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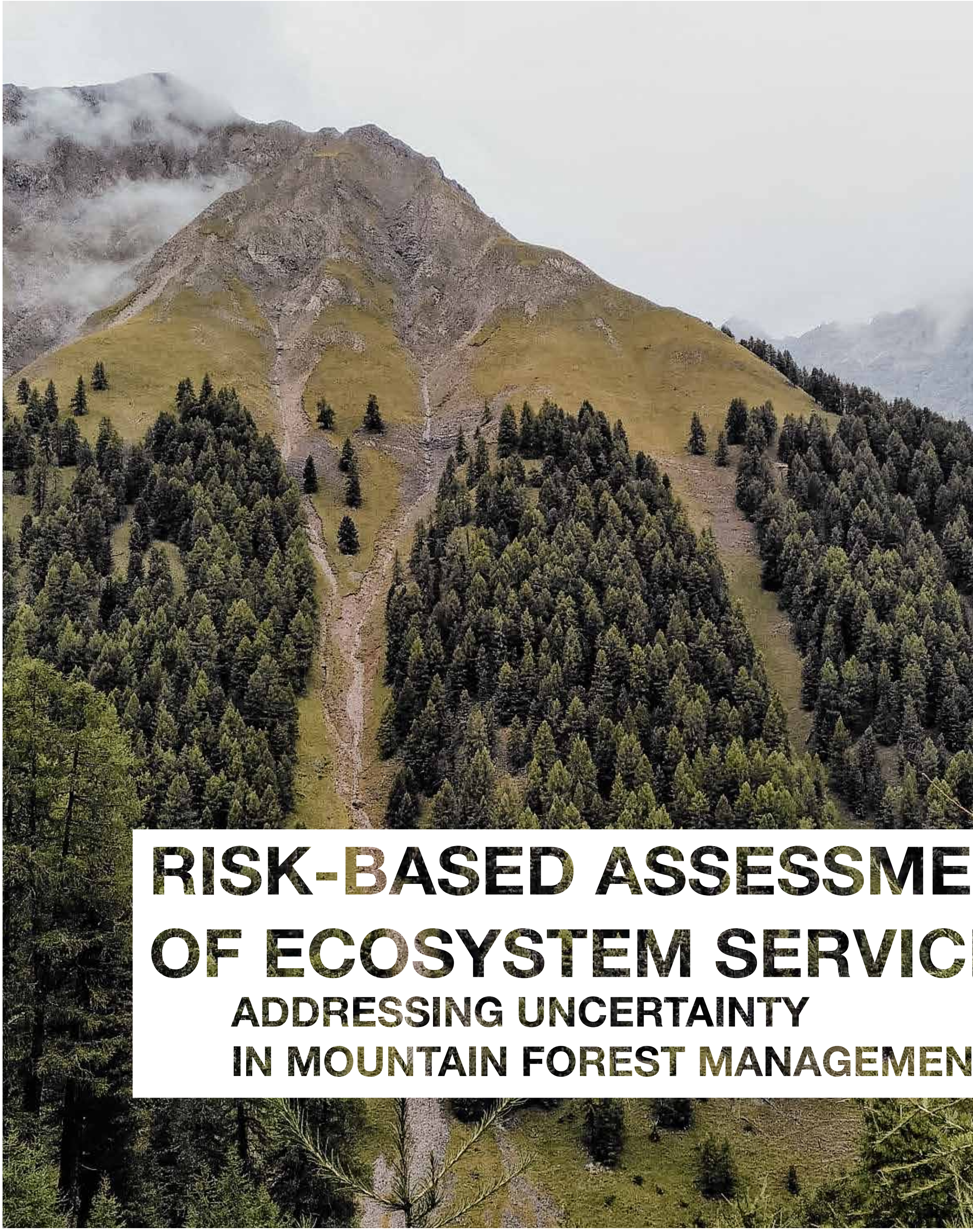

RISK-BASED ASSESSMENTS OF ECOSYSTEM SERVICES

ADDRESSING UNCERTAINTY IN MOUNTAIN FOREST MANAGEMENT

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RISK-BASED ASSESSMENTS OF ECOSYSTEM SERVICES: ADDRESSING UNCERTAINTY IN MOUNTAIN FOREST MANAGEMENT

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Summary

Mountain forests provide a wide range of benefits that are essential for human wellbeing. They protect settlements from natural hazards, store carbon, provide timber and energy, serve as places for recreation, and offer important habitats for rare species. However, many of these ecosystem services (ES) are threatened by the ongoing changes in climate and land use, and mountain forests are increasingly exposed to disturbances, such as windthrows or bark beetle outbreaks. These changes pose a challenge for mountain forest management, as they generate uncertainty about the future provision of ES. Mapping and modelling ES can potentially support decisions in ecosystem management by identifying hotspots of ES or predicting how ES may change in the future. However, ES assessments are associated with high uncertainties related to limited data availability, gaps in our understanding of the processes and functions that underpin ES, and the inherent variability of socio-ecological systems. With the rapid development of Earth observation, including satellite remote sensing and crowdsourced data, more and more spatially explicit data about the structure of ecosystems are becoming available. Combining this data with local knowledge about ecosystem functions, processes, demand for ES, and all the associated uncertainties may help improve ES mapping and support decisions about the management of these ecosystems.

In this thesis, I develop methods to integrate various types of information, including remote sensing data and expert knowledge, into Bayesian network (BN) models of ES, where uncertainties are explicitly addressed. I use these models to map mountain forest ES in the Swiss Alps and to address the risks to mountain forest ES due to natural disturbances. In particular, I address four main research questions:

i. *What are the major sources of uncertainty in forest ecosystem service assessments and to what extent can uncertainties be reduced using remote sensing?*
ii. *How can uncertainties be included in spatially explicit models of socio-ecological systems?*
iii. *Which factors influence the risk to mountain forest ecosystem services due to natural disturbances?*
iv. *How can knowledge of risk help manage forest ecosystem services?*

These questions are addressed through four papers that have been published in (or submitted to) relevant scientific journals. In **Paper I**, remote sensing data are combined with existing avalanche models and expert knowledge to map the supply of and demand for avalanche protection, one of the most important ES in the case study area of Davos, Switzerland. Uncertainties in each model component are integrated in a BN to quantify and map the overall uncertainty, and sensitivity analyses are used to disentangle different sources of uncertainty and identify knowledge gaps. Avalanche protection is associated with a high level of uncertainty mainly owing to the uncertainties regarding the avalanche process, including the natural variability of snow conditions and the uncertainty in existing models of avalanche releases and flows in forest terrain. Although a combination of several remote sensing products can help to accurately map ecosystem structure, this will not lead to a more accurate assessment of ES unless we also improve our understanding of ecosystem functions and processes.

Bayesian networks are a useful tool to address uncertainties and can also more broadly support the modelling of socio-ecological systems with their flexible and transparent graphical structure. To make spatially explicit BNs more accessible to a wide range of users, we developed gBay, an openly available online tool presented in **Paper II**. Through two case studies, modelling land-use change in Entlebuch and avalanche protection in Davos, we demonstrate how spatial processes at different scales can be included in BN models and discuss how this can help reduce uncertainties and support decision-making.

Natural disturbances, such as windthrows, bark beetle outbreaks, and forest fires, are increasingly frequent in mountain forests and increase the uncertainty about the future provision of ES. **Paper III** investigates the susceptibility of mountain forests to disturbances using a combination of remote sensing data and local forest management records from the Canton of Graubünden. The results show that forests' susceptibility not only depends on the current site and stand characteristics but is also affected by past land use – forests established on former agricultural land during the 20th century are more susceptible to disturbances than 'older' forests. Furthermore, recent management interventions can exacerbate disturbance risk, which should be taken into account in forest management planning.

To map the risks to ES due to natural disturbances, forests' susceptibility is integrated into probabilistic ES models in **Paper IV**. The services of avalanche protection, carbon sequestration, wood production, recreation, and habitats as well as the associated risks are mapped in the regions of Davos and the strictly protected Swiss National Park along with its surroundings. Disturbances have diverse effects on different services, ranging from a potential decrease in carbon sequestration and avalanche protection to a potential improvement in habitat quality, and the level of impact depends on how disturbed forests are managed and perceived, including salvage logging and visitors' perception of dead wood.

Explicitly addressing uncertainties in ES assessments can help ecosystem managers to cope with uncertainty by identifying knowledge gaps where uncertainties can potentially be reduced and by acknowledging the uncertainties that cannot be reduced but need to be considered in decision-making. Because forests with the highest current provision of ES are also those with high susceptibility to natural disturbances and uncertain future provision of ES, forest managers face trade-offs between short-term ES benefits and the long-term stability and predictability of the provision of ES. Risk-based ES assessments can therefore provide a basis for robust management strategies to provide sufficient ES under a range of uncertain outcomes.

Zusammenfassung

Gebirgswälder bieten eine Vielzahl von Leistungen, die für das menschliche Wohlbefinden unerlässlich sind. Sie dienen als Erholungsräume, schützen Siedlungen vor Naturgefahren, speichern Kohlenstoff, liefern Holz und Energie und sind wertvolle Lebensräume für seltene Arten. Viele dieser Ökosystemleistungen (ÖSL) sind jedoch durch die Veränderungen des Klimas und der Landnutzung bedroht, und Bergwälder sind zunehmend natürlichen Störungen wie Windwürfen oder Borkenkäferausbrüchen ausgesetzt. Daraus ergeben sich Unsicherheiten für das Waldmanagement, ob und wie auch zukünftig die ÖSL in Bergwäldern bereitgestellt werden können. Die Kartierung und Modellierung von ÖSL kann die Entscheidungsfindung im Ökosystemmanagement erleichtern, indem Hotspots von ÖSL identifiziert werden oder die zukünftige Entwicklung von ÖSL vorhergesagt wird. Die Erfassung von ÖSL ist jedoch mit grossen Unsicherheiten verbunden, welche insbesondere auf die begrenzte Datenverfügbarkeit zurückzuführen sind, sowie auf Lücken im Verständnis der grundlegenden Prozesse und Funktionen und der inhärenten Variabilität sozio-ökologischer Systeme. Jedoch werden mit der schnellen Entwicklung der Erdbeobachtung, einschliesslich satellitengestützter Fernerkundung und Crowdsourcing-Daten, immer mehr räumlich explizite Daten über die Struktur von Ökosystemen verfügbar. Die Kombination dieser Daten mit lokalem Wissen über Ökosystemfunktionen, Prozesse und die Nachfrage nach ÖSL, sowie allen damit verbundenen Unsicherheiten, kann helfen, die Kartierung von ÖSL zu verbessern und Entscheidungen über das Management dieser Ökosysteme zu unterstützen.

In der vorliegenden Arbeit werden Methoden entwickelt, um verschiedene Arten von Informationen, einschliesslich Fernerkundungsdaten und Expertenwissen, in Bayes'sche Netzwerkmodelle (BN) von ÖSL zu integrieren, wobei Unsicherheiten ausdrücklich berücksichtigt werden. Die Modelle werden verwendet, um verschiedene Ökosystemleistungen von Bergwäldern in den Schweizer Alpen zu kartieren und die Risiken für diese ÖSL aufgrund von natürlichen Störungen zu untersuchen. Spezifisch werden vier Forschungsfragen untersucht:

i. *Was sind die wichtigsten Quellen von Unsicherheiten bei der Erfassung von Waldökosystemleistungen und in welchem Ausmass können diese durch den Einsatz von Fernerkundungsdaten reduziert werden?*
ii. *Wie können Unsicherheiten in räumlich explizite Modelle von sozio-ökologischen Systemen einbezogen werden?*
iii. *Welche Faktoren beeinflussen das Risiko für Gebirgswaldökosystemleistungen durch natürliche Störungen?*
iv. *Wie kann das Wissen über das Risiko beim Management von Waldökosystemleistungen helfen?*

Diese Fragen werden in vier Publikationen thematisiert, die in relevanten wissenschaftlichen Zeitschriften veröffentlicht (oder eingereicht) worden sind. In **Paper I** werden Fernerkundungsdaten mit bestehenden Modellen und Expertenwissen kombiniert, um das Angebot und die Nachfrage nach Lawinenschutz, einer der wichtigsten ÖSL im Fallstudiengebiet von Davos, zu kartieren. Unsicherheiten in jeder Modellkomponente werden in ein BN integriert, um die Gesamtunsicherheit zu quantifizieren und abzubilden. Mittels Sensitivitätsanalysen werden die unterschiedlichen Quellen der Unsicherheiten entschlüsselt und so die Wissenslücken identifiziert. Die hohen Unsicherheiten beim Lawinenschutz sind mit der natürlichen Variabilität der Schneeverhältnisse und die Ungewissheit in den bestehenden

Modellen für Lawinenanrisse und -flüsse in bewaldetem Gelände verbunden. Obwohl eine Kombination verschiedener Fernerkundungsprodukte helfen kann, die Struktur von Ökosystemen genau zu kartieren, wird dies nicht zu einer genaueren Bewertung von Ökosystemleistungen führen, solange nicht auch das Verständnis der Funktionen und Prozesse von Ökosystemen verbessert wird.

Bayes'sche Netze sind ein nützliches Werkzeug, um Unsicherheiten zu erfassen, und können mit ihrer flexiblen und transparenten, grafischen Struktur auch im weiteren Sinne die Modellierung von sozio-ökologischen Systemen unterstützen. Um räumlich explizite BNs einem breiten Nutzerkreis zugänglich zu machen, haben wir gBay entwickelt, ein offen zugängliches Online-Tool, das in **Paper II** vorgestellt wird. Anhand von zwei Fallstudien, der Modellierung von Landnutzungsveränderungen im Entlebuch und dem Lawinenschutz in Davos, wird demonstriert, wie räumliche Prozesse auf verschiedenen Skalen in BN-Modelle einbezogen werden können, und diskutiert, wie dies helfen kann, Unsicherheiten zu reduzieren und Entscheidungen zu unterstützen.

Natürliche Störungen, wie Windwurf, Borkenkäferbefall und Waldbrände, treten in Bergwäldern immer häufiger auf und erhöhen die Unsicherheit über die zukünftige Bereitstellung von ÖSL. **Paper III** untersucht die Anfälligkeit von Gebirgswäldern für Störungen mit Hilfe einer Kombination aus Fernerkundungsdaten und lokalen Waldbewirtschaftungsdaten aus dem Kanton Graubünden. Die Ergebnisse zeigen, dass die Anfälligkeit der Wälder von den aktuellen Standorts- und Bestandeseigenschaften abhängt, aber auch durch die frühere Landnutzung beeinflusst wird. Dabei fällt auf, dass Wälder, die auf ehemaligen landwirtschaftlichen Flächen im 20. Jahrhundert entstanden sind, anfälliger sind als 'ältere' Wälder. Zudem können kürzlich durchgeführte Bewirtschaftungseingriffe das Störungsrisiko erhöhen, was beim Waldmanagement berücksichtigt werden sollte.

Um die durch natürliche Störungen verursachten Risiken für ÖSL zu kartieren, wird in **Paper IV** die Anfälligkeit der Wälder in probabilistische ÖSL-Modelle integriert. Die Leistungen Lawinenschutz, Kohlenstoffsequestrierung, Holzproduktion, Erholung und Habitate sowie die damit verbundenen Risiken werden in den Regionen Davos und dem streng geschützten Schweizer Nationalpark mit seiner Umgebung kartiert. Waldstörungen haben unterschiedliche Auswirkungen auf verschiedene Leistungen, von einem potenziellen Verlust der Kohlenstoffsequestrierung und des Lawinenschutzes bis zu einer potenziellen Verbesserung der Habitatqualität. Das Ausmass der Auswirkungen hängt davon ab, wie gestörte Wälder bewirtschaftet und wahrgenommen werden, einschliesslich der Räumung von Totholz und dessen Wahrnehmung durch Besucher.

Die explizite Berücksichtigung von Unsicherheiten in Bewertungen von ÖSL kann helfen, besser mit Unsicherheiten beim Management von Ökosystemen umzugehen. Dies gelingt, indem man Wissenslücken identifiziert, bei denen Unsicherheiten reduziert werden können, und diese unterscheidet von Unsicherheiten, die nicht reduziert werden können aber bei der Entscheidungsfindung berücksichtigt werden müssen. Da Bergwälder mit dem gegenwärtig höchsten Angebot an ÖSL auch eine hohe Anfälligkeit für natürliche Störungen und ein unsicheres zukünftiges Angebot an ÖSL aufweisen, müssen Waldmanager*Innen Abwägungen zwischen kurzfristigen ÖSL-Bereitstellung und der langfristigen Stabilität und Vorhersagbarkeit der ÖSL eingehen. Risikobasierte Bewertungen von ÖSL können daher eine Grundlage für robuste Managementstrategien bieten, um unter einer Vielzahl von unsicheren Entwicklungen ausreichend ÖSL bereitzustellen.

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Contents

1 Introduction

Ecosystems worldwide are facing unprecedented challenges in the form of biodiversity loss, climate and land-use change, and other anthropogenic pressures (IPBES, 2019; IPCC, 2014). These changes jeopardise the capacity of ecosystems to provide benefits that underpin human wellbeing (IPBES, 2019) and generate uncertainty about how to manage ecosystems in the future (Polasky et al., 2011). Mountain ecosystems are at the front line of these challenges, as they are particularly exposed to climate change (Pepin et al., 2015) and are vulnerable to natural hazards (Klein et al., 2019b), which can be exacerbated by climate extremes (IPCC, 2018). At the same time, they provide essential services, such as the provision of water for lowland areas, the regulation of natural hazards, and opportunities for recreation, to both local inhabitants and people living outside mountain regions (Grêt-Regamey and Weibel, 2020; Schirpke et al., 2019b) – while also harbouring hotspots of biodiversity (Rahbek et al., 2019). The provision of many of these services is affected by the increasing frequency of insect outbreaks, forest fires, and windthrow in mountain forests under global change (Bebi et al., 2017; Senf et al., 2018; Thom and Seidl, 2016), and managers of mountain forests are facing challenging decisions about how to secure the needed services in an uncertain future.

The concept of ecosystem services (ES) has developed as an approach to support more sustainable decision-making by demonstrating the value of ecosystems and biodiversity for people and by providing a basis for informed decisions in ecosystem management, spatial planning, and conservation. Since the concept of ES was first introduced (Costanza et al., 1997; Westman, 1977), researchers have developed a wide array of methods to map and quantify these services, identify trade-offs and synergies between them (Raudsepp-Hearne et al., 2010), and evaluate how they might change in the future under different scenarios (Carpenter et al., 2015). Since its beginning, which focused on the monetary value of ecosystems (Costanza et al., 1997), the concept of ES has evolved to include a plurality of worldviews and values under the framework of Nature's Contributions to People (Díaz et al., 2018; IPBES, 2019). Nonetheless, the implementation of this framework to support decisions in practice has been lagging behind the scientific developments (Albert et al., 2014; Mandle et al., 2020).

To understand mismatches between the supply of and demand for ES and how ES may change in the future, ES assessments need to address both the ecological functions that underpin the provision of ES and the socioeconomic factors that determine the demand for and actual use of ES (Mandle et al., 2020). In addition, these assessments should consider the scale and level of detail relevant for decision-makers (Albert et al., 2014). However, many studies about ES only address either the potential supply of ES or their current use (Mandle et al., 2020) and are based on broad categories of land use/land cover that neglect differences within these classes (Rieb et al., 2017), such as the legacies of past land use (Bennett, 2017). Furthermore, ES assessments are often associated with a high level of uncertainty (Schägner et al., 2013) and a lack of validation (Schulp et al., 2014a), and different ES models sometimes yield inconsistent results (Eigenbrod et al., 2010; Willcock et al., 2020). These uncertainties, which are often not reported (Schägner et al., 2013), limit the credibility of ES assessments (Andrew et al., 2015). In mountain regions, uncertainties are further exacerbated by a high level of spatial heterogeneity, where mapping requires fine-scale data that are often unavailable (Klein et al., 2019a).

