Chapter

Dealing with Uncertainties in the Assessment of the Avalanche Protective Effects of Forests

Ana Stritih

Abstract

Through the development of remote sensing and process-based models of natural hazards, an increasing amount of information on the protective effect of forests is becoming available. Such information can be used to map protection forests, which is an important tool for risk management. However, it is important to be aware of the uncertainty in such assessments. We used Bayesian Networks (BNs; using the software Netica) to combine remote sensing, process-based models (RAMMS), and expert knowledge to model forests' protective effect against avalanches, while taking into account the uncertainties in each model component. Using the online platform gBay, we mapped the protective effect of forests in the Dischma valley in Davos, Switzerland, as well as the associated uncertainty. In most areas with a high protective effect, the overall level of uncertainty is also high. To evaluate the importance of different sources of uncertainty, we performed a stepwise sensitivity analysis and visualized how information is transferred through the model. Most uncertainties are related to the inherent variability of snow avalanche processes and uncertainty in process modeling. Nevertheless, combining different remote sensing products can help to gain a more detailed picture of the forest structure and thus improve the mapping of avalanche protection. This type of analyses can help address uncertainties and risks in a spatially explicit way and to identify knowledge gaps that are priorities for future research.

Keywords: avalanche protection, uncertainty, mapping, remote sensing, Bayesian Networks

1. Introduction

Mapping and modeling the protective function and effects of forests can provide important information for natural hazard and forest management (see chapters [1, 2] of this book). However, the interactions of mountain forests with natural hazards are complex and associated with a high level of uncertainty (see chapter [3] of this book). Part of this uncertainty is related to the natural variability and complexity of the system, such as variability in snow conditions that affect avalanche formation, or heterogeneity in forest structure. This type of uncertainty cannot be reduced but should be taken into account in risk management, where one needs to consider not only the most likely outcome, but also less likely events that may have a large impact (such as extreme events). On the other hand, assessments of ecosystem functions also involve uncertainties that can potentially be reduced, such as measurement errors, model parameter uncertainties, and subjective judgment [4]. To realistically evaluate the level of confidence in such assessments, all these types of uncertainty should be integrated and finally also communicated to users. Understanding how the different sources of uncertainty affect the overall assessment of forest functions can help identify knowledge gaps and contribute to more robust decision-making in natural hazard risk management.

To map the protective effects of forests, we need to integrate spatially explicit data on forest structure with information on natural hazards, such as avalanche release areas and runouts under different scenarios. With the increasing availability of remote sensing technology such as LiDAR, forest structure can be mapped with increasing accuracy [5]. At the same time, process-based models of natural hazards are also being further developed. However, even remote sensing data still contain some errors and inaccuracies, and process-based models are sensitive to parameters that can take on a range of different values (e.g., release height or snow density in avalanche simulations). For specific effects of forests on natural hazards, such as their braking effect on avalanches, there is little empirical data, so models have to rely on expert judgment.

Bayesian Networks are a modeling approach that allows integrating different types of information and explicitly including uncertainty. Based on a study of uncertainties in the context of avalanche protection [6], we show how Bayesian Networks can be used to quantify uncertainty in the assessment of the protective effect of forests and to disentangle different sources of uncertainty.

2. Mapping avalanche protection and uncertainties

2.1 Bayesian Networks

Bayesian Networks (BNs) are probabilistic graphical models that consist of **nodes** (variables) and **links** between the nodes [7]. The links in the network are directed from "parent" to "child" nodes, representing **causal** relationships. The nodes have a set of states, which can be qualitative (e.g., forest type) or quantitative (e.g., canopy cover). The connections between nodes are quantified in **conditional probability tables**, where a probability distribution of a child node is defined for each combination of parent nodes (see example in **Figure 1**).

