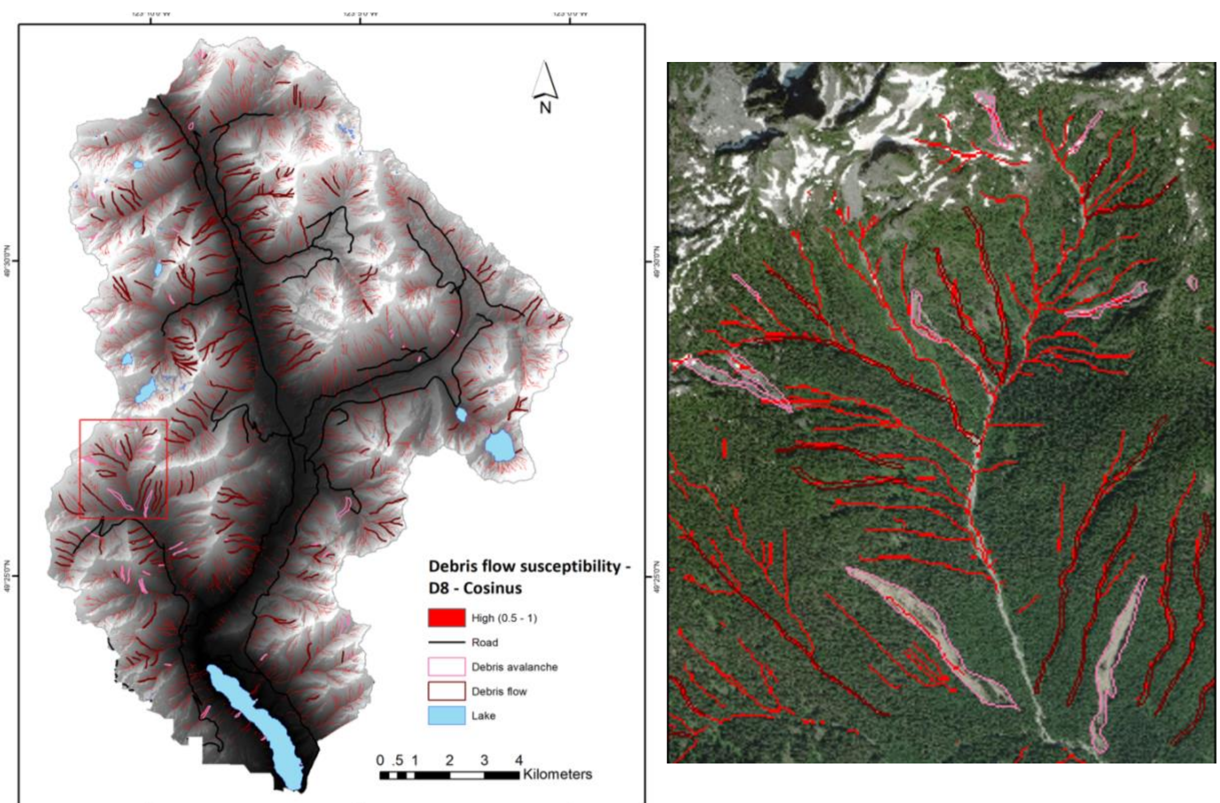

Figure 5. Susceptibility map using D8- Cosinus combination in Flow-R. The figure on the right is an enlargement of the left-hand figure's red box area showing pixels with a value of 1 in red. Debris avalanches and debris flows that have been mapped on 1992 to 2006 air photos are shown in pink and burgundy, respectively.

such as precipitation and earthquake magnitude. In contrast, for empirical approaches such as Flow - R model requirements are reduced to a DEM of the area of interest, as well as land use and geology, which are thought to improve the accuracy of the results.

Both methods require a landslide inventory. In RF, landslide data must be available from the start, since the response variables of the model are those pixels where the events occurred. In Flow-R, landslide records are not a requirement, but are useful to determine which spreading algorithm is most suitable, when comparing actual events with model results. Results improve when parameters such as the travel angle and velocity are selected based on observed events.

7 CONCLUSIONS

Landslide regional susceptibility can be assessed using statistical and empirical methods using Random Forest and Flow-R models. High susceptibility values were predicted in 47% and 27.5% of the total watershed area for debris avalanches and debris flows, respectively, with an accuracy of 76% and 82% for each landslide type. The empirical method, Flow-R, provided susceptibility values for several different spreading algorithms. Most observed pixels coincided with predicted when modeling with the Quinn et al. (1981) – Cosinus combination because this algorithm overestimates propagation, while the most accurate spreading was achieved using D8-Cosinus direction and inertial functions. In both cases, the high susceptibility class (>0.5) for debris flows comprises 4.5% of the watershed area.

Outputs from each method are different; RF as modeled with landslide initiation points predicts those locations with similar conditions to the observed occurrences and indicates the probability of those happening at each pixel. Flow-R focuses on the likelihood of the event in a specific path or track and especially a maximum runout. Further model improvements can be achieved by adding surficial geology data to account for the type of soil texture.

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