In recent years, an increasing amount of data about the state of ecosystems is becoming available through Earth observation (EO), including satellite imagery and crowdsourced data (GEO, 2016). Timely and spatially explicit EO data have high potential to improve ES assessments (Andrew et al., 2014; Ayanu et al., 2012a; Cord et al., 2017). However, transforming these data into useful information that can support decision-making requires integration with locally relevant knowledge about ecosystem processes, functions, and services.

This thesis aims to support the management of mountain forests under uncertainty by using risk-based ES assessments that integrate various sources of information and uncertainties about the provision of and demand for ES. These probabilistic ES models explicitly address epistemic uncertainties (i.e. lack of knowledge) as well as the potential changes in ES due to natural disturbances. I map the ES provided by mountain forests, and the risk to these services in the Swiss Alps, in the regions of Davos and the Swiss National Park with its surroundings. Explicitly addressing uncertainties can help identify knowledge gaps and priorities to improve ES models. Furthermore, risk-based maps of ES can help forest managers anticipate risks and identify priority areas where interventions are needed to secure the required provision of ES as well as areas where any intervention might further exacerbate risks. Rather than optimising ES under one most likely scenario, risk-based assessments provide a basis to find management strategies that provide sufficient ES under a range of possible outcomes, thus supporting more robust ecosystem management under uncertainty.

2 Background and state of the art

2.1 Mountain forest ecosystem services

Mountain forests have played an essential role in enabling the development of mountain communities by protecting them from natural hazards, such as avalanches, landslides, and rockfall. They also store carbon, regulate water flows, prevent erosion, supply timber and energy, provide habitats to rare species, and contribute to the scenic landscapes that are valued by locals and visitors from all over the world (Grêt-Regamey and Weibel, 2020; Schirpke et al., 2019b). All of these ES are underpinned by ecological processes and by co-production by people, for example, through managing the forest or maintaining recreation infrastructure (Bruley et al., 2021a; Palomo et al., 2016). Their value is further determined by the level of societal demand for ES, including factors such as the value of infrastructure at risk from natural hazards, the global demand for climate regulation, and the value that people assign to beautiful landscapes or places for recreation.

Historically, the Alpine environment was characterised by remoteness, harsh living conditions, and marginalised communities, as is still the case in many other mountain regions today (Klein et al., 2019a). Since the 19th century, the Alps have seen dramatic changes in their socio-ecological system, with the development of tourism, land abandonment, and forest expansion (Bätzing, 2003; Bruley et al., 2021b; Egarter Vigl et al., 2017; Loran et al., 2016). Today, the Swiss Alps are an attractive area for tourism and recreation (Willibald et al., 2019), and their characteristic landscapes and charismatic species are valued both locally and in many lowland areas (Schirpke et al., 2019b). The ongoing changes in land use affect both the supply of and demand for mountain ES (Brunner et al., 2017; Egarter Vigl et al., 2017; Huber et al., 2013b; Schirpke et al., 2020b).

In addition to long-term pressures such as climate and land-use change, mountain forests are also experiencing fast perturbations in the form of natural disturbances. Disturbances such as windthrow, bark beetle outbreaks, forest fires, avalanches, and snow breakage are an integral part of mountain forest dynamics (Kulakowski et al., 2017) but were suppressed by land use and biomass extraction in the Alps in the past (Bebi et al., 2017). Due to the combined effects of landscape homogenisation, biomass accumulation, and climate change, disturbances are now becoming more frequent (Bebi et al., 2017; Seidl et al., 2014b; Senf et al., 2018). An intensifying disturbance regime may jeopardise the provision of some of the ES provided by mountain forests, including natural hazard protection (Sebald et al., 2019; Vacchiano et al., 2016), carbon sequestration (Anderegg et al., 2020), and timber production (Albrich et al., 2018). Disturbances also create diverse forest structures and habitats (Rixen et al., 2007; Wermelinger et al., 2017) and can facilitate forests' adaptation to climate change (Thom et al., 2017). In the context of changing forest dynamics, forest managers are therefore faced with challenging decisions about where, and to what extent, to intervene in the ecosystem (Kulakowski et al., 2017; Seidl et al., 2018).

Mapping and modelling ES can support decisions about ecosystem management. In the Alpine context, ES have been mapped to identify bundles of co-occurring ES at the regional (Crouzat et al., 2015) and landscape scale in the French Alps (Vannier et al., 2019) and to analyse trade-offs and future changes in the landscape of Davos in the Swiss Alps (Grêt-Regamey et al., 2013b). The past development of ES in the Alps has been assessed based on land-use changes (Egarter Vigl et al., 2017), and future scenarios of ES have been modelled in South Tyrol (Schirpke et al., 2020b) and the region of Visp in Switzerland

(Brunner et al., 2017). Many of these studies rely on simple links between ES and categories of land cover/land use. However, an increasing amount of knowledge is becoming available about the ecological and social processes that underpin individual ES, as summarised below.

One of the most important services provided by mountain forests is *protection from natural hazards* (Moos et al., 2018). Forests reduce the risk of landslides (Rickli et al., 2019a), intercept rockfall (Dorren et al., 2005; Moos et al., 2017), and protect people, settlements, and infrastructure from snow avalanches (Teich and Bebi, 2009). In recent years, significant progress has been made in modelling these hazard processes (Bühler et al., 2018; Christen et al., 2010; Veitinger et al., 2016) and understanding their interactions with forests (Feistl et al., 2014; Moos et al., 2017; Rickli et al., 2019b; Teich et al., 2014; Zurbriggen et al., 2014). Such advances support the development of ecosystem-based solutions for disaster risk reduction (Eco-DRR), which are increasingly recognised as an efficient approach to reduce risks while also providing other ES (Moos et al., 2018; UNISDR, 2015a).

While forests' role in regulating natural hazards is mainly important for local inhabitants, forests also contribute to regulating the global climate by storing *carbon*. A large part of the carbon uptake in forests at the local scale is determined by tree growth (Etzold et al., 2011) and forest disturbances (Etzold et al., 2014). At a broader scale, forests in the Swiss Alps are a carbon sink due to forest expansion and increasing stocks of aboveground biomass (Brändli et al., 2020), whereas changes in belowground carbon stocks are less pronounced (Gosheva et al., 2017).

The Alps offer important *recreation* opportunities for people from nearby regions (Willibald et al., 2019) and attract visitors from all over the world due to their beautiful landscapes (Schirpke et al., 2013b). Visitors' choices are also influenced by accessibility and recreation infrastructure (Willibald et al., 2019), and the number of visitors fluctuates in relation to weather and economic conditions (Millhäusler et al., 2016). Although forests are important for nearby recreation (Kienast et al., 2012), forest expansion is often associated with a loss of the traditional *aesthetics* of the open Alpine landscape that is dominated by mountain agriculture (Rewitzer et al., 2017; Schirpke et al., 2019a), which is an important part of the *local identity* (Brunner and Grêt-Regamey, 2016).

The *timber* and *energy* resources provided by forests in mountain regions have been essential for the development of mountain communities in the past and are still a crucial resource for many mountain dwellers today (Klein et al., 2019a). In the Swiss Alps, high labour costs and low wood prices currently make wood production unprofitable in most areas, and forest management is subsidised in order to maintain forests' protective function (Temperli et al., 2017). However, this may change in case of a growing demand for wood fuel as a source of renewable energy (Thees et al., 2020).

Biodiversity underpins the provision of other ES by maintaining the ecological integrity and resilience of the systems that provide them (Millennium Ecosystem Assessment, 2005; Schröter et al., 2014). However, the links between biodiversity and ES are not clear-cut (Anderson et al., 2009; Ricketts et al., 2016), and some authors have urged caution when using the concept of ES in conservation planning (Ridder, 2008; Vira and Adams, 2009). Biodiversity is also recognised in society as having an inherent, intrinsic value (Chan et al., 2012; Mace et al., 2012). This value is expressed in policy at the national level (FOEN, 2012) as well as in local forest management strategies that prioritise the maintenance of specific habitats, such as that of the capercaillie (*Tetrao urogallus* L.), a keystone species in structurally rich mountain forests (AWN, 2018).

2.2 Earth observation

According to the Group on Earth Observations (GEO, 2016), the term Earth Observation (EO) includes space-based, remotely sensed, and ground-based data about our planet. EO data are becoming increasingly available due to developments in remote sensing, such as new satellites, as well as through the increasing amount of open data available online, including crowdsourced data from citizen science (Fritz et al., 2017) or social media platforms (Di Minin et al., 2015).

Rapidly developing remote sensing technologies provide cost-effective, timely, and spatially explicit information about our environment, even in areas where other data are scarce. Openly available satellite data are increasingly used to monitor changes in our environment (Hansen and Loveland, 2012), but also have a high potential to inform ES mapping and modelling efforts (Ayanu et al., 2012a; Cord et al., 2017; Skidmore et al., 2015). Multispectral imagery (e.g. from Landsat ETM and Sentinel-2 satellites) is widely used to map and monitor land cover (Hansen and Loveland 2012), one of the most commonly used proxies for ES (Cord et al., 2017; Seppelt et al., 2011). Remote sensing is also used to measure ecosystem properties that are direct proxies for ES or serve as inputs to biophysical models (Ayanu et al., 2012a; Pasetto et al., 2018; Plummer, 2000). For example, vegetation indices can be derived from multi- or hyperspectral images and used to estimate primary production and carbon fluxes in forests (Olofsson et al., 2008; Rahman et al., 2004) and grasslands (Fuentes et al., 2006; Gianelle et al., 2009). In forests, airborne LiDAR (light detection and ranging) technology has proven to be particularly useful for estimating forest biomass (Babcock et al., 2015; Koch, 2010) and structure (Leiterer et al., 2015), which is closely linked to habitat quality for many species (Zellweger et al., 2013). In addition to proxies for the provision of ES, EO has some potential to provide spatially explicit information on the societal demand for ES (Ayanu et al., 2012a) – for example, by detecting buildings (Ehrlich and Tenerelli, 2013) – and to provide input data for process-based models of ecosystem processes (Brožová et al., 2020).

Crowdsourced data can serve as ground truth for the calibration and validation of remotely sensed products (Fritz et al., 2017) and are also increasingly being used for ES assessments. Data from social media, especially Flickr, are now commonly used to map cultural ES (Havinga et al., 2020; van Zanten et al., 2016; Wood et al., 2013), although social media may not be representative of all ES users (Di Minin et al., 2015; Oteros-Rozas et al., 2016). Social media data have also been used to relate cultural ES to remotely sensed indicators (Vaz et al., 2020) and to characterise user groups (Gosal et al., 2019). Other examples of crowdsourced information include participatory mapping of cultural ES (Jaligot et al., 2018) and citizen science observations of species (Jacobs and Zipf, 2017).

Despite the growing availability of EO data, several challenges hamper the widespread use of EO in ecosystem management. An important technical challenge is the trade-off between the spatial, temporal, and spectral resolution of remote sensing data (Kennedy et al., 2009). For example, airborne LiDAR can provide good estimates of forest structure and biomass at a high spatial resolution (e.g. below 1 m), but LiDAR flights have so far mostly been sporadically carried out, and differences between sensors on repeated flights limit their potential to evaluate changes over time (Meyer et al., 2013) – for example, to estimate carbon sequestration. In contrast, satellite images are available at a high temporal resolution (e.g. daily or weekly) but have a lower spatial resolution than airborne images (e.g. 10 m for Sentinel-2 and 30 m for Landsat). Although vegetation indices (most commonly NDVI) from optical satellites have been used as a proxy for net primary productivity, the relationship between NDVI and productivity reaches saturation in dense forests (Olofsson et al., 2008), which limits its potential as a proxy for carbon sequestration. Such limitations of individual EO products create the need for combining various types of remote sensing data (Shen et al., 2016).

To address the challenge of processing the growing amount of EO data, ready-made algorithms to process 'big data' are increasingly accessible through platforms such as Google Earth Engine (Gorelick et al., 2017). However, translating EO products into information relevant for ecosystem management requires interpretation (Sudmanns et al., 2020), and this information often contains uncertainties that are not explicitly communicated (Petrou et al., 2015). In addition, many state-of-the-art remote sensing techniques are developed for specific case studies (Fassnacht et al., 2016), and transferring them to other areas requires additional ground-truth data as well as significant time and effort for calibration and validation. These challenges limit the usability of EO data for users who are not specifically trained in programming and data processing (Sudmanns et al., 2020), such as managers of protected areas (PAs).

This thesis was embedded in the large Horizon 2020 project ECOPOTENTIAL: improving future ecosystem benefits through earth observations. The project aimed to advance the use of EO data for ecosystem modelling (Pasetto et al., 2018) to support the management of PAs across Europe (Wanke et al., 2019) and to develop openly available and operational tools for the use of EO products (Lucas et al., 2015; Nativi et al., 2016). Within this broad frame, the work in this thesis focused on developing ES models that can integrate EO products and serve as a tool to support decisions about ecosystem management under uncertainty.

2.3 Socio-ecological system modelling

The ES framework was developed to support more sustainable decision-making in ecosystem management (Costanza et al., 1997; Daily et al., 2009). Whereas using proxies to map the current state of ES can help identify trade-offs between ES (Raudsepp-Hearne et al., 2010) or mismatches between supply and demand (Burkhard et al., 2012), predicting future changes requires some form of modelling of the ecological and social processes that underpin ES (e.g. Brunner et al., 2017; Morán-Ordóñez et al., 2020; Price et al., 2015). Models of socio-ecological systems can also be a useful tool to improve our understanding of the systems and to build a common understanding with stakeholders, decision-makers, or experts from different fields (Steger et al., 2021; Voinov et al., 2016).

In the last two decades, various decision-support tools based on socio-ecological models have been developed (Grêt-Regamey et al., 2017). Platforms such as InVEST (Tallis and Polasky, 2009) and ARIES (Villa et al., 2014) provide ready-made ES models that can be applied across a variety of ecosystems and scales (Ruckelshaus et al., 2015). Dynamic landscape models can be used to simulate the effects of management alternatives (Langner et al., 2017; Seidl et al., 2014a) and have been coupled with agent-based models to understand how individual actors' decisions interact and influence changes in the landscape (Huber et al., 2013a; Rammer and Seidl, 2015). Such models can also be used to identify strategies needed to achieve desired levels of ES (Brunner et al., 2016).

Building models of socio-ecological systems is often a transdisciplinary effort (Steger et al., 2021), as this involves incorporating knowledge from natural and social sciences as well as biophysical and socio-economic data. For modelling results to be utilised for decision-support, they need to be perceived as credible by decision-makers (Jakeman et al., 2006). Involving stakeholders and decision-makers in the modelling process can improve the credibility and usability of modelling results and can support learning and communication (Jakeman et al., 2006; Voinov and Bousquet, 2010). Participatory modelling is therefore becoming increasingly common in the field of socio-ecological systems (Steger et al., 2021; Voinov et al., 2016).

Bayesian networks (BNs) are a flexible modelling tool that can integrate both quantitative and qualitative data (Kelly (Letcher) et al., 2013). This enables the use of BNs even when data are limited (Hamilton et al., 2015b) by including incomplete data and expert (Celio et al., 2014; Grêt-Regamey et al., 2013b) or stakeholder knowledge (Bromley, 2005; Celio et al., 2019; Salliou et al., 2017). They can be updated whenever new evidence becomes available, thus supporting adaptive management (Gonzalez-Redin et al., 2016; Marcot et al., 2006). Furthermore, their transparent graphical structure facilitates communication with stakeholders; this makes BNs a popular tool in participatory modelling (Celio et al., 2015; Chen and Pollino, 2012; Voinov et al., 2018). BNs have been used as a tool in natural resource management (Bacon et al., 2002; Barton et al., 2012; Pagano et al., 2018) and ecological modelling (Hamilton et al., 2015b; Marcot et al., 2006). They have also been made spatially explicit (Landuyt et al., 2015) and used for risk assessment (Grêt-Regamey and Straub, 2006), land-use change modelling (Celio et al., 2014), and ES mapping (Gonzalez-Redin et al., 2016; Grêt-Regamey et al., 2013b).

2.4 Uncertainty and risk

Models of socio-ecological systems are often associated with high levels of uncertainty. Part of this uncertainty is *epistemic*, reflecting our lack of knowledge about the modelled systems (Maier et al., 2016). This uncertainty stems from limited process understanding and from the data and models used. The data used as model inputs may contain measurement errors or misclassifications, whereas models contain uncertain parameter estimates and structural uncertainty about the choice of variables and the relationships between them (Ascough et al., 2008). In addition, because data on some components of socio-ecological systems are often lacking, many ES models partly rely on expert judgement, which also comes with some epistemic uncertainty and subjective judgement (Regan et al., 2002). Whereas epistemic uncertainty can potentially be reduced as more data become available and our process understanding improves, part of the uncertainty in ES models stems from the inherent variability and complexity of socio-ecological systems (Ascough et al., 2008). This intrinsic or *aleatory* uncertainty cannot be reduced, but evaluating and communicating it can contribute to more robust decision-making (Ascough et al., 2008; Maier et al., 2016).

Conceptually, there are different approaches to dealing with uncertainty in modelling. In classical frequentist statistics, probability distributions are defined by frequencies of events, and model parameters are treated as estimates of 'true' quantities (Ellison, 2004). Frequentist statistics therefore only deals with aleatory uncertainty – that is, the variability of observable events (Schweder, 2018). In contrast, Bayesian inference defines probabilities as the degree of belief in the likelihood of an event, and model parameters are treated as random variables (Ellison, 2004), which allows for explicitly addressing epistemic uncertainty (Wagenmakers et al., 2008). Bayesian inference also allows for taking into account prior beliefs (e.g. models from previous studies) and for updating beliefs as new information becomes available (Ellison, 2004).

In practice, model uncertainty can be evaluated using independent data for validation (Regan et al., 2002). However, these data are often not available in the case of ES models because many ES are difficult to directly measure (Bennett et al., 2009) and the measured proxies rarely match the exact definition of the ES (Schulp et al., 2014a). Alternatively, uncertainty can be addressed by ensemble modelling – that is, running different types of models and comparing their outputs (Willcock et al., 2020; Willibald et al.,

2020) – or using BNs, where each variable is expressed as a probability distribution (Kjaerulff and Madsen, 2013). As such, BNs explicitly address uncertainty (Grêt-Regamey et al., 2013a) and take into account not only the most likely outcome but also extreme outcomes at the tails of probability distributions. However, most often, uncertainty in ES models is only discussed qualitatively, if at all (Schägner et al., 2013).

In other fields that deal with complex systems and high levels of uncertainty, such as finance or hazard management, decisions are often based on *risk*, which takes into account the uncertainty of outcomes. In finance, risk is defined as the product of asset returns and their variability (i.e. aleatory uncertainty) and includes both negative and positive outcomes. Portfolio managers use calculations of risk to optimise the combination of assets in their portfolio (Markowitz, 1952). This portfolio optimisation approach has been applied to optimise the economic value of forest management, taking into account the risk of natural disturbances (Hanewinkel et al., 2011), and to evaluate risks and returns for forest owners under a payments for ES scheme (Matthies et al., 2015). However, it is often difficult to quantify the returns of ES (Alvarez et al., 2017), particularly for services that do not have a market value and are difficult to monetise (Martín-López et al., 2014), such as cultural services or biodiversity. In addition, the portfolio manager for whom to optimise returns is not always clearly defined, as ecosystems provide benefits to different users across space and across scales (Alvarez et al., 2017), not only to the land owners or managers.