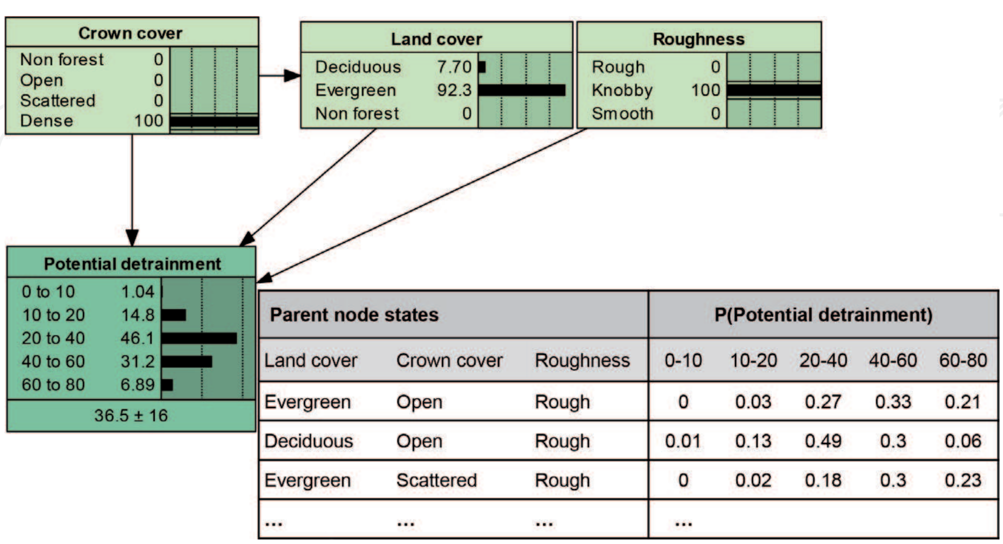

Figure 1.
Example of a Bayesian Network for potential braking effect of the forest during avalanches (detrainment of snow), which is a child node of the parent nodes crown cover, land cover, and terrain roughness, with the corresponding conditional probability table, which contains the probability distribution of potential detrainment for each combination of its parent nodes. In this example, the states of the nodes "crown cover" and "roughness" are known with 100% certainty, while "land cover" is known with some uncertainty, and this information propagates to the other nodes in the network.

Each conditional probability table in the network can be defined independently, which makes BNs a flexible tool for integrating different types of quantitative or qualitative information. The tables can be defined by "learning" from empirical data or existing simulations, calculated from existing models or filled based on expert knowledge.

Once the network is compiled, we can run it on spatial data by specifying the state of the input nodes for each pixel in a raster of the study area. The information is propagated through the network in a process called inference, resulting in an updated probability distribution of all nodes. We used the software Netica [8] to develop the network, and the online platform gBay [9] to run it with spatial data.

2.2 Avalanche protection model

We model two main forest effects that contribute to avalanche protection: release **prevention** and **detrainment**, the braking effect that affects the runout of small to medium avalanches. The probability of an avalanche release depends on topography (slope, curvature, terrain roughness) [10] but is lower in forested areas [11]. In addition, when an avalanche flows through a forest, some of the snow is stopped behind trees (detrainment), which reduces the mass and velocity of the avalanche [12].

To characterize the avalanche process in the study area, we used a probability distribution of maximum new snow heights based on long term observations in the region [13], and simulated avalanche velocities under different scenarios using the mass movement simulation tool RAMMS::Avalanche [14]. To estimate the uncertainty in the simulations, we ran the simulations with varying input parameters (including snow height, temperature, and coherence).

The capacity of a forest to provide avalanche protection depends on its structure and species composition [11], which can be assessed using remote sensing. We used high-resolution LiDAR to quantify the forest structure and terrain roughness and combined it with Sentinel-2 images to classify evergreen (spruce-dominated) and deciduous (larch-dominated) forests. Ground-truth data was collected at 110 plots in the Dischma valley to train the classification and to estimate the measurement and classification uncertainties in the remote sensing data.