In hazard management, risk is defined as the combination of the probability of an event and its (usually negative) impact and is described as a function of hazard (i.e. the magnitude of an extreme event), exposure (the value assets that are subject to potential losses), and vulnerability (the probability that a hazard will cause damage to an asset) (UNISDR, 2015b). This framework has recently been applied to ES, for example, to identify hotspots of risk to ES from a wide range of hazards in Czechia (Pártl et al., 2017) and to characterise forests' vulnerability to climate change (Lecina-Diaz et al., 2021a). In this thesis, *risk to ES* is defined as the probability of a hazard and its impact on the provision of ES to society (Schröter et al., 2019), which depends on exposed ES and their vulnerability. Anticipating risks and mitigating their impacts requires some level of predictability of risks (e.g. where hazard events are likely to occur) as well as knowledge about effective measures to mitigate them (Seidl, 2014).

3 Research questions

The overall aim of this thesis is to contribute to the field of ES research by advancing methods to address uncertainty and risk in ES assessments by integrating various sources of information about the supply of and demand for ES. More specifically, the thesis aims to support decision-making in mountain forest management under uncertainty and a changing disturbance regime through risk-based mapping of ES, where both epistemic uncertainties and risk to ES due to natural disturbances are explicitly considered.

In particular, four main research questions are addressed:

i. *What are the major sources of uncertainty in forest ecosystem service assessments and to what extent can uncertainties be reduced using remote sensing?*

Hypothesis: ES assessments include a high level of uncertainty, in part due to the inherent natural variability of ecosystem structure, function, and demand for ES but also owing to data and model uncertainties, which can be reduced as data that are more accurate become available. Using remote sensing for ES mapping can therefore help reduce uncertainty in ES assessments.

ii. *How can uncertainties be included in spatially explicit models of socio-ecological systems?*

Hypothesis: BNs can be used to integrate different types of uncertainty in models of socio-ecological systems and can be run with spatial data, making it possible to propagate and quantify uncertainty in a spatially explicit manner. Spatial BNs can be coupled with geoprocessing tools to integrate spatial relationships, such as neighbourhood effects.

iii. *Which factors influence the risk to mountain forest ecosystem services due to natural disturbances?*

Hypothesis: The risk of natural disturbances depends on the probability of a disturbance, the susceptibility of a forest to disturbances, and the potential loss of ES in case of a disturbance. Forests' susceptibility to natural disturbances is determined by site and stand characteristics and is influenced by legacies of past management. The potential loss of ES due to disturbances differs between different types of ES, and the spatial pattern of risk to ES is influenced by local differences in demand for ES.

iv. *How can knowledge of risk help manage forest ecosystem services?*

Hypothesis: Risks to ES are heterogeneous in space, and mapping them can help identify areas of high risk – that is, where specific ES are particularly important for users but are likely to decrease under a changing disturbance regime – which are priority areas for interventions that mitigate risks or increase resilience. Analysing risks in areas with different management regimes, such as PAs and non-protected areas, can help identify how management interventions (or lack thereof) affect the risk to forest ES.

3.1 Structure of the thesis

In Chapters 1 and 2, I introduce the main issues addressed in this thesis and provide a theoretical background, which leads to the research questions described in Chapter 3. The research questions are addressed in the main part of the thesis, which comprises four papers.

In **Paper I** (Chapter 4), I present a methodology for integrating, quantifying, and disentangling uncertainties in ES models and apply it to the example of avalanche protection. **Paper II** introduces gBay, an online platform for spatial BN models that was developed in the frame of this project, and shows how spatial interactions can be included in probabilistic models.

The following chapters focus on natural disturbances in mountain forests. In particular, **Paper III** investigates the factors that affect forests' susceptibility to disturbances based on a large dataset of forest disturbances in the Canton of Graubünden. The modelled susceptibility is integrated into ES models in **Paper IV**, where I map the risks to ES due to natural disturbances and compare them between the strictly protected Swiss National Park, its surrounding, and the region of Davos.

The findings of all four papers are synthesised in Chapter 8, where I also discuss the limitations of this work and suggest an outlook for further research. Furthermore, I discuss the implications of the findings for science and policy.

4 Paper I: Quantifying uncertainties in earth observation-based ecosystem service assessments

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Abstract

Ecosystem service (ES) assessments are widely promoted as a tool to support decision-makers in ecosystem management, and the mapping of ES is increasingly supported by the spatial data on ecosystem properties provided by Earth Observation (EO). However, ES assessments are often associated with high levels of uncertainty, which affects their credibility. We demonstrate how different types of information on ES (including EO data, process models, and expert knowledge) can be integrated in a Bayesian Network, where the associated uncertainties are quantified. The probabilistic approach is used to map the provision and demand of avalanche protection, an important regulating service in mountain regions, and to identify the key sources of uncertainty. The model outputs show high uncertainties, mainly due to uncertainties in process modelling. Our results demonstrate that the potential of EO to improve the accuracy of ES assessments cannot be fully utilized without an improved understanding of ecosystem processes.

Keywords: ecosystem services; Earth Observation; uncertainty; Bayesian Network; avalanche protection

4.1 Introduction

The ecosystem service (ES) concept is increasingly promoted as a framework to support decision-making (Convention on Biological Diversity, 2010; European Commission, 2011), in order to improve the management of ecosystems and maintain the services they provide to society (Daily et al., 2009; Maes et al., 2012). These efforts are supported by the growing body of scientific literature on ES assessments (Schägner et al., 2013; Schröter et al., 2016), and the increasing availability of spatial data, particularly through Earth Observation (EO), which provides information on a variety of ecosystem properties (Andrew et al., 2014; Ayanu et al., 2012b). However, the use of ES assessments in planning and decision-making remains limited (Albert et al., 2014). ES assessments are associated with large uncertainties, which are often unreported (Schägner et al., 2013), and different ES assessment methods show inconsistent results (Eigenbrod et al., 2010; Schulp et al., 2014a), which may affect their credibility as tools for decision-makers (Andrew et al., 2015).

Ecosystem service assessments combine data on biophysical structures and processes with models of ecosystem function and measures of socio-economic value (de Groot et al., 2010; Haines-Young and Potschin, 2009). Modelling the whole ES cascade (Haines-Young and Potschin, 2009) comprises not only various types of data and models, but also various types of uncertainty (Ascough et al., 2008). On the one hand, uncertainty in these assessments stems from the inherent spatial and temporal variability of socio-ecological systems (Regan et al., 2002). This type of uncertainty cannot be reduced, but should be taken into account in management decisions (Ascough et al., 2008). On the other hand, ES assessments involve uncertainties that can potentially be reduced, such as measurements errors, model structure and parameter uncertainties, and subjective judgment (Regan et al., 2002). To realistically evaluate the level of confidence in ES assessments, all these types of uncertainty should be integrated (Maier et al., 2008) and finally also communicated to users. Moreover, understanding how the different sources of uncertainty propagate to the final assessment can help identify knowledge gaps and contribute to more robust decision-making (Neuendorf et al., 2018; Polasky et al., 2011; Uusitalo et al., 2015).

The data most commonly used in ES assessments are proxies describing ecosystem structure (Eigenbrod et al., 2010; Schägner et al., 2013), such as land use/land cover (LULC) (Costanza et al., 1997; Troy and Wilson, 2006), plant functional traits (Lavorel et al., 2011; Schirpke et al., 2013a), or aboveground biomass (Barredo et al., 2008; Nelson et al., 2009). Such data is subject to uncertainty due to limited sample sizes, different data collection and processing techniques, and sampling biases (Ascough et al., 2008). Earth Observation (EO) is expected to reduce these uncertainties, as it provides spatially explicit and up-to-date information on many of these ecosystem properties (Andrew et al., 2014; Cord et al., 2017; Feng et al., 2010). So far, the EO product most commonly used in ES assessments is land cover (Cord et al., 2017). However, several studies have highlighted the shortcomings of LULC-based ES assessments (Eigenbrod et al., 2010; Plummer, 2009). By combining LULC with other EO products, such as NDVI, biomass, or vegetation density, the accuracy of ES assessments can potentially be improved (Andrew et al., 2014). Nonetheless, EO data also contain measurement errors or misclassifications that are often not reported (Ayanu et al., 2012b; Petrou et al., 2015). The valuation of ES further depends on proxies of demand for ES, such as visitor counts or travel-cost estimates (Koetse et al., 2015; Wolff et al., 2015), or social valuation methods such as choice experiments (Brunner et al., 2016; Garmendia and Gamboa, 2012), where subjective judgment plays an important role. Furthermore, when categorical variables (such as LULC) are used, differences in people's definitions of categories lead to linguistic uncertainty (Regan et al., 2002).

A wide variety of approaches is used to link proxies of ecosystem structure to ecosystem services (Lavorel et al., 2017). Most common are proxy based approaches, where expert-based look-up tables are used to link LULC or habitat types to ES provision (Kienast et al., 2009; Seppelt et al., 2011). More complex approaches combine proxies with spatial analyses (e.g. Grêt-Regamey et al., 2014). When sufficient data are available, empirical models are used to predict the distribution of ecosystem service providers (e.g. species, Schulp et al., 2014b) or to derive the link between ecosystem traits and ES (e.g. Lavorel et al., 2011), while process-based models explicitly represent the mechanisms underpinning ecosystem functioning (e.g. Lautenbach et al., 2013). However, uncertainties in model parameters and structure are often not quantified (Schägner et al., 2013), and many ES models are unvalidated due to a lack of validation data (Schulp et al., 2014a). Large discrepancies have been found between LULC-based ES maps and maps based on process-based models (Eigenbrod et al., 2010), highlighting the need to quantify and communicate uncertainties when using ES to support decision-making (Carpenter et al., 2009; Vorstius and Spray, 2015).

In this paper, we use a Bayesian Network (BN) to model avalanche protection, an essential regulating service provided by mountain forests (Grêt-Regamey et al., 2013a). BNs can include both expert knowledge and empirical data, while their transparent graphical structure facilitates participatory modelling (Aguilera et al., 2011; Landuyt et al., 2013).Therefore, BNs have been used to address water management (Ames et al., 2005; Bacon et al., 2002), land use change (Celio et al., 2014; Sun and Müller, 2013), and ES modelling (Gonzalez-Redin et al., 2016; Grêt-Regamey et al., 2013a; Landuyt et al., 2013). The probabilistic structure of BNs allows the quantification and propagation of uncertainties (Barton et al., 2012; Borsuk et al., 2004; Kelly (Letcher) et al., 2013). Accounting for uncertainties is particularly relevant when modelling ES related to natural hazards, where extreme events at the tails of probability distributions are important (Straub and Grêt-Regamey, 2006). We use EO data to model both the provision and demand for avalanche protection, and disentangle the effects of data quality and process understanding on uncertainty in the ES assessment. In addition, we demonstrate how knowledge gaps can be identified and discuss how understanding the sources of uncertainty can help improve ES assessment methods.

4.2 Methods

4.2.1 Bayesian Networks

Bayesian Networks are directed probabilistic graphs, where nodes represent the variables of the studied system, and the links between nodes represent dependencies between them (Kjaerulff and Madsen, 2013). Underlying the graph is a joint probability distribution $P(X) = P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|Pa(X_i))$, which consists of a conditional probability distribution $P(X_i|Pa(X_i))$ of each node (X_i) for each combination of its parent nodes' ($Pa(X_i)$) states. The conditional probabilities are expressed in conditional probability tables (CPTs) or conditional continuous probability distributions. The conditional probability of each node can be quantified independently (Borsuk et al., 2004), which allows us to integrate various data and model types (Uusitalo, 2007), and to account for different types of uncertainty. Evidence on any of the nodes is propagated through the Bayesian network and the joint probability distribution is updated by applying Bayes' theorem: $P(X) = \sum_{Pa(X)} P(X|Pa(X)) * P(Pa(X))$. Evidence on input nodes will therefore result in a new, updated posterior probability distribution of all other nodes in the network.

To efficiently perform inference, most Bayesian Network software relies on algorithms such as the Junction Tree algorithm (Lauritzen and Spiegelhalter, 1988), which are limited to discrete or Gaussian variables. This means that most continuous variables need to be discretized, which can lead to a loss of information (Benjamin-Fink and Reilly, 2017; Landuyt et al., 2013; Ropero et al., 2013). At the same time, using discretized probability distributions means that non-normal or even multi-modal distributions can more easily be captured (Myllymäki et al., 2002; Uusitalo, 2007), and non-linear relationships can be expressed in CPTs. Since increasing the number of discretization intervals exponentially increases the CPTs, the discretization is a trade-off between accuracy and computational efficiency.

4.2.2 Accounting for uncertainty

The probabilistic structure of the Bayesian network allows us to incorporate uncertainty in the input data of the ES model (Cha and Stow, 2014), as well as model uncertainties in the links between variables (Landuyt et al., 2013; Qian and Miltner, 2015). The methods to account for different types of uncertainty in the BN are summarized in Table 4.1. When sufficient data is available to estimate the level of *natural variability*, variables in the modelled system are characterized as probability distributions, instead of single values. For example, the probability of heavy snowfall is commonly modelled using a Gumbel extreme-value distribution (Salm et al., 1990), which we use as the prior probability distribution of "Max new snow height" in the network.

When input data represents a measured proxy with a known error rate, we make the uncertainty explicit by creating separate nodes representing the observed value (Y) and the actual state (X) of the variable. The observation is caused by the actual state, not vice-versa, and defining the structure of the network based on this causality helps to define conditional probabilities. We explain this principle on the example of a land cover classification. *Classification errors* are commonly expressed in confusion matrices, which contain counts of predicted classes for objects where the true class is known (e.g. from ground truth data), with rows representing the classes in reality (c), and columns representing the classes predicted by the classification (c'). Based on these counts, we can calculate either backward probabilities $P(X = c \mid Y = c')$ (e.g. the probability that a patch classified as forest is a forest in reality); or the forward probabilities $P(Y = c' \mid X = c)$ (that a forest patch will be classified as forest). The backward probabilities depend on the prior distribution of land cover – if we sample ground truth locations in a densely forested landscape, it is likely that many of the patches classified as forest will in fact be forested, leading to a higher backward probability than if we sample in a sparsely vegetated area. However, forward probabilities are inherent to the error process in the remote sensing data and the classification algorithm (Cripps et al., 2009), and are therefore consistent over the whole area. If we define the classification node Y as the child of the actual class X, the rows of its CPT correspond to the forward probabilities $P(Y \mid X)$.

For continuous variables with a known *measurement error* rate, we similarly define the measurement node Y as a child of the actual state of the variable X. Assuming a normal distribution of errors, we can define the conditional probability of Y as a normal distribution $p(Y|X = x) = N(x, \sigma^2)$ where the mean is the value of the actual state (x), and the standard deviation σ is defined by the measurement error. If we have no prior information about the actual state of X, a finding on the child Y (measurement) node will then result in a normal distribution $p(X|Y = y) = N(y, \sigma^2)$ of the parent X (actual state).

Bayesian networks can incorporate information about links between variables that is already available in the form of empirical or process-based models. *Empirical models* typically include information about the error in parameter estimates. The model parameters can be included in the BN not as single values, but as distributions, by specifying equations such as $Y = N(\beta_0, \sigma_{\beta 0}^2) + N(\beta_1, \sigma_{\beta 1}^2)* X1 + \ldots + N(\beta_n, \sigma_{\beta n}^2)* Xn$, where $X_1, \ldots, X_n$ are the parent nodes of Y, $\beta_0, \ldots, \beta_n$ are the corresponding model parameter estimates, and $\sigma_{\beta 0}, \ldots, \sigma_{\beta n}$ are the standard errors of the estimates. The conditional probability distribution of Y can be derived by repeatedly computing the value of Y for each combination of its parents', with parameter values sampled from the parameter distributions.

Another approach to quantify links between variables is so-called "parameter learning". When data on a child variable and its parents is available, an algorithm such as Expectation Maximisation (Dempster et al., 1977; Lauritzen, 1995) can be used to estimate the corresponding CPT. When information about links between variables is available in the form of *process-based models*, the model outputs can be used as an input for parameter learning. The uncertainties in the process-based model can be captured by learning from Monte-Carlo simulations with varying input parameters (Ames et al., 2005; Borsuk et al., 2004; Cain, 2001; Kuikka et al., 1999).

When data is limited and no models are available to quantify links between nodes, the CPTs can be elicited from experts. Expert elicitation is frequently used in ecology and risk assessments (Kuhnert et al., 2010; Speirs-Bridge et al., 2010), and uncertainty in *expert knowledge* can be addressed by eliciting probability distributions, rather than single values. While experiments have shown that experts can more accurately estimate quantiles of a distribution than its mean and variance (O'Hagan, 2012), the estimates are often affected by overconfidence (Kuhnert et al., 2010). To limit this problem, Speirs-Bridge et al. (2010) developed the "four-point estimation method", where experts are asked for the lowest and highest value they would expect, the most likely value, and their confidence that the true value is within this range (Metcalf and Wallace, 2013). We thus obtain information about the quantiles and mode of the distribution, as well as its shape, which allows us to fit a suitable distribution (O'Hagan, 2012). Commonly, normal distributions are used (Metcalf and Wallace, 2013). However, in our case the elicited expert estimates (for node "Potential detrainment") showed an asymmetrical unimodal distribution, so we chose to use a simple triangular distribution (Johnson, 1997). Other approaches to quantify uncertainty in expert knowledge involve combining estimates from several experts (O'Neill et al., 2008; for a review of expert elicitation methods see Kuhnert et al., 2010).

Often, expert knowledge is related to qualitative categories rather than quantitative variables. For example, it may be easier for an expert to estimate the avalanche protection capacity of forests that are either "open", "scattered", or "dense", rather than based on a percentage of crown cover. Linking such categories to numerical values is associated with a type of *linguistic uncertainty* (vagueness), where the delineation between categories is not sharp (Regan et al., 2002). Linguistic uncertainty is commonly addressed using fuzzy logic (Zadeh, 1965; Zimmerman, 2001), where membership functions m(y) define the level of membership (between 0 and 1) in a specific class for continuous values of y. For example, we define trapezoidal membership functions m(y) of crown cover (Y) for the classes of forest density (X) (method adapted from Petrou et al., 2013, see Appendix A.2). At the expert-defined threshold between a "scattered" and "dense" forest (Y = 70 %), the probability of the forest being classified as "dense" is 0.5, while a forest with 100 % crown cover will certainly be classified as "dense" (P(X = dense) = 1). In the language of Bayesian Networks, the membership function corresponds to the probability of the class (X) given an observation on Y, $P(X|Y=y)$, and can be used to populate the corresponding CPT. When a class is defined by multiple attributes, membership functions can be combined through fuzzy OR- or AND- operators (Zadeh, 1965), as used by Veitinger et al. (2016) to identify potential avalanche release areas.

Table 4.1: Selection of methods, which can be used to incorporate different types of uncertainty in Bayesian Networks.