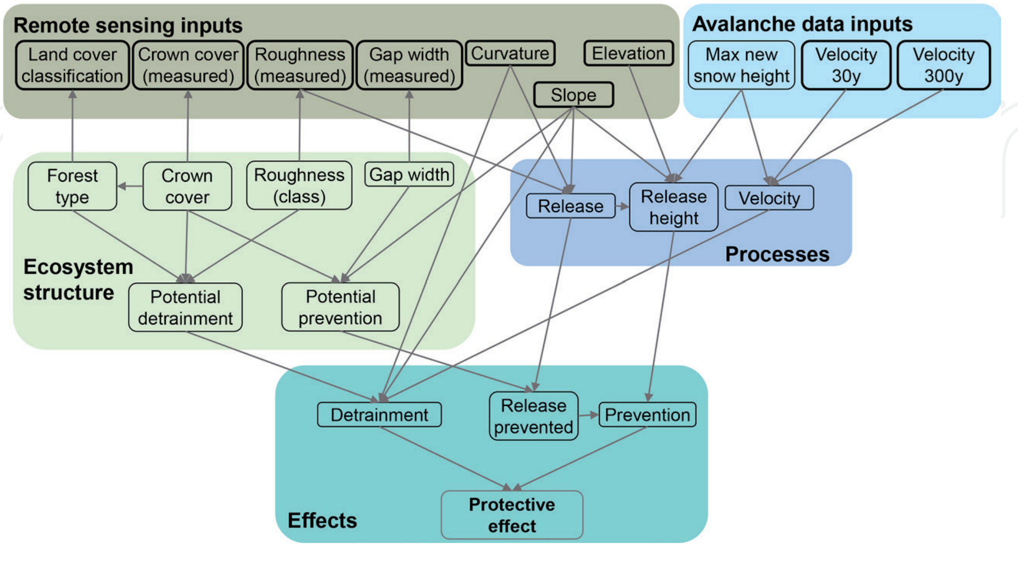

Figure 2.
Bayesian Network developed to model the avalanche protective effect of forests. The nodes are grouped and colored based on the types of variables they represent. Spatial inputs (shown with a thick outline) are linked to variables describing ecosystem structure, avalanche hazard processes, and ecosystem effects. Arrows represent causalities, not the flow of information, and are therefore oriented from ecosystem structure variables to the corresponding remote sensing inputs (the observations from remote sensing are caused by the actual state in the field, not vice-versa). Adapted from [6].

The links between forest structure and effects were defined on the basis of an existing empirical model of avalanche releases in forest areas [11] for release prevention, expert knowledge on potential detrainment (the ability of the forest to act as a brake on avalanches), and simulations of actual detrainment under different scenarios (with different release heights corresponding to 30- and 300-year scenarios for the region, and varying snow conditions). To capture the uncertainty about potential detrainment, experts were asked to estimate not only the expected value of potential detrainment, but also the lowest and highest possible value and their level of confidence. The final output of the model is a combination of release prevention and detrainment, expressed in the total height of snow stopped (see complete network in **Figure 2**).

2.3 Case study

We ran the avalanche protection BN in the lower Dischma valley, Davos, in the eastern part of the Swiss Alps (**Figure 3**). While the town of Davos (1560 m a.s.l.) is a well-developed urban and touristic center, its side valleys remain relatively rural, with a few scattered settlements and a landscape still strongly dominated by mountain agriculture. Snow avalanches are the most common natural hazard in the area, and mountain forests play a key role in reducing the risk for settlements below.

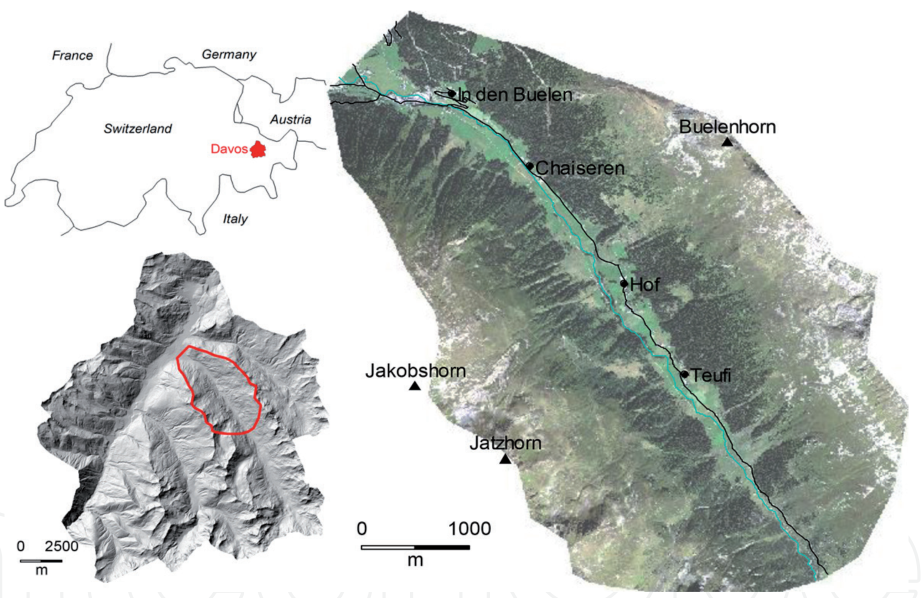

Figure 3.
Map showing the location of the study area on the DTM hillshade of Davos, Switzerland, with an orthophoto of the Dischma valley (swisstopo).

2.4 Mapping uncertainty

The output of the BN contains not only the most likely predicted value, but also a whole probability distribution for each pixel, which allows us to quantify the uncertainty of the output. As a measure of uncertainty, we use the **Evenness index** [15], where a value of 0 indicates complete certainty about the state of the output and 1 corresponds to a uniform distribution between all possible states (maximum uncertainty). In this way, both the predicted value and the uncertainty can be mapped (see **Figure 4**).

The spatially explicit modeled avalanche protection, i.e., the protective effect of forest that was quantified as the total height of snow stopped in each raster pixel, is spatially heterogeneous, and shows an overall high level of uncertainty (**Figure 4**). Areas with a high level of avalanche protection are the steeper, densely forested areas, particularly at high elevations where larger avalanche releases are more likely. Although remote sensing inputs (particularly the land cover classification) are more uncertain in heterogeneous forests near the upper tree line, this pattern is not reflected in the spatial distribution of uncertainty about avalanche protection. Most areas with a high level of avalanche protection also have a high level of uncertainty. In addition, there are many areas with a low predicted value of avalanche protection, but a high uncertainty, indicating that these forests may provide no or only limited avalanche protection under specific conditions, such as at times of very high avalanche risk, when avalanche releases can occur in less likely areas. Higher levels of certainty are achieved only in areas with a very low or zero level of protection provided by the forest.

2.5 Flow of information and sources of uncertainty

To visualize the flow of information and sources of uncertainty in the network, we use a stepwise sensitivity analysis. For each node in the BN, we calculate how much its uncertainty can be reduced by new information about the state of other