Type of uncertainty	**Method to implement in BN**
Natural variability	Probability distribution
Classification error	Confusion matrix
Measurement error	Normal distribution
Empirical model	Probabilistic equations
Process-based model	Learning from Monte-Carlo simulations
Expert knowledge	Four-point estimation method (distribution based on elicited lowest and highest expected value, best estimate, and confidence)
Linguistic uncertainty	Fuzzy logic

There are many methods to quantify uncertainty in the posterior probability distributions of Bayesian Network model outputs. For continuous variables, the spread of a distribution is commonly expressed with its second central moment, the standard deviation. However, standard deviation is less informative for skewed distributions (Landuyt et al., 2015). In information theory, Shannon's entropy (Shannon, 1948) is used to quantify uncertainty in discrete variables: $H = -\sum_{i=1}^{N} p_i \log_2 p_i$, where p_i is the probability of state i and N is the number of states. To evaluate uncertainty and compare it between output nodes with different numbers of states, we calculate the evenness index (Hill, 1973) of the posterior probability distribution, $J = H/H_{max}$, where $H_{max} = \log_2(N)$ (Marcot, 2012). The index has values between 0 and 1, where 1 denotes a uniform distribution between all possible states (maximum uncertainty), and 0 denotes complete certainty that the output node is in a specific state.

4.2.3 Sensitivity analysis and flow of information

In Bayesian Network modelling, sensitivity analysis is often used to evaluate the influence of variables in the modelled system on the posterior probability distribution of a node of interest (Marcot, 2012; Uusitalo, 2007). Sensitivity to findings can be measured by the reduction in uncertainty (e.g. entropy or variance) in the target node due to a finding on another node. Entropy reduction is expressed by the measure of mutual information (Kjaerulff and Madsen, 2013):

$$I(X,Y) = H(X) - H(X|Y) = H(Y) - H(Y|X) = \sum_Y P(Y) \sum_X P(X|Y) \log_2 \frac{P(X,Y)}{P(X)P(Y)}$$

where H(X) is the entropy of X and H(X|Y) is the entropy of X after a new finding on Y.

The analysis of sensitivity to findings gives us an indication of which variables in the system have the highest influence on the outcome of the model. In addition, we use a stepwise sensitivity analysis to visualize the flow of information in the network. For each node X, we calculate the proportion of its entropy that can be reduced by a finding on each of its parents Pa(X), MI[%] = I(X, Pa(X))/H(X). These relative mutual information values are used as weights for links between nodes in a Sankey diagram of the network, which is used to identify the most relevant sources of uncertainty in the model. When findings are added to the network (e.g. setting the value of node Y to state y), this alters the probability distributions and sensitivities of other nodes, and the sensitivity to node Y becomes zero. Therefore, we also perform the stepwise sensitivity analysis for specific combinations of input variables, to identify sources of uncertainty under different conditions.

4.2.4 Case study: avalanche protection

We illustrate the approach to quantify uncertainties in EO-based ES assessments on the example of a regulatory ES, avalanche protection. The case study is located in the region of Davos, in the eastern part of the Swiss Alps. The principal town, Davos, is a well-developed urban and touristic centre, located in the central part of the main valley at an elevation of 1500 m above sea level. The rest of the main valley and the three side valleys are 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 (Kulakowski et al., 2011), and mountain forests play a key role in reducing the risk for settlements below through two main functions: prevention and detrainment. The probability for an avalanche release depends on topography (Bühler et al., 2013; Veitinger et al., 2016), but is lower in forested areas (Bebi et al., 2009). 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 (Feistl et al., 2014; Teich et al., 2014). The anthropogenic value of avalanche protection can be quantified based on the risk to people and buildings (Planat, 2008). Previous ES valuations indicate that avalanche protection is among the most valuable ES in the region of Davos (Grêt-Regamey et al., 2013a).

We based our avalanche protection model on previous models developed for this ES (Grêt-Regamey et al., 2013a; Grêt-Regamey and Straub, 2006), but extended it to incorporate newly available remote sensing inputs as well as recent developments in modelling forest-avalanche interactions. The BN structure (Figure 4.2) was developed through an iterative process of literature review, consultation with experts, and testing the behaviour of the network with different input values. The BN was constructed in Netica (Norsys, 2010), where we also performed sensitivity analyses using the function "Sensitivity to findings".

The data available for modelling the avalanche protection service are in-situ data on the temporal and spatial distribution of avalanches, and remote sensing variables, which are proxies for the actual state of the ecosystem. We accounted for the *spatial variability* of the avalanche process by running the BN for each pixel of a 5 m resolution raster of the study area. We used input data that describe the spatial patterns of the hazard process under a frequent (30-year) and extreme (300-year) scenario ("Velocity 30y" and "Velocity 300y"), where occurrence of both scenarios depends on the probability of heavy snowfall. The *temporal variability* of these events is incorporated through a probability distribution of maximum new snow heights based on long-term observations (SLF, 2017). High resolution LiDAR data (August 2015, LMS-Q780 sensor, ca. 20 points /m2) data was processed using LAStools (Isenburg, 2016) to derive 1 m resolution digital terrain (DTM) and canopy height (CHM) models, to measure crown cover in forests, and to detect buildings. The CHM was combined with an aerial CIR image (August 2013, Leica ADS 80, 0.25 m resolution (swisstopo, 2013)) and a Sentinel2 image from May 2016 (European Space Agency, 2016) for an object-based supervised random forest classification into non-forested areas, evergreen, and deciduous forests (Fassnacht et al., 2016). Ground-truth data was collected at 110 plots in the valley to train the classification and to estimate the *measurement and classification uncertainties* in the remote sensing data.

Ecosystem structure and processes were linked to ecosystem functions using *fuzzy logic* ("Crown cover (class)", "Release", (Veitinger et al., 2016)), *expert knowledge* ("Potential detrainment"), an *empirical model* from literature ("Prevention" (Bebi et al., 2001)) and learning from *process-based* simulation results (Christen et al., 2010) ("Detrainment"). Since the simulation results showed high spatial autocorrelation, we did not perform the learning directly in the BN software, but fitted a spatial regression model in R

(Pinheiro et al., 2017; R Core Team, 2019), and used it to populate the CPT. In order to combine both ecosystem functions, the total per-pixel level of ES provision was expressed in the quantity of snow (prevented from releasing or stopped), which is the ES benefit carrier in this case (Bagstad et al., 2013). To quantify the demand for avalanche protection, we used a probabilistic risk assessment approach (Grêt-Regamey and Straub, 2006), with values of risk factors as determined by experts for evaluating protection measures against natural hazards (BAFU, 2015). At each step, the uncertainties are quantified as described in Section 2.2.

The BN for avalanche protection was applied for the lower Dischma, one of the side valleys of Davos (see Figure 4.1). Using an application based on the Netica API (Celio et al., 2014), we set evidence on nodes where data is available and performed inference for each pixel in a 5 m resolution raster of the study area. Since the provision and demand for avalanche protection do not occur at the same location, and spatial processes could not be modelled in the pixel-based BN, we quantified provision and demand separately. Thus, we obtained posterior probability distributions of avalanche protection provision and demand for each pixel. In order to map the outputs, we calculated the per-pixel median and evenness index (uncertainty) of the posterior probability distributions. To illustrate the process of inference in the BN, we show the joint probability distributions of all variables for some example pixels in Appendix A.4.

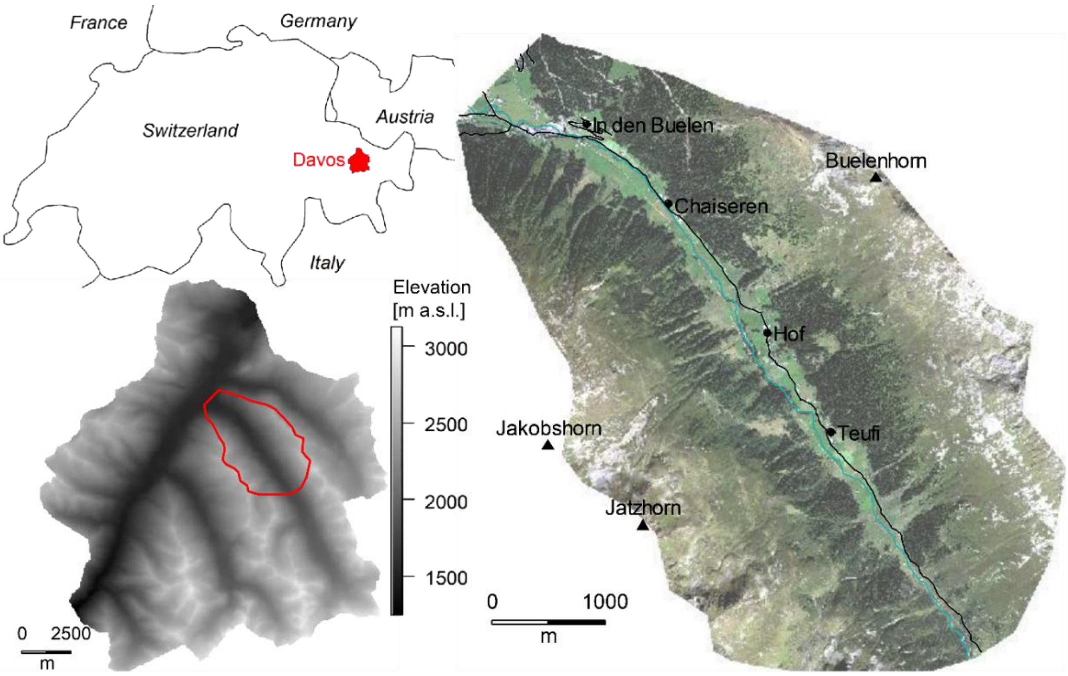

Figure 4.1: Map showing the location of the study area on the DTM of Davos, Switzerland (swisstopo, 2015)*, with an orthophoto of the Dischma valley (swisstopo, 2013).*

4.3 Results

The process of integrating available data, models, and knowledge on the avalanche protection service resulted in a BN with 37 nodes and 53 links, which is shown in Figure 4.2. The inputs to the model are remote sensing variables and in-situ data on avalanches. These are linked to intermediate nodes that describe ecosystem structure, the natural hazard process, and risk assessment. The model outputs are posterior probability distributions of the provision (expressed in height of snow stopped by the forest) and the demand for avalanche protection (expressed in CHF). For forested areas, the model predicts a bimodal distribution of ES provision, with a peak at 0 (corresponding to conditions with no avalanche events) and another between 0.1 and 0.5 m of snow prevented from releasing and/or stopped during avalanches. On average, areas with a predicted value of provision above 0 have a CV of 110 %. Descriptions of the BN nodes and their states are provided in the Supplementary material (Appendix A.1), as well as examples of posterior probability distributions (Appendix A.4) for ES provision and demand.

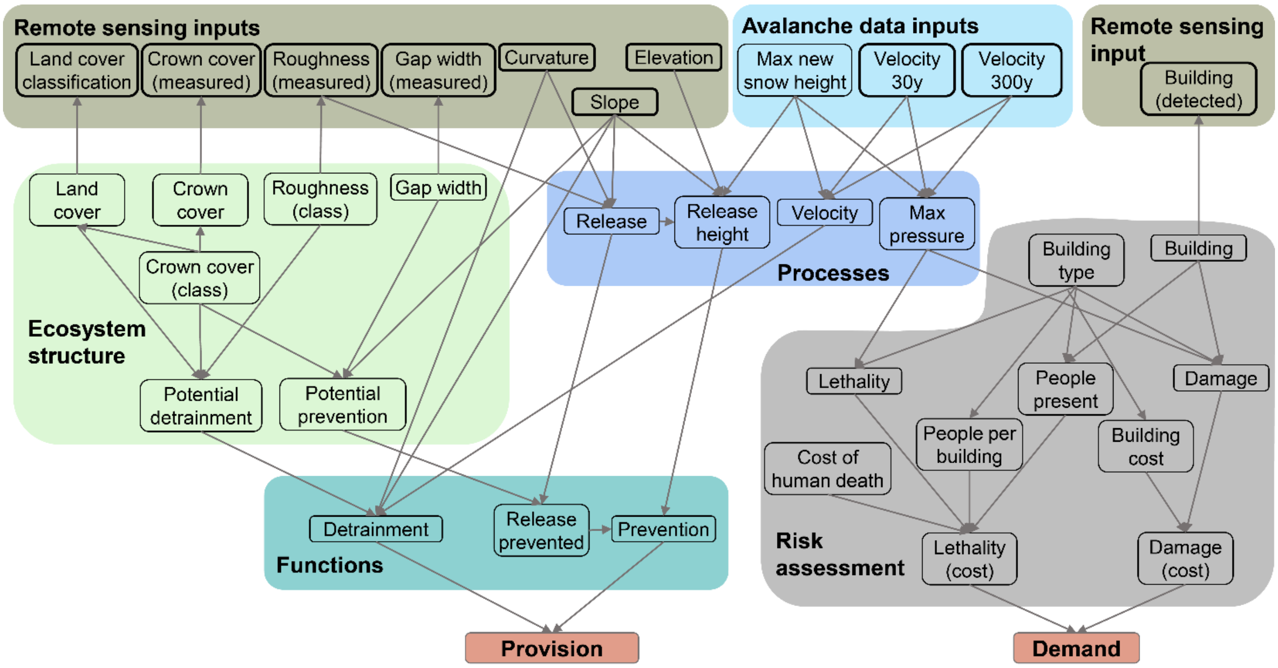

Figure 4.2: Bayesian Network developed to model the ES of avalanche protection. The nodes are grouped and coloured based on the types of variables they represent. Spatial inputs (shown with a thick outline) are remote sensing and avalanche data, which are linked to variables describing ecosystem structure, avalanche hazard processes, ecosystem functions, and risk factors. The outputs of the network are the provision and demand for avalanche protection. Arrows represent causalities, not the flow of information, and are therefore oriented from ecosystem structure variables to the corresponding remote sensing inputs.

The spatially explicit model output of ES provision shows a high spatial heterogeneity (Figure 4.3). Areas with a high level of avalanche protection provision are the steeper, densely forested areas, particularly at high elevations where larger avalanche releases are more likely. Although EO 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 in the provision of the avalanche provision. The uncertainty is related to the level of avalanche protection, where pixels with high levels of provision show high levels of uncertainty. In addition, there are many areas with a low predicted value of avalanche protection provision, but a high uncertainty, indicating that these forests may provide no or only limited avalanche protection under certain infrequent (extreme) conditions. Higher levels of certainty are achieved only in areas with a very low or zero level of protection service.

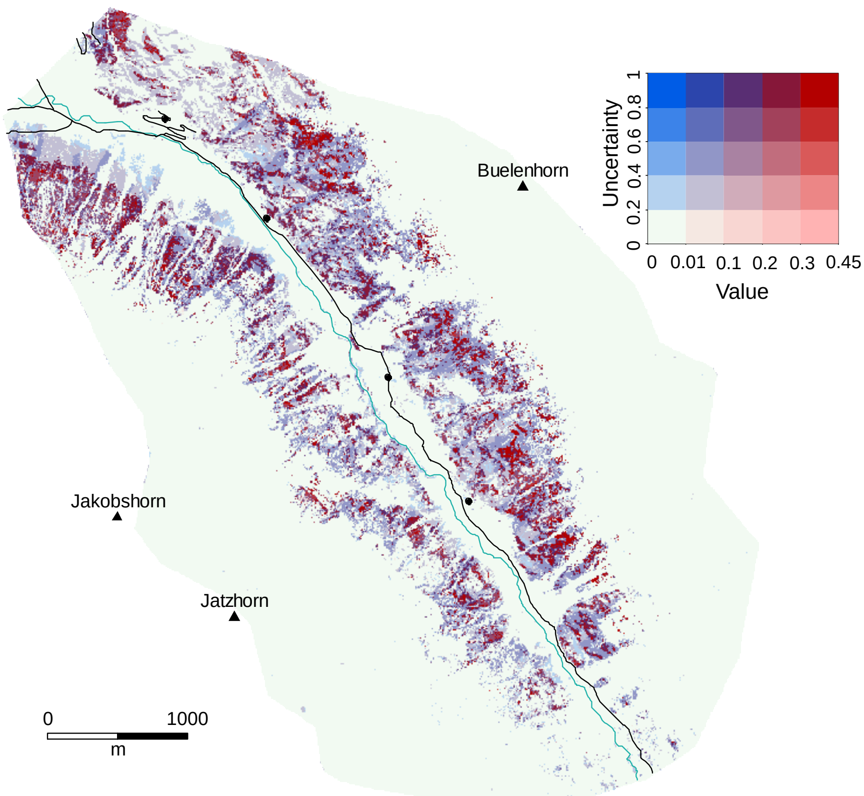

Figure 4.3: Modelled provision of avalanche protection in the Dischma valley (5 m resolution). The value is expressed in m of snow, while the uncertainty is calculated as the evenness index of the posterior probability distribution. Most areas with a high value of the service also have a high uncertainty (dark red), as do some forested areas with a predicted low protection value (dark blue). Only areas with a zero or very low (light blue) value of the service show a high certainty.

The factors underlying the spatial distribution of the ES were analysed using a sensitivity analysis of the target nodes of the BN (Provision and Demand, Table 4.2). Provision of avalanche protection is most sensitive to nodes describing the ecosystem functions and the avalanche process. The modelled provision is more sensitive to inputs of in-situ avalanche data (especially the distribution of maximum new snow height) than to remote sensing variables of ecosystem structure. Among these, the LiDAR-derived crown cover is most important. Since inference can run in different directions in a BN, the sensitivity analysis also shows indirect influences. For example, knowledge about potential lethality of avalanches on a specific pixel would increase the knowledge about the potential provision of avalanche protection at that location. On the demand side, the most influential node is the cost of damage to buildings, while the most important input are buildings detected from LiDAR.

Overall, the nodes closer to the target variables have a stronger influence than nodes farther away. This is due to uncertainty in the intermediate links. For example, detecting a building from remote sensing (MI = 49.6 %) has a smaller effect on the distribution of demand than certain knowledge of a building's location would (MI = 60.8 %). Similarly, certain knowledge of the actual land cover (MI = 4.98 %) would more strongly reduce the uncertainty about provision than the land cover classification does (MI = 1.42 %), because there is some uncertainty in the classification. In order to understand these relationships in more detail, we performed a stepwise sensitivity analysis.

Table 4.2: Sensitivity analysis of the output nodes of the Bayesian Network for avalanche protection. The values of mutual information MI [%] indicate how much a finding on a node would reduce the uncertainty (entropy) on the target node. All nodes with MI > 0 are shown. The nodes are grouped by type, and sorted by their influence on the target nodes.

Sensitivity - Provision		
Group	**Node**	**MI [%]**
Function	Detrainment	77.2
	Prevention	19.7
	Release prevented	14.2
Process	Velocity	38.1
	Max pressure	37.7
	Release height	13.2
	Release	7.57
Avalanche	Max new snow height	24.1
	Velocity 30y	5.46
	Velocity 300y	0.45
Ecosystem structure	Potential detrainment	5.73
	Crown cover (class)	5.32
	Land cover	4.98
	Crown cover	4.06
	Potential prevention	2.49
	Gap width	1.3
	Roughness (class)	1.01
Remote sensing	Crown cover (Lidar)	3.7
	Roughness (measured)	2.49
	Land cover classification	1.42
	Slope	1.39
	Gap width (measured)	1.28
	Elevation	0.26
	Curvature	0.03
Risk	Lethality	9.17
	Damage (cost)	0.05
	Damage	0.05
	Lethality (cost)	0.01
Target	Demand	0.05

Sensitivity - Demand		
Group	**Node**	**MI [%]**
Risk	Damage (cost)	96.1
	Damage	88.4
	Building	60.8
	People present	16.8
	Lethality (cost)	10.7
	Building cost	7.72
	Lethality	5.16
	Building type	3.53
	People per building	3.33
Remote sensing	Building (Lidar)	49.6
Process	Max pressure	18.2
	Flow velocity	18.1
	Release height	0.50
Avalanche	Max new snow height	12.4
	Velocity 30y	2.79
	Velocity 300y	0.23
Function	Detrainment	10.3
	Prevention	0.17
Target	Provision	9.66

The results of the stepwise sensitivity analysis are visualized in a Sankey diagram (Figure 4.4). For each node, the thickness of incoming (from the left) links show how much the entropy on the node can be reduced by findings on preceding nodes. Mutual information is not additive, i.e. if both parent nodes can reduce the entropy 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, this means that the node will have a wide probability distribution even when the states of its parents are known, implying high uncertainty in the corresponding links. If such a node has a large influence on the outcome of the network, this indicates a knowledge gap.

Overall, the uncertainties related to avalanche processes contribute more to the final uncertainty in ES provision than uncertainties about ecosystem structure. 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 findings on its parents ("Slope", "Roughness (measured)" and "Curvature") can only reduce a small part of its entropy, so it is a major source of uncertainty in the model. Some remote sensing inputs have a strong effect on the knowledge about ecosystem structure ("Gap width" and "Crown cover"), while others have higher uncertainty (e.g. "Roughness"). There is high uncertainty in land cover classification, as its mutual information with actual land cover is only 29 %. However, additional information on actual land cover is gained from the crown cover class (MI = 59 %). The links from ecosystem structure to the potential provision of ES also contain high uncertainty, regarding both the potential of a forest to prevent avalanches (empirical model-based "Potential prevention") and to stop snow during an avalanche (expert-based "Potential detrainment"). However, "Potential detrainment" has a relatively low influence on the corresponding ecosystem function (process model-based "Detrainment"). This function is affected more strongly by the avalanche process ("Velocity"), which in turn is affected by the natural variability in release conditions ("Max new snow height").

On the demand side (Appendix A.3), the remote sensing input ("Building (detected)") is rather certain, while uncertainty about the total risk is most affected by the natural variability of the avalanche process. Additionally, uncertainty comes from the wide distribution of building types, which affect the costs of potential damages and number of people per building, and which could not be differentiated in the remote sensing input.

The sensitivities of the BN change after we enter evidence, and are therefore different for each combination of input nodes. Nonetheless, the general pattern remains the same with high uncertainties related to the avalanche processes, due to natural variability and model uncertainty. Furthermore, the uncertainty about ES provision would be significantly reduced by additional knowledge on avalanche release areas ("Release" node). Examples of sensitivities for posterior probability distributions (after input data are added to the network) are shown in Appendix A.4 for one pixel of ES provision and demand.

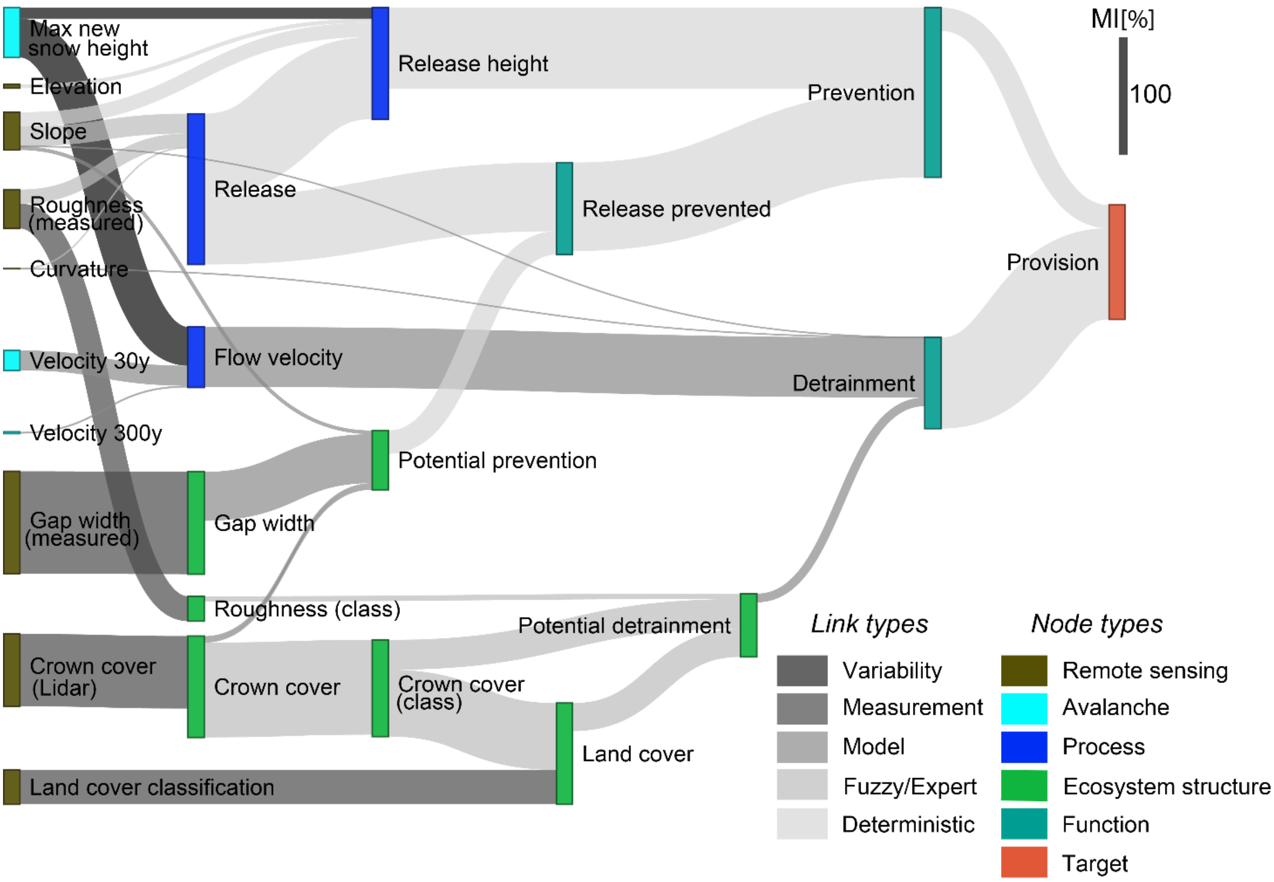

Figure 4.4: Stepwise sensitivity analysis of the BN, where the width of a link between two nodes corresponds to the relative mutual information (MI %), i.e. the percentage of the entropy on a node that can be reduced by a finding on a preceding node. The nodes are labelled and coloured by the type of variable represented (see Fig. 2), while the link colours represent the types of uncertainty taken into account while quantifying the link in the BN.

4.4 Discussion

4.4.1 Uncertainties in avalanche protection

In this study, we used recent developments in EO techniques and natural hazard modelling to assess avalanche protection by forests, an important ES in mountain regions. We integrated EO data, empirical and process-based models, and expert knowledge into a BN, while accounting for the uncertainty in each of these components. Thus, we were able to quantify the total uncertainty in the ES assessment, and evaluate the influence of different sources of uncertainty on the model output. Although high-resolution EO data was available in our study area, uncertainties in the ES assessment remain high (with a coefficient of variation well above 100 %). While there was some uncertainty in the EO products used, these had a limited effect on the final model output. The total uncertainty was more strongly affected by the uncertainties regarding avalanche processes, particularly the variability of snow heights, the probability of avalanche releases, which was defined using a fuzzy approach based on expert knowledge (Veitinger et al., 2016), and avalanche velocities and detrainment in forests, which were quantified based on a process-based model (Christen et al., 2010). These uncertainties can be explained in part by the high natural variability of avalanche hazards, related to complex terrain and temporal variability in snow and weather conditions (Schweizer, 2008). In addition, currently available avalanche models and expert knowledge are based on limited observational data (Bühler et al., 2009), which contributes to high model uncertainty.

4.4.2 Added value of Earth Observation data

By combining different EO inputs (high-resolution LiDAR, aerial, and satellite multispectral images), we could include more information at a higher spatial resolution compared to previous ES assessments in the region, which relied mainly on LULC data (Grêt-Regamey et al., 2013a). We were able to differentiate tree species and measure terrain roughness, both of which have an impact on ecosystems' potential to provide avalanche protection (Feistl et al., 2014; Teich and Bebi, 2009). The use of EO data enabled us to model the ES at a 5 m spatial resolution, which allows us to observe the high spatial heterogeneity of ES provision in complex terrain, and identify individual forest stands that are particularly important for avalanche protection.

However, the EO products used, particularly the land cover classification, contained considerable uncertainties. High error rates are common in classifications, for example, tree species classifications often report error rates of around 20 % (Fassnacht et al., 2016). Since errors are propagated to the final model output, it is crucial for EO-product users that these uncertainties are reported (Petrou et al., 2015; Rocchini et al., 2010). Uncertainties in EO are spatially heterogeneous, so they should be reported spatially (e.g. per pixel), which can be achieved by using fuzzy classifications (Petrou et al., 2013) or random forest classifiers (Breiman, 2001) that provide a probability distribution of classes for each classified pixel. Although most ES assessments rely on LULC classifications, their quality could be further improved by including other EO-based ecosystem properties (Cord et al., 2017). For example, we were able increase the certainty about actual land cover by including information on LiDAR-based crown cover measurements.

Nonetheless, even if errors in EO data could be reduced, uncertainties in the avalanche protection assessment would remain high, due to natural variability, model uncertainty, and limited data availability. This can be generalized to models of other ES, where complex socio-ecological systems are modelled (Hou et al., 2013) with limited data on ES for model calibration and validation (Landuyt et al., 2013; Schulp et al., 2014a). To address this issue, EO data should be used not only as a model inputs, but also to calibrate, validate, and update our models of socio-ecological systems (Plummer, 2000). For example, the data used to validate avalanche models (Christen et al., 2010, Veitinger et al. 2016) is mostly limited to individual observations in the field. Detecting avalanches and their release areas from remote sensing (Bühler et al., 2013, 2009) could increase the dataset available for model calibration and validation, thus reducing model uncertainties.

4.4.3 Advantages and limitations of the Bayesian Network approach

A major advantage of Bayesian Networks as a tool for ecosystem services modelling is their probabilistic nature (Kelly (Letcher) et al., 2013), which allowed us to quantify different types of uncertainty in the ES assessment. An additional type of uncertainty that we did not explicitly address is structural uncertainty, which relates to the selection of variables relevant to the model, and the causal relationships between them (Ascough et al., 2008). Unlike model parameter uncertainty, structural uncertainty is difficult to quantify, particularly when validation data is lacking (O'Hagan, 2012), so it is often not discussed, or only evaluated through expert assessment (Uusitalo et al., 2015). BNs can facilitate discussions about model structure with experts through the graphical representation of the variables and causalities in the network (Barton et al., 2012; Bromley, 2005; Landuyt et al., 2013; Voinov et al., 2016). The stepwise sensitivity analysis supports this by visualizing the strength of the causal relationships, and identifying nodes with large uncertainties, which may indicate that important variables are missing from the model.

Although the spatially explicit BN can capture uncertainties at the level of an individual pixel, it is not able to take into account spatial interactions (Landuyt et al., 2015). This is a major limitation in ES modelling, where spatial mismatches and cross-scale effects are common (Bagstad et al., 2013). For example, linking ES provision to demand would require integrating the provision across service-providing areas (Villa et al., 2014), in this case avalanche tracks. This requires a spatial analysis that cannot be performed within the BN, so information about probability distributions is lost. Johnson et al. (2012) address this issue by using stochastic agent-based models to map the flow of ecosystem services. In some cases, accounting for spatial interactions could also help reduce uncertainties. For example, a pixel is more likely to be in an avalanche release area if the area is large (Bühler et al., 2013), i.e. if neighbouring pixels also have a high probability of release. Such interactions cannot be modelled directly in a BN, but could potentially be addressed in two steps, by calculating release probabilities for individual pixels, and then correcting them based on the number of surrounding pixels with probabilities above a certain threshold. However, such fuzzy neighbourhood approaches depend on arbitrary threshold probabilities (Arnot et al., 2004), neglecting the full information about pixels' probability distributions.

4.4.4 Disentangling uncertainties in ES assessments

By performing the stepwise sensitivity analysis, we were able to identify the components of the ES model where uncertainties are high, and where these uncertainties have a strong impact on the ES assessment. Identifying such knowledge gaps could help define research priorities. In the case of avalanche protection, the uncertainties with the highest influence on the model output are related to the natural hazard process, both in nodes that were quantified through expert knowledge (e.g. the fuzzy definition of avalanche release areas), and those based on models (e.g. the process-based model used to quantify avalanche velocities and detrainment). improved identification of potential avalanche release areas under varying snow conditions (Bühler et al., 2013; Veitinger et al., 2016) would significantly reduce uncertainties about the ES, while more sophisticated methods of forest type classification would have only a minor impact on the model output. For other ES, where the underlying processes are better understood (e.g. food production or carbon sequestration), improved EO inputs could significantly improve ES assessments (Andrew et al., 2014; Feng et al., 2010). Applying the same approach to disentangle uncertainties for other ES would also help determine whether some methods of quantifying links between variables systematically produce higher uncertainties (e.g., are expert assessments more uncertain than process-based simulations).

Quantifying uncertainties is also important for potential users of ES assessments (Carpenter et al., 2009; Polasky et al., 2011), who face trade-offs between model accuracy and time/data requirements (Vorstius and Spray, 2015). Their decisions on which models and data to use require information on the associated uncertainties, and how they propagate to the final ES maps (Neuendorf et al., 2018). Moreover, mapping uncertainties can improve model understanding and the credibility of the modelling results (Grêt-Regamey et al., 2013a), and may affect the decision-making process (Kunz et al., 2011; MacEachren et al., 2005). Identifying the uncertainties that can be reduced through better models and data, as well as understanding the uncertainties that are inherent to the system, could lead to more robust decisions about ES management (Ascough et al., 2008; Brunner et al., 2017).

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5 Paper II: An online platform for spatial and iterative modelling with Bayesian Networks

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Abstract

Bayesian Networks (BNs) are commonly used to model socio-ecological systems, as their graphical structure supports participatory modelling, they can integrate quantitative data and qualitative knowledge, and account for uncertainty. Although the spatial and temporal dimensions are important in socio-ecological systems, there is a lack of openly available and easy-to-use tools to run BNs with spatial data over time. Here, we present gBay (gbay.ethz.ch), an online platform where users can link their BNs to spatial data, run the network iteratively to incorporate dynamics and feedbacks, and add geo-processing calculations to account for spatial interactions. We demonstrate the use of this tool on the examples of a modelling a regulating ecosystem service, where we account for neighbourhood effects, and land-use decisions, where we include regional-level boundary conditions. The gBay platform supports users with its graphical interface and instructive wiki page, and provides a step towards more accessible and flexible socio-ecological modelling.

Keywords: Bayesian Networks; online tool; ecosystem services; land-use decisions; spatial interactions

Software availability

Name:	gBay (Bayesian Networks with geo-data)
Developed by:	Orencio Robaina, Enrico Celio, Ana Stritih, Sven-Erik Rabe (ETH Zürich, PLUS)
Availability:	online at gbay.ethz.ch, free for non-commercial use
Software requirements:	Netica (Norsys) or similar software to create Bayesian Networks
Programming language:	Web interface in HTML/Javascript, back-end in C using the Netica API, Python to support intermediate processing scripts.
Source code:	https://github.com/ethzplus/gbay

Instructions and examples available at wiki.gbay.ethz.ch

5.1 Introduction

As ecosystems undergo changes that jeopardize their capacity to provide essential services to society (Cardinale et al., 2012; Foley et al., 2005), natural resource managers and landscape planners face challenging decisions on sustainable landscape development (Wu, 2013). Modellers aim to support these decisions, e.g. through mapping ecosystem services and assessing trade-offs between them (Carpenter et al., 2009), or predicting scenarios of future land use (Carpenter et al., 2015; Verkerk et al., 2018). However, modelling complex socio-ecological systems requires integrating various types of information (Hamilton et al., 2015a), such as Earth Observation and in-situ data, empirical or process-based models, and socio-economic data. Models are often associated with high uncertainties, due to both the inherent variability of socio-ecological systems and the common lack of data (Ascough et al., 2008; Ropero et al., 2013). At the same time, local experts and stakeholders often have valuable knowledge about their socio-ecological systems, and involving them in the modelling process facilitates communication and learning (Ruckelshaus et al., 2015; Voinov and Bousquet, 2010). Involving stakeholders and producing credible results that can support decision-making requires a flexible and transparent modelling process (Jakeman et al., 2006; Voinov et al., 2016).

An increasingly common approach to deal with these challenges is the use of Bayesian Networks (BNs), directed graphs where variables are linked through conditional probabilities (Bruce G Marcot and Penman, 2019). Key advantages of BNs include their capacity to integrate qualitative and quantitative information, their explicit treatment of uncertainty, and their graphical structure (Uusitalo, 2007). The graphical structure of a BN represents causalities in the modelled system, which increases modelling transparency in comparison to black-box (e.g. empirical) models (Jakeman et al., 2006), and facilitates communication with stakeholders (Voinov and Bousquet, 2010). For example, co-developing BNs with stakeholders has been used to address ambiguities in water management (Henriksen et al., 2012) and to build a common understanding of an agricultural socio-ecological system (Salliou et al., 2017). A BN of forest ecosystem services provided a common language for experts from different fields, thus supporting planning (Gonzalez-Redin et al., 2016).

Different types of information can be integrated in a BN, since the links between variables in a BN can be quantified individually (Borsuk et al., 2004). Often, information on some components of the modelled system is already available in the form of empirical and process-based models, which can be translated to conditional probabilities (Borsuk et al., 2004; Stritih et al., 2019a). BNs can also learn relationships between variables directly from data (Stelzenmüller et al., 2010), such as remote sensing (Dlamini, 2010), water quality measurements (Ames et al., 2005), or species observations (Hamilton et al., 2015b). When data are scarce or unavailable, they can be supplemented with expert knowledge (Ames et al., 2005; Borsuk et al., 2004; Hamilton et al., 2015b; Pollino et al., 2007).

The probabilistic structure of BNs means that uncertainties are explicit and propagated through the network. Socio-ecological systems are inherently complex and variable, leading to high uncertainties that are exacerbated by limited data availability (Regan et al., 2002). It is particularly important to consider these uncertainties in risk assessments, where unlikely extreme events are relevant (Grêt-Regamey and Straub, 2006; McDonald et al., 2016). BNs can be used to identify knowledge gaps (Hamilton et al., 2015b; Stritih et al., 2019a), and can easily be updated as soon as new information becomes available (Hamilton et al., 2015b).

In environmental applications, the spatial and temporal components are often crucial (Carpenter et al., 2009). The spatial composition of ecosystems and land use in landscapes is essential to their function, and needs to be taken into account when trying to understand landscape change or identify trade-offs or synergies between ecosystem services (Nelson et al., 2009; Raudsepp-Hearne et al., 2010). Therefore, models of socio-ecological systems are often spatially explicit. Spatially explicit BNs, where the network is linked to a raster, have been used to model scenarios of future land use (Carpenter et al., 2015; Celio et al., 2014) and map ecosystem services (Gonzalez-Redin et al., 2016; Grêt-Regamey et al., 2013a; Landuyt et al., 2013; Villa et al., 2014). The temporal dimension has been addressed less frequently in BN-modelling, as BNs are most commonly static, and the construction of dynamic BNs is often seen as cumbersome (Uusitalo, 2007). Dynamic BNs use the "time-sliced" approach (Kjaerulff and Madsen, 2013), where each variable of the system is represented by a separate node in each time step, resulting in a copy of a network for each time slice, with temporal links between these iterations. This approach can be used to model landscape changes over time (Chee et al., 2016).