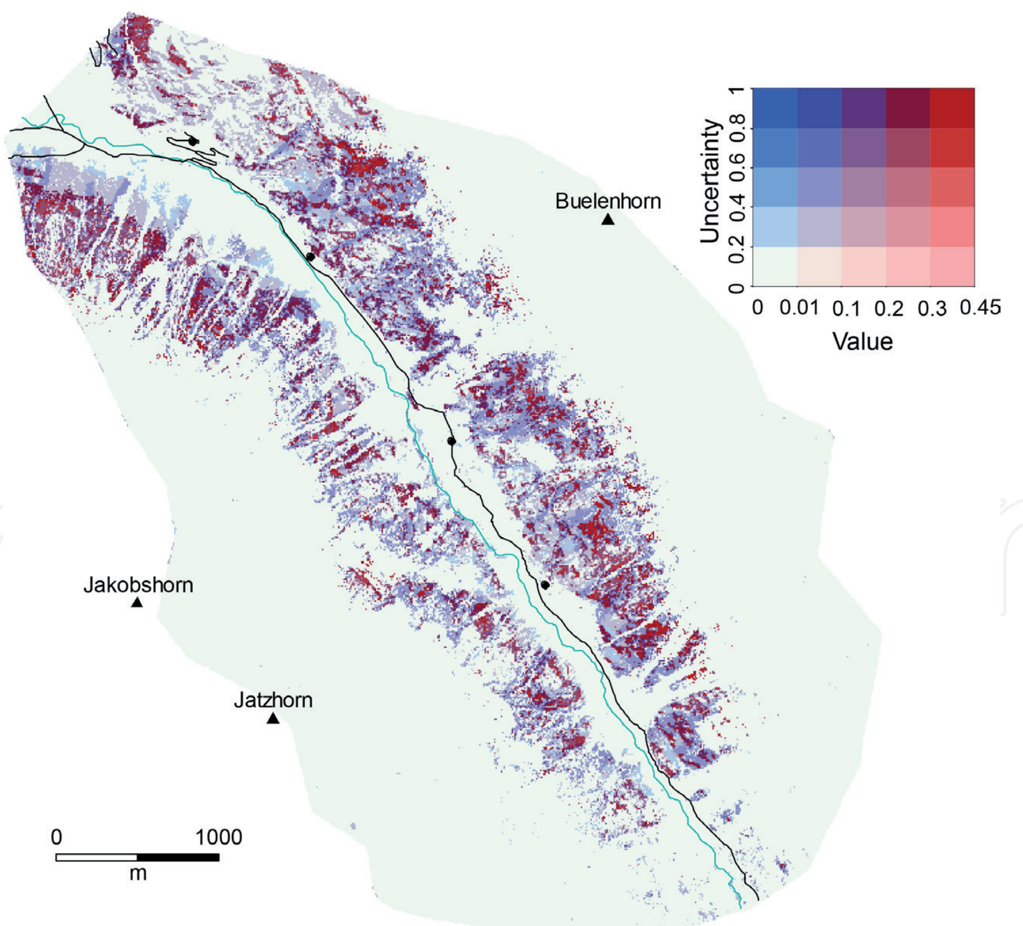

Figure 4.
Modeled avalanche protective effect in the Dischma valley (5 m resolution). Most areas with a high value also have a high uncertainty (dark red), as do some forested areas with a predicted low protective effect value (dark blue). Only areas with a zero or very low (light blue) value of the protective effect show a high certainty. Reprinted from [6].

nodes in the network. These relative **mutual information** (MI) values are used to weigh the links between nodes in a Sankey diagram of the network (**Figure 5**). The width of the connections in the diagram shows how much uncertainty about a node on the right can be reduced by information about the node on the left.

Mutual information is not additive, i.e., if both parent nodes can reduce the uncertainty of a child by 50%, this does not mean that findings on both parents will result in complete certainty on the child node. Nonetheless, plotting the MI gives an indication of the main sources of uncertainty in the model. When the value of MI for all the parents of a node is rather low (i.e., the connections on the left of a node are narrow), this means that the node will have a high uncertainty even if the states of its parents are known. If such a node has a large influence on the outcome of the network, this indicates a major source of uncertainty in the model. For example, the node "Release" (describing whether a pixel is in a potential avalanche release area) has an important influence on subsequent nodes in the network but it has a high uncertainty – even if its parents ("Slope", "Roughness (measured)" and "Curvature") are known, it is uncertain whether an avalanche release will occur.

Some remote sensing inputs have a strong influence on the knowledge about ecosystem structure ("Gap width" and "Crown cover"), while others have higher uncertainty (e.g., "Roughness"). There is some uncertainty in the land cover classification due to the chance of misclassifying vegetation types based on satellite images. More certainty about actual forest types can be gained by combining the satellite-based classification with crown cover data from LiDAR, which reduces the uncertainty about ecosystem structure. However, the information about forest types has a small influence on the overall assessment of the protective effect, partly because of the uncertainty about the detrainment capacity of different forest types (i.e., the link between forest