In most spatial applications of BNs so far, the models have been run for every individual pixel of a raster. A major limitation of this approach is that is fails to take into account spatial interactions (Landuyt et al., 2015; Stritih et al., 2019a) and cross-scale effects, which often have an important influence both on ecological and socio-economic processes (Peters et al., 2007). For example, a habitat is only suitable for a species if it is large enough to support a viable population or connected to other habitats. Farmers' decisions to cultivate a parcel of land may depend on the decisions of other farmers or an overarching policy that prescribes certain amounts of ecological set-aside to be eligible for subsidies (Celio and Grêt-Regamey, 2016). In case of ecosystem services such as flood protection or pollination, the provision and demand for the services do not occur at the same location (Bagstad et al., 2013), and the provision of services is related to the spatial composition of ecosystems in the landscape (Grêt-Regamey et al., 2014; Syrbe and Walz, 2012). Therefore, interactions across space at different levels should be taken into account when modelling socio-ecological systems.

Several tools have been developed to run BNs with spatial data (see Table 5.1), but most do not explicitly support iterative inference over time, feedback loops, or spatial interactions. For such more complex applications, modellers typically use the API of common BN software packages such as HUGIN or Netica (Pérez-Miñana, 2016) to link their BNs to spatial data (Celio et al., 2014; Chee et al., 2016; Grêt-Regamey et al., 2013a; Sun and Müller, 2013). However, there is a lack of openly available and easy-to-use tools (i.e. including a graphical user interface), which would allow users to run spatially explicit BNs over multiple time steps.

In this paper, we present gBay, an online platform with a simple graphical interface that links BNs to spatial data. Users can run their BNs iteratively, over multiple time steps, with raster or vector data. In addition, the platform includes the possibility to account for spatial interactions, such as neighbourhood effects. We describe the architecture of the platform and its use. Furthermore, we illustrate how accounting for effects at different spatial scales, such as neighbourhood effects and regional boundary conditions, can help improve the realism and reduce uncertainties in models of ecosystem services and land-use change. We discuss the advantages of BNs and the gBay platform, as well as the limitations of this modelling approach and ongoing challenges.

Table 5.1: Overview of existing tools for spatial Bayesian Network applications.

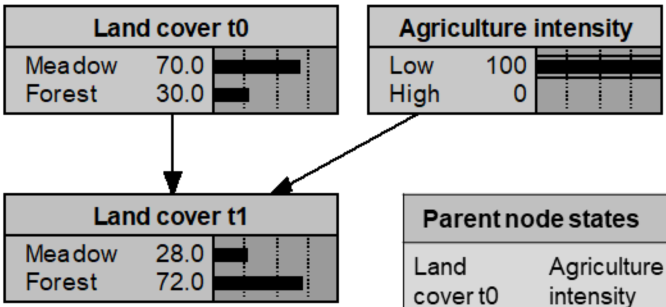
Tool	**GUI**	**Requirements**	**Data type**	**Dynamics/ Feedbacks**	**Spatial interactions**	**Development ongoing**	**Availability**	**Publications**
GeoNetica	Yes	Netica	Raster	No	No	Yes	Commercial https://www.norsys.com/WebHelp/NETICA/X_GeoNetica.htm	Mayfield et al., 2018
PMAT (Probabilistic Map Algebra tool)	Yes	QGIS and Netica	Raster	No	No	No	Open https://github.com/DriesLanduyt/PMAT	Landuyt et al., 2015
Bnspatial R package	No	R	Raster	Potentially	No	Yes	Open http://github.com/dariomasante/bnspatial	Masante, 2019
GeoBUGS	No	WinBUGS	Vector	Yes	Partially (spatial autocorrelation)	No	Open https://www.mrc-bsu.cam.ac.uk/software/bugs/the-bugs-project-winbugs/	Thomas et al., 2004

5.2 Methods

5.2.1 Bayesian Networks

A Bayesian Network is a directed, acyclic graph with an underlying joint probability distribution (Jensen, 2001; Kjaerulff and Madsen, 2013; Pearl, 1988). It consists of **nodes** representing variables, each with a set of mutually exclusive states. The states of a node can be categorical (e.g. land use types) or quantitative (e.g. the distance to the nearest forest). The **links** between nodes represent the (directed) causal relationships or dependencies between these nodes (e.g. X→Y). The **joint probability distribution** P(X, Y) of the nodes is condensed in **conditional probability tables** (CPTs), which contain the probability distribution of each node for each combination of its parent nodes' states. The probability that node Y is in state y can be calculated by summing its conditional probabilities over the states x of its parent nodes: $P(Y = y) = \sum_x P(Y = y \mid X = x) * P(X = x)$, in a process called marginalization (Kjaerulff and Madsen, 2013).

Figure 5.1 shows an example of a BN, which predicts land-cover change in a system where meadow abandonment leads to forest encroachment. The future land cover (LC_t1) is a child node of the current land cover (LC_t0) and the intensity of agricultural use. The causal relationships between the nodes are quantified in the CPT of node LC_t1, which specifies the belief that the future land cover will be either a meadow or a forest for each combination of the states of its parent nodes.



Parent node states		P(Land cover t1)	
Land cover t0	Agriculture intensity	Meadow	Forest
Meadow	Low	**0.4**	0.6
Meadow	High	0.8	0.2
Forest	Low	**0**	1
Forest	High	0	1

$$P(Y = y) = \sum_{x} P(Y = y|X = x) \cdot P(X = x)$$

$$\begin{aligned} &P(LC\_t1 = meadow) = \\ &P(LC\_t1 = meadow \,/\, LC\_t0 = meadow, agr\_int = low) \cdot P(LC\_t0 = meadow) + \\ &P(LC\_t1 = meadow \,/\, LC\_t0 = forest, agr\_int = low) \cdot P(LC\_t0 = forest) = \\ &(0.4 \cdot 0.7) + (0 \cdot 0.3) = 0.28 \end{aligned}$$

Figure 5.1: Example of a simple Bayesian Network representing land cover change, where the future land cover (LC_t1) is a child node of the current land cover (LC_t0) and agriculture intensity (agr_int), with the corresponding conditional probability table (CPT). In this network, hard evidence has been added to the node 'agriculture intensity' and soft evidence to the node 'land cover t0'. Marginalization is used to calculate the posterior probability that the future land cover is a meadow P(LC_t1 = meadow), with the corresponding probabilities in the CPT shown in bold.

Once the BN is compiled, it can be updated for specific cases by adding evidence. **Evidence** can be data (e.g. when we know the type of land cover in a pixel) or scenarios (e.g. when we explore what happens in a system if agricultural use changes). When we know the state of a node with 100% certainty, this is called **hard evidence** (e.g. that the agricultural intensity of a pixel is low), while **soft evidence** contains some uncertainty and is in the form of a probability distribution (e.g. our observation indicates that the land cover is a meadow with 70% probability and a forest with 30% probability).

When evidence is added to the network, the joint probability distribution is updated through a process called inference, which results in a **posterior probability distribution** (PPD) of all the nodes in the network, thus providing information about the expected (most likely) state of target nodes, as well as the associated uncertainty (Jensen, 2001). Evidence can also be propagated along a chain of nodes (e.g. X→Y→Z) according to the chain rule: P(X, Y, Z) = P(Z|Y) * P(Y|X) * P(X), and from child nodes to parent nodes. For example, in the network in Figure 5.1, knowledge about current land cover could be used to infer the past land cover.

5.2.2 Coupling BNs and spatial data with gBay

Here, we present gBay (**Bay**esian Networks with **g**eo-data), an online tool to link a BN to spatial data and run a process over multiple time steps. Figure 5.2 illustrates the functionalities of the gBay platform. Spatial data is used as evidence on specific nodes in a BN. Inference is then performed for each pixel or object of the input data, where the output is a probability distribution across the possible states of target nodes for each spatial unit. The outputs of inference can be used as inputs in the next iteration to account for temporal dynamics (see Section 2.3). In addition, spatial inputs or outputs can be processed with a Python script to account for spatial interactions at different scales (see Section 2.4).

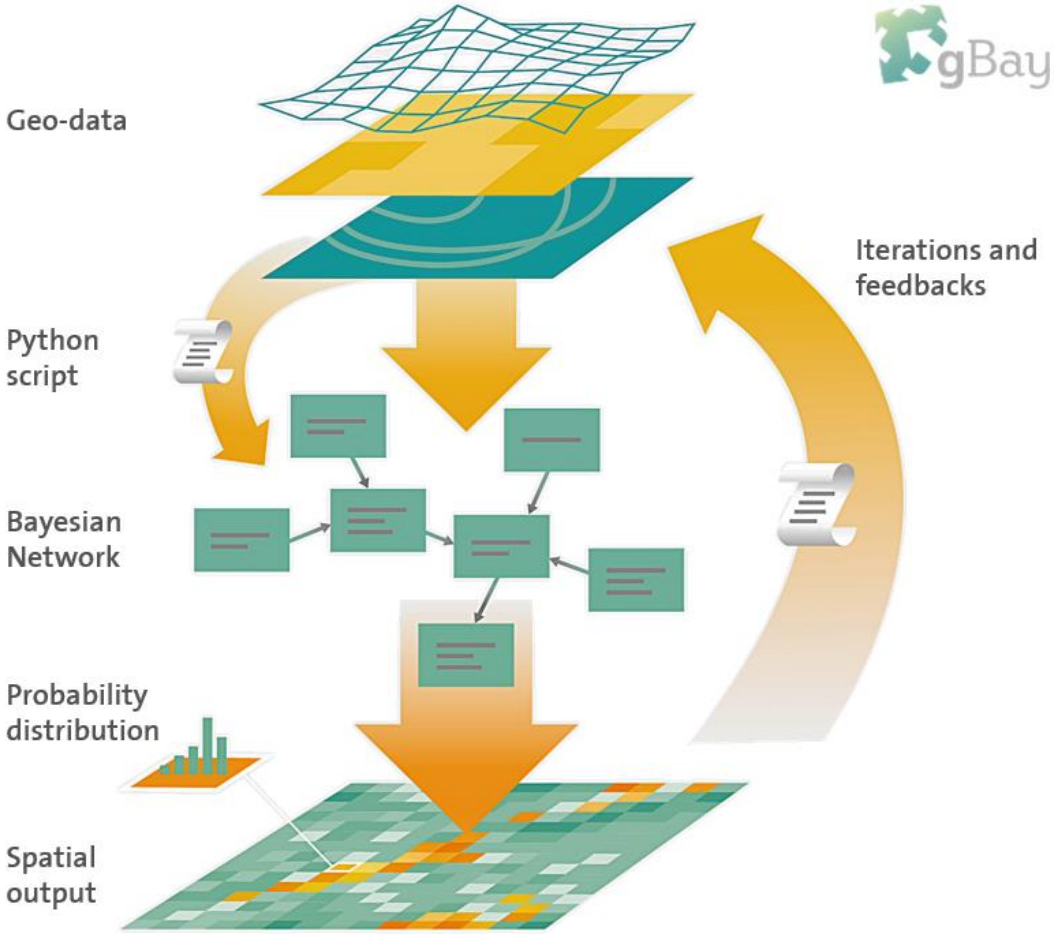


Figure 5.2: Conceptual model of the gBay platform. Spatial inputs can be used as direct inputs to a BN, or processed using a Python script. The output of the BN is a spatial dataset with a probability distribution for each pixel or object. The output can be an input to the next time step in an iterative BN, to incorporate dynamics and feedbacks.

The gBay platform consists of an online graphical user interface (Figure 5.3) where the users can upload a network (in the .dne format), developed in Netica or a similar BN software. The uploaded network is visualized in the GUI, where users can select one or more “target nodes”, the PPD of which they wish to calculate. Spatial data can be added to the network in the form of raster (a GeoTIFF file for each input node) or vector files (a shapefile or geodatabase, with attributes corresponding to input nodes) by dragging the file to the designated location in the network or by using the menu provided for each node. gBay can take into account both hard and soft evidence (see Table 5.2). To set hard evidence, the input raster (or attribute table of the vector data) contains only one value per pixel (or object). For soft evidence, the input raster or vector file has a band (or attribute) for each state of the input node. In addition, users can set non-spatial hard or soft evidence (for the whole area) by simply clicking on the state of the node or entering the soft evidence probabilities. All configurations (links, iterations, hard and soft evidence) including the corresponding geo-data can be saved and reloaded later if necessary.

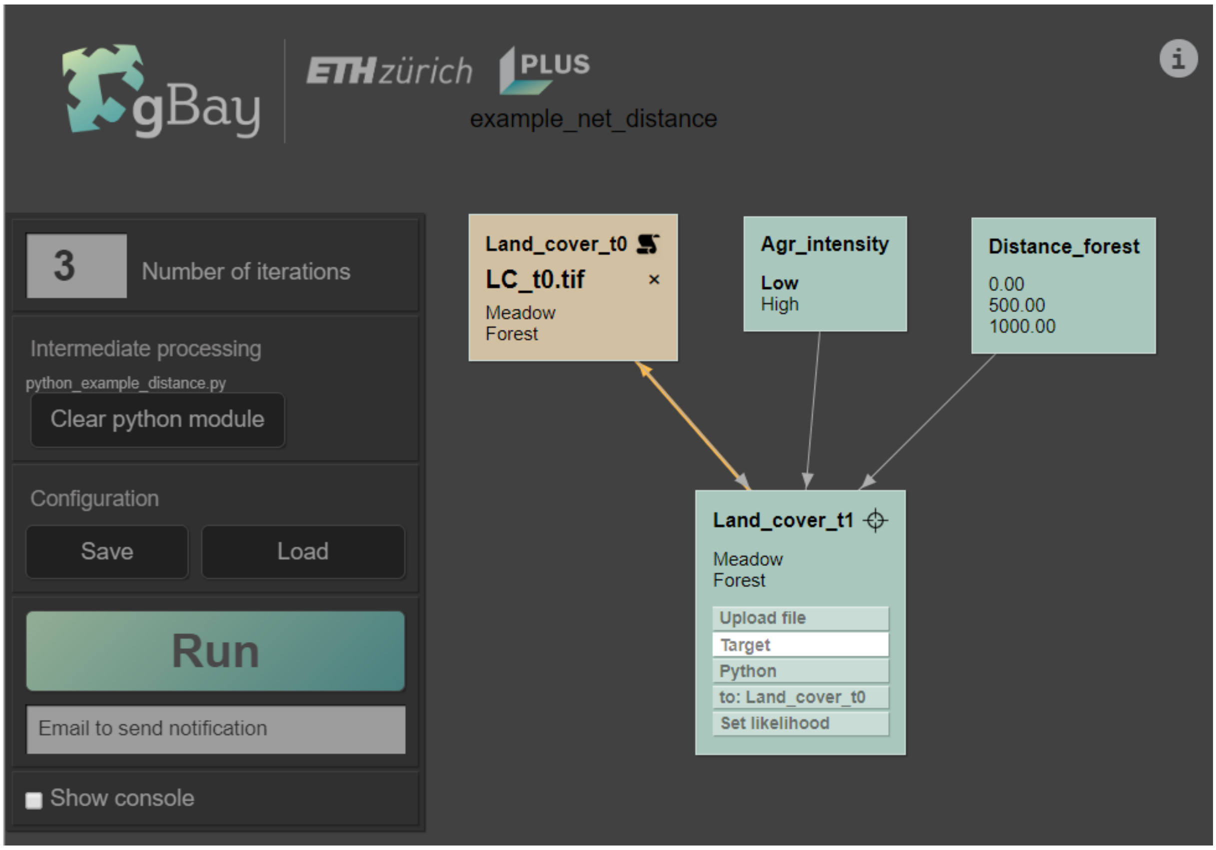


Figure 5.3: The gBay interface, where the uploaded BN is visualized. The orange-coloured nodes indicate that spatial data has been added as evidence, and the names of the datasets are displayed. Icons next to the node names indicate the target nodes and nodes used in the intermediate processing Python script. When hovering over a node, a set of options appear (to upload a file with spatial evidence, set the node as a target, use it in a Python script, link it to another node across time steps, or set soft evidence – likelihood). In this case, 'land cover t1' is linked across time steps to 'land cover t0' (indicated with an orange arrow). In the panel on the left, the number of iterations can be specified, and a Python script can be uploaded. The configuration (the network, evidence, spatial data, target nodes, intermediate processing options) can be saved and re-loaded. For long processing times, users can receive a link to their results via email in case of a browser timeout. The console can be viewed in order to monitor the processing.

The output has the same geometry as the input spatial files, and contains the probability of each state of the target node for each spatial unit (i.e. the whole PPD in a multi-band raster or attribute table), as well as information about the most likely state. In addition, Shannon's evenness index of the PPD is calculated: $J = H/H_{max}$, where $H = \sum_{i=1}^{N} p_i \cdot log_2 p_i$, $H_{max} = \log_2(N)$, where p_i is the probability of state i and N is the number of states. The index is a standardized measure of entropy, which expresses uncertainty and can be compared between nodes with different numbers of states (Marcot, 2012). It has values between 0 and 1, where 1 denotes a uniform distribution between all possible states (maximum uncertainty), and 0 denotes complete certainty about the state of the node. For continuous target nodes, the output additionally contains information about the mean, median, and standard deviation of the PPD.

Table 5.2: Overview of spatial inputs and outputs for the gBay platform. The inputs can be in raster or vector form, and may represent hard evidence (certain knowledge of a node's state) or soft evidence (a probability distribution), while the outputs represent the whole probability distribution across the states of the target nodes.

<table>
<tr><th></th><th>Input format</th><th>Input values</th><th>Output</th></tr>
<tr><td rowspan="2">Raster</td><td rowspan="2">.tif file per input node (same resolution and extent)</td><td>Hard evidence:
Single-band raster of the known value of a node (discrete or continuous)</td><td rowspan="2">target.tif:
Multi-band raster of the probability distribution across the states of the target node:

band 1: probability of state 1
band 2: probability of state 2
…
band n: probability of state n
band n+1: most probable state

target_stats.tif:
band 1: Evenness index
For continuous nodes:
band 2: mean
band 3. median
band 4. standard deviation</td></tr>
<tr><td>Soft evidence:
Multi-band raster of the probability distribution across the states of a node
band 1: probability of state 1
band 2: probability of state 2
…
band n: probability of state n</td></tr>
<tr><td rowspan="2">Vector</td><td rowspan="2">one .shp file or geodatabase .gdb including one feature class (reads the attribute table)</td><td>Hard evidence:
Attribute with the name of the input node, where the value corresponds to the known value of the node (discrete or continuous).</td><td rowspan="2">Same geometry as input with attributes representing the probability distribution across the states of the target node:

target_s1: probability of state 1
target_s2: probability of state 2
…
target_sn: probability of state n
target_sn+1: most probable state</td></tr>
<tr><td>Soft evidence:
Values in the attribute table represent the probability distribution across the states of a node:
input_s1: probability of state 1
input _s2: probability of state 2
…
input _sn: probability of state n</td></tr>
</table>

Running BNs with large spatial data can be computationally intensive. At the moment, gBay runs on a virtual server (Ubuntu 16.04.4, with 6 cores at 3 GHz), and its processing speed depends on the size of the network and spatial data. For example, when running a network of 17 nodes and 1128 CPT rows with four input rasters, gBay can process around 4000 pixels per second. When processing large networks or datasets, users can receive the outputs via email in case of a browser timeout. User data (including BNs, spatial data and scripts) are automatically deleted from the server after one day.

5.2.3 Temporal dynamics through iterations

Bayesian Networks usually represent a static state of the studied system, and one of their major drawbacks is that they cannot incorporate feedback loops (Uusitalo, 2007). This limitation can be overcome by dynamic BNs, using the so-called "time-slicing" approach (Kjaerulff and Madsen, 2013), where each time step is represented by a separate network. However, developing such dynamic BNs can be very cumbersome (Uusitalo, 2007). In gBay, a simplified version of the time-slicing approach is implemented, where the BN is run iteratively, in multiple time steps, and the outputs of one time step are used as inputs to the next.

For example, when modelling land-cover change, we start with a map of current land cover (LC_t0). During one time step, land-use change takes place, and through inference, we obtain the probability distribution of land use after the first time step (LC_t1, e.g. after 5 years). This LC_t1 then becomes the input for starting land use in the second time step; in other words, the result of one iteration is used as starting condition for a second iteration (see Celio et al., 2014, for an example).

On the gBay platform, BNs can be run iteratively by specifying temporal links (between nodes representing time steps) and the number of iterations. For example, if the output node (LC_t1) is selected as a "Link" node, an arrow appears that can be connected to the corresponding input node (LC_t0). Multiple links can be used reflecting different variables that are connected over time.

5.2.4 Multi-scale processes using Python scripts

The gBay platform can account for spatial processes at different levels corresponding to different types of geoprocessing operations (Tomlin, 1994). In the basic mode of gBay, inference is performed at the **local** level, for each individual pixel or object. However, gBay also provides the option to consider processes at different levels. Calculations across scales can be implemented by running an intermediate processing Python script (indicated with a script icon in Figure 5.2).

At the **focal** level, a Python script can be used to take into account the neighbouring pixels or objects, e.g. to obtain the land cover of neighbouring pixels within a specified window, or calculate the distance to the nearest pixel of a specified land cover type. In the land-cover change example, forest encroachment on a meadow depends on the distance to the nearest forest patch, which can be calculated from the input land cover raster using a python script (see Appendix B.1). This information can be used to set new evidence on a node (e.g. "Distance to forest").

At the **zonal** level, the Python script evaluates pixels or objects across the whole study area, for example to check whether regional boundary conditions have been reached. An example of such boundary conditions is a minimum percentage of a specific land use category, defined by an agricultural policy.

A Python script can be run before performing inference, i.e. to calculate spatial evidence (such as focal statistics) based on the input data, or in between iterations. It can also be used to modify evidences over time (e.g. to implement a policy that changes between time steps). gBay currently supports intermediate processing scripts written in Python, using openly available libraries including gdal, ogr, numpy, and math. Python was chosen as the language of the intermediate processing scripts since it is one of the most widely used programming languages, with a large community, particularly in spatial modelling, and provides many open access libraries. A set of scripts to model spatial interactions at the focal and zonal levels are available on the gBay wiki and can be downloaded and adapted. In addition, advanced users can develop their own scripts, where the input and output format must match the format used by gBay (a list of nodes, containing an array of probabilities across states for every pixel or object, see Appendix B.1 for details). It is important to note that the processing time of gBay increases when more complex geoprocessing is performed. Two examples of BN models that incorporate spatial interactions are described in more detail below.

5.2.5 Case studies

5.2.5.1 Avalanche protection in Davos: accounting for neighbourhood effects

Protection from snow avalanches is one of the most important ecosystem services provided by forests in the Swiss Alps (Grêt-Regamey et al., 2008). An avalanche release is less likely inside a forest (Bebi et al., 2009), and forests also reduce the mass and velocity of avalanches that flow through them (Feistl et al., 2014). The release and size of avalanches depend on terrain characteristics and snow conditions, the protection capacity of the forest is related to its structure and species composition, and the value of the service depends on the risk to settlements and infrastructure. A BN was used to combine Earth Observation data on terrain and forest structure, existing process-based and empirical models about the avalanche process, and expert knowledge about risk factors. The BN was run with spatial data to map the provision and demand for avalanche protection in the region of Davos, Switzerland (Stritih et al., 2019a). The resulting maps of avalanche protection contain large uncertainties, and a sensitivity analysis was used to identify the key sources of uncertainty in the model. One of the main sources of uncertainty was the definition of potential release areas of avalanches.

The probability of an avalanche release depends on topography (slope, curvature, terrain roughness), as well as snow conditions. In the BN, the topographical factors were combined using fuzzy logic (Veitinger et al., 2016). For each factor, a membership function (describing the probability that a pixel belongs to a potential release area as a function of the factor) was defined by experts. The membership function describes the probability that a pixel belongs to a potential release area as a function of the factor). For example, the factor of slope has a trapezoid-like membership function, where avalanche releases can occur on slopes between ca. 28 and 55 degrees, but the release probability is highest between 35 and 45 degrees. The factors of slope, curvature, and terrain roughness were then combined using a fuzzy-AND operator (for details, see Veitinger et al., 2016) to fill the CPT of the node "Release". This way, an avalanche release probability can be calculated for each pixel of the study area.

This pixel-based approach neglects the interactions between neighbouring spatial units, i.e. whether a release pixel is connected to other release pixels. However, the probability of an avalanche release depends on the size of the potential release area (Bühler et al., 2013). An avalanche release can only occur when there is a sufficient volume of snow to be released, which depends on the amount of snow (i.e. the avalanche release depth, which is estimated using a probability distribution of maximum new snow, based on long-term observations (SLF, 2017a)) and the size of the release area.

In order to incorporate neighbourhood effects, we implemented an updated version of the BN from Stritih et al. (2019) in gBay. The model is implemented in two iterations (see Figure 5.4). First, the avalanche release probability of each individual pixel is calculated based on its slope, curvature, and roughness. Then, these probabilities are used as an input to a Python script that calculates the size of the release area. Spatial metrics (such as patch sizes) are commonly calculated based on Boolean class memberships – either a pixel is a release area, or it is not. However, since the definition of release areas is uncertain, such an area calculation would depend on an arbitrary threshold probability (e.g. 50 %) at which we consider a pixel to be in a release area. To avoid this problem, we used a fuzzy geographical area calculation (Fonte and Lodwick, 2004). We defined a set of probability thresholds α (between 0 and 1). For each threshold, all pixels with P(release) > α were considered to be release pixels, and adjoining release pixels form a release area. A release area size was calculated for each α, and based on the different sizes for different threshold probabilities, we could estimate a probability distribution of release area size (see Appendix B.2 for an illustration).

In the second iteration, the probability distribution of release area size was used as soft evidence on the node "Release area size". Combined with the maximum new snow height, the release area defined whether the snow volume (release area*new snow height) was sufficient for an avalanche release. If the snow volume was below the threshold for small snow avalanches as defined by the Canadian classification of avalanche sizes (SLF, 2018), we assumed that the release will not occur, setting the "Release (corrected)" probability to zero.

The updated BN model of avalanche protection was run in gBay with spatial inputs (at a 5-m resolution) for the Dischma valley in Davos. The whole network is illustrated in Appendix B.2. The release probability, the total provision of avalanche protection and the associated uncertainty were calculated, and compared with the results of the previous model that did not account for release area size.

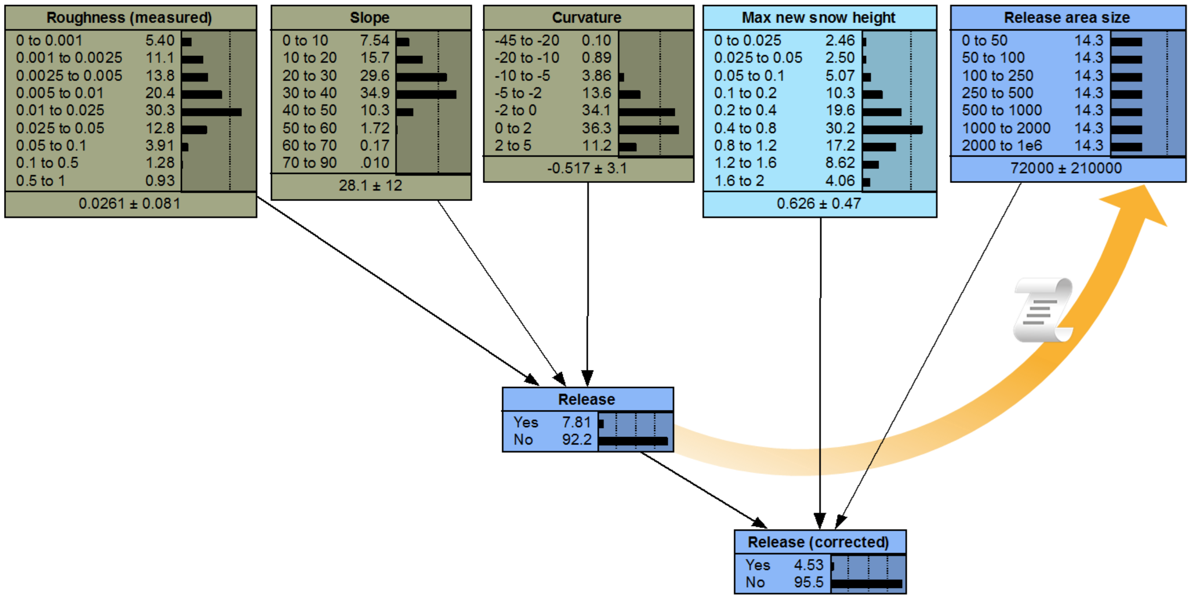


Figure 5.4: Part of the avalanche protection BN used to calculate the avalanche release probability. In the first step, the per-pixel release probability is calculated based on the local slope, curvature, and terrain roughness. The release probability is an input to a Python geoprocessing script, which calculates the fuzzy size of each connected release area. In the second step, this size influences the release probability ('Release (corrected)'). The nodes show the prior probability distributions, before evidence is added to the network.

5.2.5.2 Implementing boundary conditions for land-use change in the Entlebuch UNESCO Biosphere

Land-use decisions have a strong impact on landscape development, and are influenced by an interplay of biophysical and socio-economic factors, policies, and personal preferences. Celio & Grêt-Regamey (2016) used a participatory approach to develop a model of farmers' decisions and resulting land-use change in the Entlebuch UNESCO Biosphere in the Canton of Lucerne, Switzerland. After identifying potential factors influencing land-use decisions through literature review, an expert group was formed. The experts weighted the influencing factors to find a subset of the most relevant variables, and defined the causal relations between them. Then, they defined node states and the conditional probabilities.

The BN was updated with local actors' knowledge, and validated through a review by experts (Celio et al., 2012). For a detailed description of the participatory modelling process, see Celio et al. (2014).

The resulting BN predicts land-use change based on biophysical factors (such as slope and potential natural vegetation), agricultural policy (amount and types of direct payments), zoning (e.g. vicinity to a residential area), and individual farmers' characteristics, such as their education, whether they have a part-time business, and their view on ecological policies (see Figure 5.5). The land-use change probabilities are defined for a time-step of 5 years and the BN can be run iteratively to model longer periods. The BN was used to model scenarios of agriculture policy (AP; old agricultural direct payments or the more ecology-oriented agricultural policy implemented in 2014) and farmer characteristics (production- or ecology- oriented farmers). The scenario maps illustrated the trends of the different combinations of APs and actor characteristics. However, the scenarios were calculated only taking into account individual parcel information, not considering limitations on the regional scale, such as prescribed minimum amounts of specific land-use types to support cattle production. The cell-level approach means that the exogenous limits of farmers' decisions were neglected.

In order to account for the regional boundary conditions, we adapted the BN developed by Celio and Grêt-Regamey (2016) for agricultural land use, and implemented it in gBay. The limits of land-use change were defined based on the maximum number of cattle grazing per hectare, as defined by the Federal Office for the Environment (2013). Assuming that the number of cattle in the region remains constant, we estimated the minimum area of extensive, medium- and intensive agricultural land required to fulfil this legal obligation. This limited the conversion of agriculture to other land-use types through extensification and abandonment. When certain minimum areas of agricultural land-use had been reached, no further cells were converted to other land-use types. This boundary condition was implemented at the end of every iteration (time step) of the network in gBay. Using a Python script, we checked the amount of extensive, medium-intensive, and intensive-agriculture cells across the whole study area. If the required amount of a certain agricultural land-use category was not reached, the script searched among the cells that had been converted from other land-use categories to find those where the change was least likely, and converted them back to their previous probability distribution until the minimum area of the category was reached. In other words, land-use change was prevented by the minimum-amount-condition in those cells where it was least likely to occur. This "roll-back" mechanism is explained in more detail in Appendix B.3.

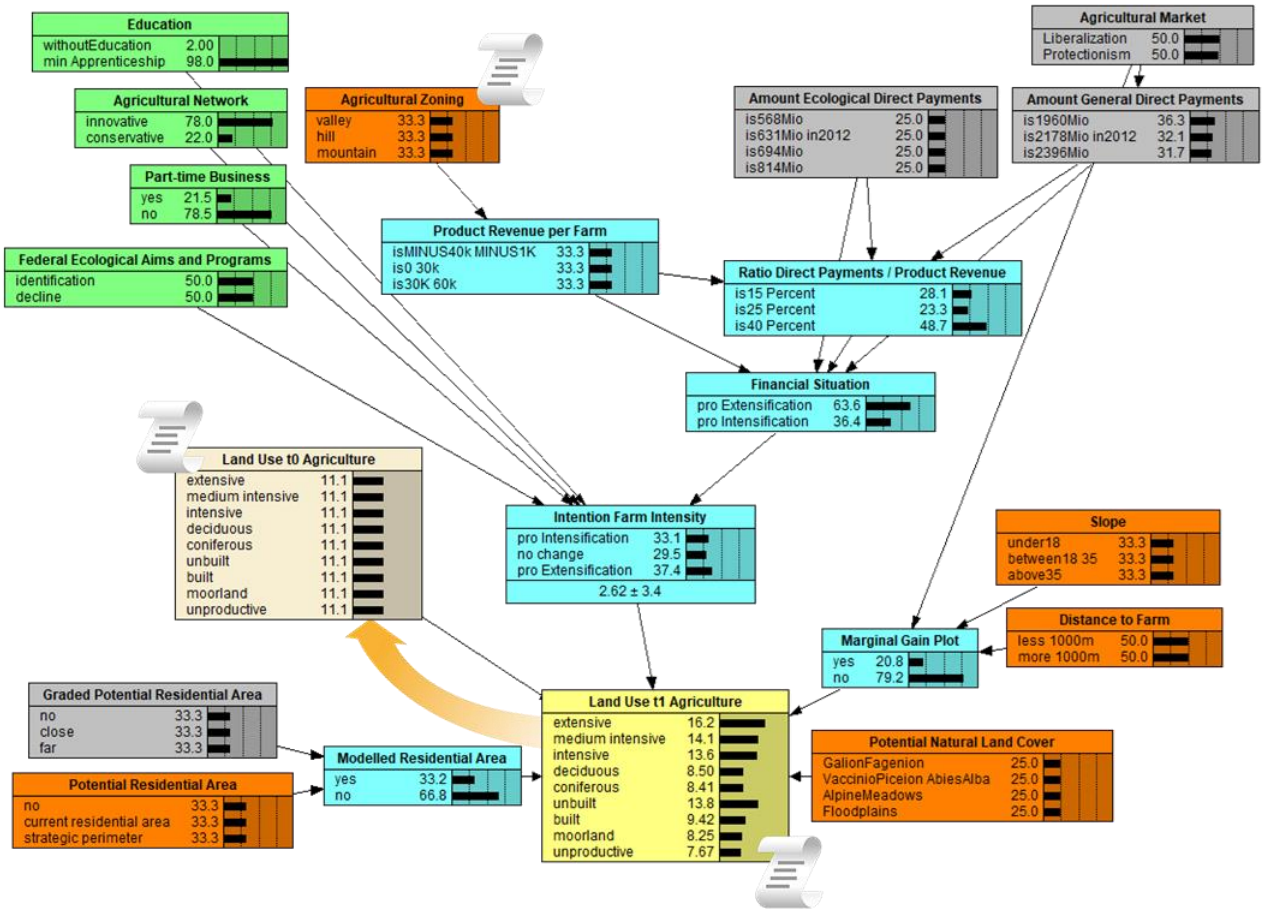


Figure 5.5: BN for agricultural land-use decisions in the Entlebuch, where land-use change is driven by spatial factors (orange, mainly biophysical factors), agricultural policy (grey), farmer characteristics (green). The target node is depicted in yellow. Intermediate nodes are shown in blue, and nodes used in the Python script to implement boundary conditions are indicated with a script icon (Source of the BN: Celio and Grêt-Regamey 2016).

5.3 Case study results

5.3.1 Avalanche protection

We mapped the provision of avalanche protection and associated uncertainty in the Dischma valley in Davos, using a BN adapted from (Stritih et al., 2019a). Since the definition of avalanche release areas was a major source of uncertainty in the model, we adapted the model to account for neighbourhood effects in the release process. Figures 5.6a and 5.6b show the resulting maps with and without accounting for spatial interactions, where the colours indicate the mean value of avalanche protection provision (expressed in height of snow stopped) and the uncertainty (entropy of the posterior probability distribution). The most important areas providing avalanche protection are steeper, densely forested areas, but the model shows a high spatial heterogeneity and high uncertainty. In the basic model (without neighbourhood effects), the mean coefficient of variation across the whole study area amounts to 95%. When taking the size of the release area into account, the spatial pattern remained similar, but the uncertainty was reduced (mean CV of 87%, see Appendix B, Table B.2).

Figures 5.6c and 5.6d show the release probability without and with the correction for spatial interactions (release area size). The BN that accounts for the release size results in fewer release areas (Figure 5.6d), as smaller areas are less likely to reach a sufficient volume of snow for an avalanche release.

In addition, in areas that are originally assigned a low release probability, the probability is additionally reduced as they are unlikely to form part of a large release area. Thus, a clearer spatial pattern of potential release areas emerges, with the mean entropy (uncertainty) of the release probability map reduced from 29% to 19% (see Appendix B, Table B.2).