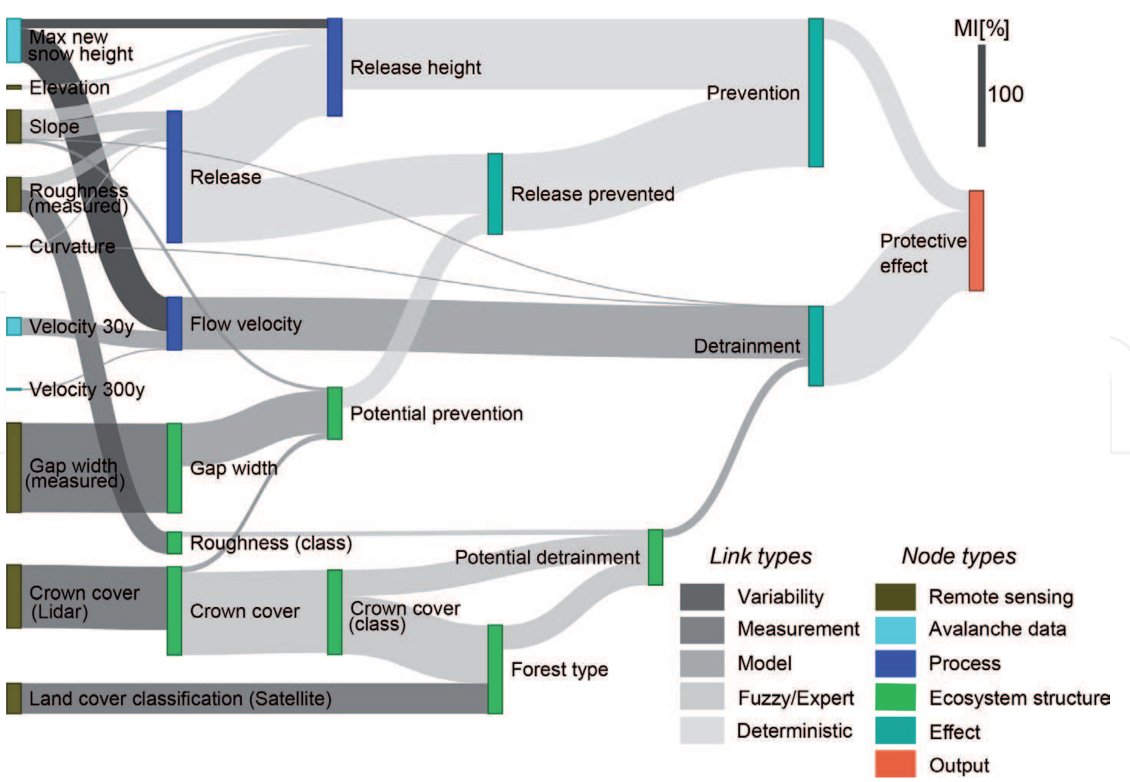

Figure 5.
*Stepwise sensitivity analysis of the BN, where the width of a link between two nodes corresponds to the relative mutual information (MI %), i.e., how much of the uncertainty of a node on the right than be reduced by information about the node on the left. When the connections on the left side of a node are narrow, this indicates a high uncertainty. The nodes are labeled and colored by the type of variable represented (see **Figure 2**), while the link colors represent the types of uncertainty taken into account while quantifying the link in the BN. Adapted from [6].*

type and potential detrainment). Furthermore, even if the detrainment capacity is known, the actual level of detrainment depends largely on the avalanche flow, as detrainment is important mainly for small and medium-sized avalanches and is therefore affected by the natural variability of the release conditions (i.e., release height).

This analysis shows that the overall uncertainty about avalanche protection is mostly affected by the uncertainties regarding avalanche processes, particularly the variability of snow heights, the probability of avalanche releases, and avalanche velocities and detrainment in forests. These uncertainties can be explained by the high natural variability of avalanche hazards, related to complex terrain and temporal variability in snow and weather conditions. In addition, currently available avalanche models and expert knowledge are based on limited observational data, which contributes to high model uncertainty.

3. Outlook

Using a Bayesian Network, we were able to analyze the information flow and quantify uncertainties related to data, models, and expert knowledge that we chose to map the protective effects of forests against avalanches. The most important sources of uncertainty are related to the avalanche process itself, both in nodes that were quantified through expert knowledge, and those based on models. Identifying such knowledge gaps could help to define research priorities. For example, improved identification of potential avalanche release areas under varying snow conditions [10, 16] would reduce the overall uncertainties about avalanche protection, while more sophisticated methods of classifying forest types would have a smaller impact on the model output.

An additional type of uncertainty that was not explicitly addressed is structural uncertainty, which relates which variables are included in the model and the links between them. Structural uncertainty is difficult to quantify, particularly when validation data is lacking, and is often not addressed. BNs can facilitate discussions about model structure with experts by visualizing the relationships between variables in the network [17] and identifying nodes with large uncertainties, which may indicate that important variables are missing from the model.

Besides modeling the protective effect of forests, this modeling approach can also be used to assess the avalanche risk to people and infrastructure, i.e., the demand for avalanche protection [6]. Because of the transparent graphical structure of BNs and their capacity to integrate both quantitative and qualitative data, they are particularly useful for participatory modeling with experts and stakeholders [18]. Even when data is lacking, a BN model can be developed based on practitioners' knowledge and used to discuss and improve the understanding of the system. While this chapter focuses on how a probabilistic model can be used to analyze the uncertainties about the current state of the system, it can also be used to address risks and uncertainties related to future scenarios, such as changes in forest structure due to climate change [19] or a changing disturbance regime. Such models can help identify strategies to not only maximize forests' protective effect in the present, but also ensure a stable protection under a range of possible outcomes [20]. However, Bayesian Network models are less well suited to model long-term dynamics since feedbacks cannot be directly included in the directed network structure. To model changes over time, each time step must be represented with a copy of the network, using the outputs of one time step as inputs to the next time step [9].

Understanding uncertainty is important for users of risk assessment tools who face trade-offs between model accuracy and time or data requirements [21]. Mapping uncertainties can improve model understanding, increase the credibility of the modeling results and inform the decision-making process [22]. However, interpreting such maps is not straightforward. In the example shown here (**Figure 4**), we used darker colors to draw attention to areas of higher uncertainty. In other applications, different users may have different preferences for visualizing uncertainty [23], so it may be useful to include this type of information in interactive maps (see chapter [1] of this book).

4. Conclusions

Our findings show that avalanche protection provided by forests is associated with a high degree of uncertainty, largely due to the inherent variability of the avalanche process and uncertainty in current avalanche models. Although the structure of forests can be precisely mapped using remote sensing, this cannot improve the accuracy of avalanche protection maps without an improved understanding of the hazard process. However, even if more data become available for model calibration and validation, the inherent variability and complexity of the system remains, and the resulting uncertainty should be considered in decision-making.

We demonstrate that Bayesian Networks can be a useful tool to integrate different types of information, including data, models, and expert knowledge, while taking uncertainty into account. Using such tools to map risks, identify knowledge gaps, and understand the inherent uncertainties in the system can help support more robust decisions about risk.

Acknowledgements

This work was supported by the European Union's Horizon 2020 research and innovation programme [ECOPOTENTIAL project, grant agreement No 641762]. I would like to thank Yves Bühler, Marc Christen, Thomas Feistl, and Michaela Teich for their support with avalanche modeling, Peter Bebi for his comments on the manuscript, and Adrienne Grêt-Regamey for supporting this work.

Conflict of interest

The authors declare no conflict of interest.

Additional information

Further details about the models and data are available in [6].

Author details

Ana Stritih[1,2]

1 ETH Zurich, Institute for Landscape and Spatial Development, Planning of Landscape and Urban Systems (PLUS), Zürich, Switzerland

2 WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland

*Address all correspondence to: astritih@ethz.ch

References

[1] Bebi P, Bast A, Helzel K P, Schmucki G, Brozova N, Bühler Y. Avalanche protection forest: From process knowledge to interactive maps. In: Teich M, Accastello C, Perzl F, Kleemayr K, editors. Protective Forests as Ecosystem-based Solution for Disaster Risk Reduction (Eco-DRR). London: IntechOpen; 2021. DOI: 10.5772/intechopen.99514

[2] D'Amboise C J L, Teich M, Hormes A, Steger S, Berger F. Modeling protective forests for gravitational natural hazards and how it relates to risk-based decision support tools. In: Teich M, Accastello C, Perzl F, Kleemayr K, editors. Protective Forests as Ecosystem-based Solution for Disaster Risk Reduction (Eco-DRR). London: IntechOpen; 2021. DOI: 10.5772/intechopen.99510

[3] Perzl F, Bono A, Garbarino M, Motta R. Protective effects of forests against gravitational natural hazards. In: Teich M, Accastello C, Perzl F, Kleemayr K, editors. Protective Forests as Ecosystem-based Solution for Disaster Risk Reduction (Eco-DRR). London: IntechOpen; 2021. DOI: 10.5772/intechopen.99506

[4] Regan HM, Colyvan M, Burgman MA. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecological Applications. 2002;**12**(2):618-628. DOI: 10.1890/1051-0761(2002)012[0618,ATATOU]2.0.CO;2

[5] Brožová N, Fischer JT, Bühler Y, Bartelt P, Bebi P. Determining forest parameters for avalanche simulation using remote sensing data. Cold Regions Science and Technology. 2020;**172**:102976. DOI: 10.1016/j.coldregions.2019.102976

[6] Stritih A, Bebi P, Grêt-Regamey A. Quantifying uncertainties in earth observation-based ecosystem service assessments. Environmental Modelling and Software. 2019;**111**:300-310. DOI: 10.1016/j.envsoft.2018.09.005

[7] Kjaerulff U, Madsen A. Bayesian Networks and Influence Diagrams. Springer; 2013. 385 p

[8] Norsys. Netica API Programmer's Library [Internet]. Vancouver: Norsys Software Corp; 2010. p. 236. Available from: www.norsys.com

[9] Stritih A, Rabe SE, Robaina O, Grêt-Regamey A, Celio E. An online platform for spatial and iterative modelling with Bayesian Networks. Environmental Modelling and Software. 2020;**127**:104658. DOI: 10.1016/j.envsoft.2020.104658

[10] Veitinger J, Stuart Purves R, Sovilla B. Potential slab avalanche release area identification from estimated winter terrain: A multi-scale, fuzzy logic approach. Natural Hazards and Earth System Sciences. 2016;**16**(10):2211-2225

[11] Bebi P, Kienast F, Schönenberger W. Assessing structures in mountain forests as a basis for investigating the forests' dynamics and protective function. Forest Ecology and Management. 2001;**145**(1-2):3-14

[12] Feistl T, Bebi P, Teich M, Bühler Y, Christen M, Thuro K, et al. Observations and modeling of the braking effect of forests on small and medium avalanches. Journal of Glaciology. 2014;**60**(219):124-138

[13] SLF. Davos Fluelastr., 1560 m: Gumbel-Statistik. Davos: WSL Institut für Schnee- und Lawinenforschung SLF; 2017

[14] Christen M, Kowalski J, Bartelt P. RAMMS: Numerical simulation of dense

snow avalanches in three-dimensional terrain. Cold Regions Science and Technology. 2010;**63**(1-2):1-14. DOI: 10.1016/j.coldregions.2010.04.005

[15] Marcot BG. Metrics for evaluating performance and uncertainty of Bayesian network models. Ecological Modelling. 2012;**230**:50-62. DOI: 10.1016/j.ecolmodel.2012.01.013

[16] Bühler Y, Kumar S, Veitinger J, Christen M, Stoffel A, Snehmani. Automated identification of potential snow avalanche release areas based on digital elevation models. Natural Hazards and Earth System Science. 2013;**13**(5):1321-1335

[17] Voinov A, Kolagani N, McCall MK, Glynn PD, Kragt ME, Ostermann FO, et al. Modelling with stakeholders – Next generation. Environmental Modelling & Software. 2016;**77**:196-220. DOI: 10.1016/j.envsoft.2015.11.016

[18] Voinov A, Bousquet F. Modelling with stakeholders. Environmental Modelling and Software. 2010;**25**(11):1268-1281. DOI: 10.1016/j.envsoft.2010.03.007

[19] Grêt-Regamey A, Brunner SH, Altwegg J, Bebi P. Facing uncertainty in ecosystem services-based resource management. Journal of Environmental Management. 2013;**127**:145-154. DOI: 10.1016/j.jenvman.2012.07.028

[20] Stritih A, Bebi P, Rossi C, Grêt-Regamey A. Addressing disturbance risk to mountain forest ecosystem services. Journal of Environmental Management. 2021;**296**:113188. DOI: 10.1016/j.jenvman.2021.113188

[21] Vorstius AC, Spray CJ. A comparison of ecosystem services mapping tools for their potential to support planning and decision-making on a local scale. Ecosystem Services. 2015;**15**:75-83. DOI: 10.1016/j.ecoser.2015.07.007

[22] Kunz M, Grêt-Regamey A, Hurni L. Visualization of uncertainty in natural hazards assessments using an interactive cartographic information system. Natural Hazards. 2011;**59**(3):1735-1751

[23] MacEachren AM, Robinson A, Hopper S, Gardner S, Murray R, Gahegan M, et al. Visualizing geospatial information uncertainty: What we know and what we need to know. Cartography and Geographic Information Science. 2005;**32**(3):139-160