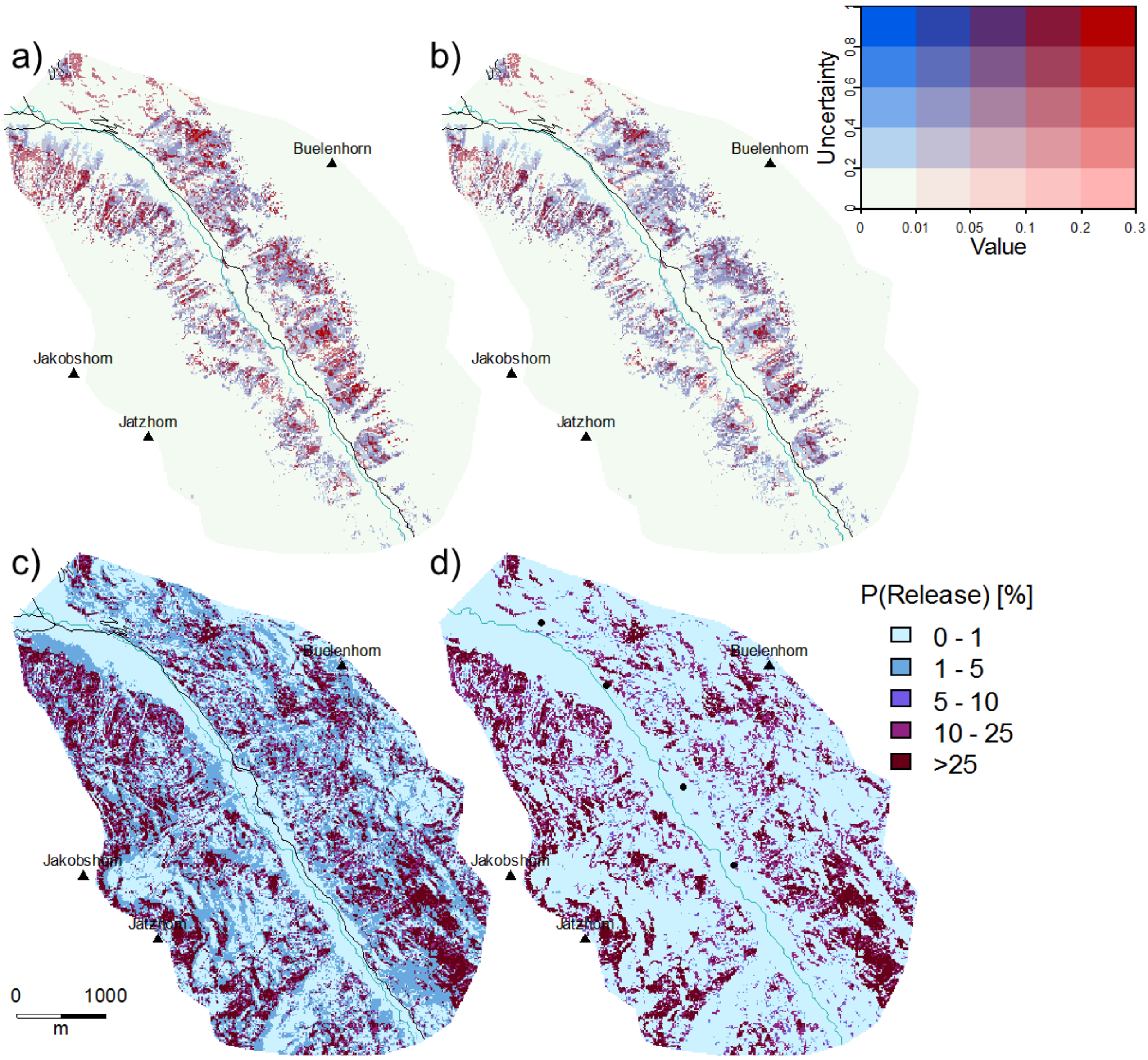


Figure 5.6: Maps of avalanche protection in the Dischma valley, Davos: a) & b) The value of avalanche protection provision, expressed in height of snow stopped, with the associated uncertainty; c) & d) The probability of an avalanche release; without taking into account the neighbourhood effect in the avalanche release process (a & c) and with the neighbourhood effect calculated in gBay (b and d).

5.3.2 Land-use decisions

The BN of agricultural land-use decisions in the Entlebuch was run in the iterative mode in gBay, with and without the inclusion of boundary conditions (minimum area of medium- and intensive agriculture due to legal requirements for cattle breeding). The resulting land-use maps and distribution of land-use types are shown for two scenarios (production-oriented farmers with the old direct payment system and ecology-oriented farmers with the new agricultural policy) across three time steps (Figure 5.7). In both scenarios, the boundary conditions had an effect on the final land-use change.

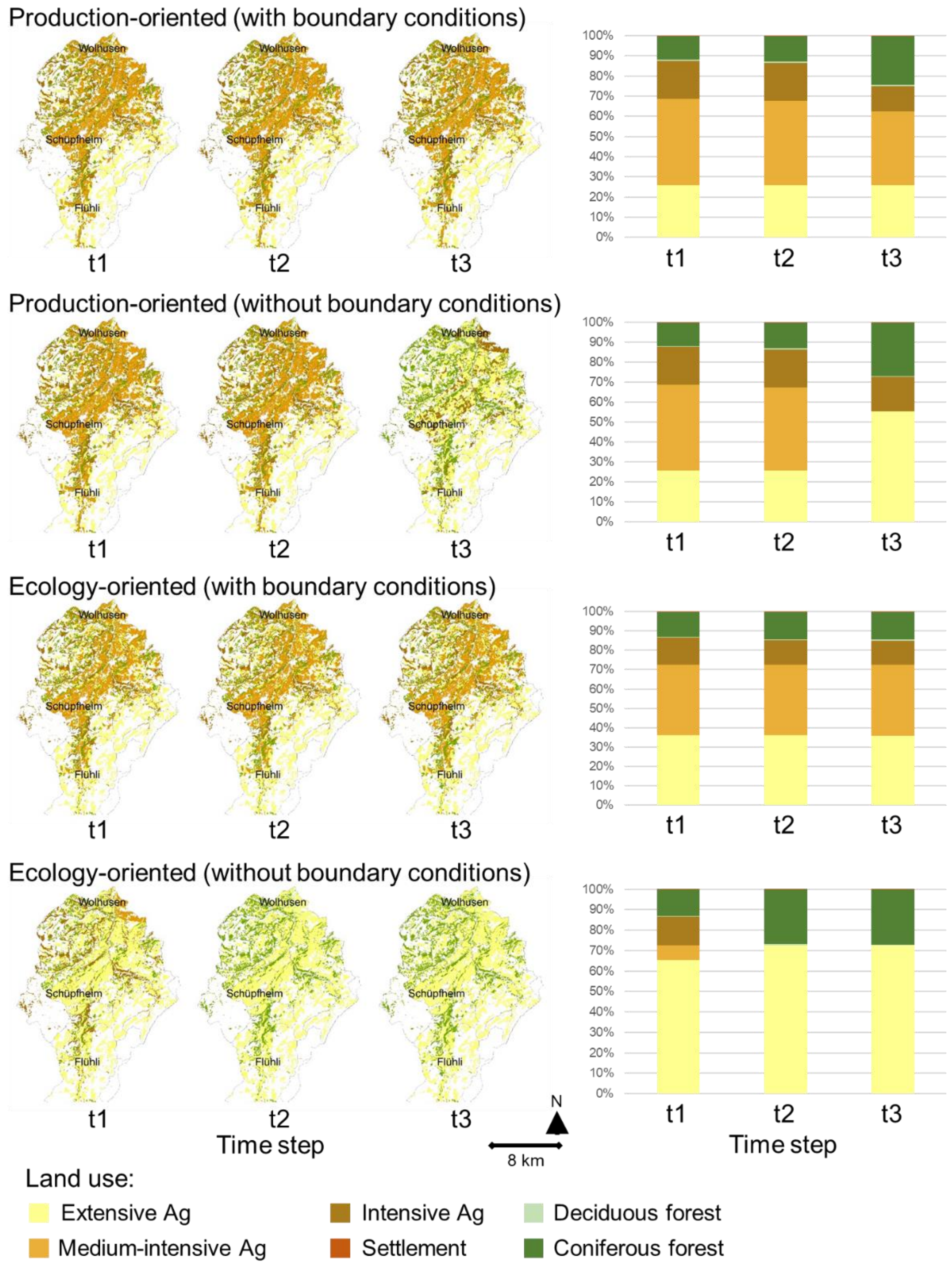


Figure 5.7: Predicted land-use change in the Entlebuch under two different scenarios (production-oriented farmers with the old agricultural direct payments, and ecology-oriented farmers with the new agricultural policy), with and without zonal boundary conditions that limit farmers' decisions implemented through a Python script in gBay. The maps show the land use in three time steps, i.e. after 5, 10, and 15 years. The bar plots show the distribution of land-use types in the study region for the three time steps. The ecology-oriented scenario without boundary conditions shows the fastest land-use change, with all agriculture changing to extensive agriculture or forest. In both the production- and ecology-oriented scenario, the implementation of boundary conditions limits the land-use change.

In the ecology-oriented scenario, the farmers' decisions drive extensification, leading to a rapid loss of intensive agricultural land when no limits are implemented. When the boundary conditions are implemented, the minimum is reached very quickly (within one time step), preventing further land-use change. In the production-oriented scenario, the boundary conditions have a smaller effect, as farmers are more likely to maintain their intensive agriculture. However, the medium-intensive plots are converted to extensive use if the minimum limits are not implemented.

5.4 Discussion

In this paper, we presented gBay, an openly available online platform for spatially- and temporally-explicit Bayesian Networks. The platform offers an easy-to-use GUI to run BNs with spatial data, over multiple time steps. As such, it aims to facilitate spatial BN modelling of socio-ecological systems, by including the temporal component and spatial interactions, as well as making it more accessible to practitioners. BN models can be used to integrate different types of information, account for uncertainty, and can facilitate participatory modelling. In the following, we discuss how the gBay platform can help users draw on these advantages, as well as the associated challenges and limitations. In addition, we discuss the implications of our case studies for landscape planning.

5.4.1 Integrating information across scales

Data on socio-ecological systems is becoming increasingly available through sources such as Earth Observation and social media, and information is also available in the form of local actors' or expert knowledge. BNs are well suited to integrating these different types of information, as is illustrated in the avalanche protection case study, where remote sensing inputs were combined with process-based, empirical models and expert knowledge (Stritih et al., 2019a). However, while BNs are commonly used to integrate information about a static system, the temporal and spatial are often not explicitly represented in BNs, although they are essential in most socio-ecological systems (Hamilton et al., 2015a).

The gBay platform provides the possibility to incorporate dynamics by using the iterative BN approach, which can include feedback loops, thus addressing one of the major limitations of BN models (Kelly (Letcher) et al., 2013; Uusitalo, 2007). However, the iterative BNs are mainly suitable for systems where one (or few) variables change over time (e.g. land-use change), while other variables act as drivers of this change (such as state-and-transition models, see Chee et al. 2016), and feedbacks only occur between time steps. For more complex dynamic interactions, other modelling approaches, such as coupled-component models or system dynamic models, may be more appropriate (Kelly (Letcher) et al., 2013; Lauf et al., 2012; Schreinemachers and Berger, 2011).

In addition to the temporal component, gBay can also account for processes that occur at different spatial scales or organizational levels. Socio-ecological systems are influenced by different processes at different scales (Verburg et al., 2004), and interactions between these processes across scales can result in non-linear dynamics or threshold effects (Peters et al., 2007). In BN models, processes at higher organisational levels (e.g. regional policies, market conditions, climate) are often represented by a node in the network (Celio et al., 2014; Grêt-Regamey et al., 2013a; Kleemann et al., 2017), but potential feedbacks from the lower to the higher level are not accounted for. Using the Python module in gBay, the cumulative effects at the local level can be calculated and used to update the higher-level node in the next time step. For example, while land-use decisions the level of individual parcels depend on regional policies, rapid land-use change across many parcels may in turn affect the policies in a feedback effect that can be accounted for in gBay.

While the Python module increases modelling flexibility and allows us to incorporate spatial interactions or boundary conditions, the intermediate calculations used to modify BN inputs or outputs should be compatible with the probabilistic logic of BNs. The explicit treatment of uncertainties is a major advantage of BNs, but it is challenging to include the information about the whole probability distribution per each pixel in spatial calculations. A simple approach is to set a threshold probability (each pixel with a probability of forest above 50% is considered a forest in a neighbourhood calculation). However, this means a loss of information about the probability distribution, and results can be strongly affected by the arbitrary threshold (Arnot et al., 2004). To deal with this, fuzzy landscape metrics can be applied to account for uncertain membership in a class (e.g. land cover) (Arnot et al., 2004; Fonte and Lodwick, 2004), such as the fuzzy area calculation used in the avalanche protection example. However, these do not account for variability in spatial processes (e.g. flows). In ecosystem services assessments, the directional flow between service providing and receiving areas is important. To account for ES flows in space in a probabilistic manner, Johnson et al. (2012) have used a combination of BNs and agent-based models that simulate the flow of ES units. Such an approach would add an additional level of complexity, but offers a probabilistic perspective on spatial processes that should be addressed.

5.4.2 Dealing with uncertainty

Socio-ecological models often contain high uncertainties, partly due to limited data, measurement errors, and subjective judgement, but partly also related to the inherent spatial and temporal variability of the modelled systems (Regan et al., 2002). These uncertainties should be acknowledged and taken into account in decision-making (Maier et al., 2008). A major advantage of BNs is that uncertainties can be explicitly accounted for and propagated through the models (Stritih et al., 2019a; Uusitalo, 2007). The output of inference in gBay contains a probability distribution across all the possible states of the target node for each pixel or object of the study area, which means that the output uncertainty can be quantified in a spatially explicit way. gBay automatically provides the user with measures of uncertainty including the entropy (Marcot, 2012) and standard deviation (for continuous nodes) of the probability distribution. These can be used to map uncertainties, as demonstrated in the avalanche protection case study (see Figure 5.6). Mapping uncertainties is particularly important when these are spatially heterogeneous, such as in remote-sensing based classifications (Petrou et al., 2013).

Although maps of uncertainty can be easily generated in gBay, interpreting them is not straightforward (Landuyt et al., 2015). The way in which spatial uncertainties are visualized may have a strong effect on how they are understood by end-users (Kunz et al., 2011). In the avalanche protection example (Figure 5.6), we used a bivariate map to depict both the modelled value and associated uncertainty, with darker colours indicating higher uncertainty, thus drawing attention to areas of high uncertainty (Kunz et al., 2011). In other applications, it may be more appropriate to emphasize areas of higher certainty by linking uncertainty to transparency or fuzziness. Since different types of users prefer different visualizations of uncertainty (MacEachren et al., 2005), gBay is currently limited to providing data on uncertainty, which users can use in their preferred visualization mode.

5.4.3 Increasing the accessibility and transparency of BN modelling

Involving stakeholders in modelling socio-ecological systems can increase the credibility of model results and support learning (Jakeman et al., 2006; Voinov and Bousquet, 2010). A key requirement for credible participatory modelling is transparency (Voinov and Bousquet, 2010). BNs have been promoted as a tool for participatory modelling due to their transparent model structure and capacity to incorporate expert knowledge (Bromley, 2005). This type of use is demonstrated in our land-use decision case study, where the model was co-developed with experts from different fields and updated with local stakeholder knowledge. However, participatory modelling is an iterative process, and models should be updated as new information becomes available, which is often not within the frame of research projects. Models are more likely to have an impact on decision-making when local experts and decision-makers take ownership of the model (Jakeman et al., 2006), and can generate new results as new information becomes available in an iterative process (Ruckelshaus et al., 2015). Open access and easy-to-use web-based tools can support the adoption of models by local experts and practitioners (Voinov et al., 2016).

Although the structure of a BN model is in itself transparent, and many graphical tools are available to develop BNs, the application of BNs to spatial data usually requires programming skills to use the API of BN software (such as Netica or HUGIN) (Pérez-Miñana, 2016). The gBay platform aims to reduce this gap and make spatial BNs more accessible to a wider range of users. Because of its simple user interface, users without programming experience can use gBay to link their BNs with spatial data. This is supported by the gBay wiki page (wiki.gbay.ethz.ch) with instructions, examples of BNs and associated data that can be downloaded to test the platform.

Nonetheless, developing a BN is not straightforward. Model co-development with stakeholders is a time-consuming process, and it is important to ensure stakeholder diversity and consider group dynamics (Voinov and Bousquet, 2010). When experts are asked to parametrize a BN model, challenges include potential biases (Kuhnert et al., 2010), fatigue during elicitation of extensive CPTs (Das, 2004), and over-confidence (Speirs-Bridge et al., 2010). When learning a BN from data, the quality of the model is limited by the quality and amount of data available (Hamilton et al., 2015b). Because of such challenges, making BN modelling more accessible will require not only tools such as gBay, but also training and capacity building among potential users.

Although the code of gBay is published, it is based on the proprietary Netica API (Norsys, 2010). In addition, the platform is not designed for BN development, and requires users to upload their own BNs in the .dne format, as developed in Netica, GeNIe (BayesFusion, 2017), or a similar BN software. Netica is currently the most commonly used BN software in the ecosystem service modelling community (Pérez-Miñana, 2016), and to our knowledge, no open source software currently offers a graphical interface for BN development with comparable functionalities, including the integration of discrete and continuous nodes, learning from data, and sensitivity analyses. The development of such an open source software would be an important step towards increasing the accessibility and transparency of BN modelling.

5.4.4 Implications for environmental management and landscape planning processes

Our case studies on ecosystem service mapping and land-use decision modelling demonstrated the use of gBay for spatial BNs, incorporating focal (neighbourhood) effects and zonal boundary conditions. Accounting for such spatial interactions can help to reduce uncertainties, improve model realism, and take into account knowledge at different scales or organizational levels.

High uncertainties in ecosystem services maps limit their usability as a support for decision-makers (Andrew et al., 2015; Schulp et al., 2014a). In the case of the avalanche protection service (section 3.1.1), considering neighbourhood effects between pixels in potential avalanche release zones reduces overall uncertainty, by excluding areas that are too small to produce an avalanche release. However, due to the fuzzy geographical area calculation algorithm, the corrected release probability is also reduced in large areas of low P(release), which could lead to neglecting large releases that occur only under very extreme conditions. Thus, adding the area condition likely reduces false positives (i.e. increases the specificity of detecting release areas), but may also lead to more false negatives (some release areas may be excluded). Higher levels of specificity in detecting potential release areas may be useful to identify the forest patches that play the most important role in preventing avalanche releases, which is important in prioritizing the management of these protection forests (Teich and Bebi, 2009). However, the purpose of hazard risk mapping, it is also important to consider releases that only occur in extreme snowfall conditions, with very low probabilities, although validation data on these extreme events is lacking (Bühler et al., 2018). Better estimates of extreme scenarios could be achieved by running the BN for a scenario with high new snow, or choosing a low threshold for pixels to be considered part of a release area.

In the land-use decision case study (section 3.1.2), taking into account boundary conditions offers a more regional perspective, where farmers decisions are limited by regulations. In other words, the more realistic representation limits the option space. The constrained model may be more useful for short-term forecasts of landscape development, under the assumption that boundary conditions will stay constant, while unconstrained, exploratory models can better represent the whole range of possible futures (Maier et al., 2016; Rounsevell and Metzger, 2010). Modelling more extreme scenarios may be useful to clearly observe the impacts of different scenarios of agricultural policy and farmers' characteristics, and may offer a wider perspective on potential solutions in landscape planning processes. Hence, combining both perspectives (i.e. with and without boundary conditions) and observing the differences between them can yield additional insights. In our case study, the comparison demonstrates how strongly the decision-making of farmers at their plot level is constrained by larger-scale regulations.

In both cases studies, the appropriate choice of method (e.g. considering boundary conditions or not) and the interpretation of results will depend on the needs of decision-makers, which highlights the need to involve stakeholders and decision-makers in the modelling process (Voinov and Bousquet, 2010). Tools such as gBay can contribute to the flexibility and accessibility of modelling socio-ecological systems over time and space, and thus have the potential to support decision-makers in environmental management and landscape planning.

5.5 Acknowledgements

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6 Paper III: The impact of land-use legacies and recent management on natural disturbance susceptibility in mountain forests

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Abstract

Mountain forests provide a wide range of ecosystem services, including carbon sequestration and protection from natural hazards. Forest cover in the European Alps has increased over the last century, but in recent years, these forests have experienced an increasing rate of natural disturbances by agents such as windthrow, bark beetle outbreaks, and forest fires. These disturbances pose a challenge for forest management, making it important to understand how site and stand characteristics, land use legacies and recent management influence disturbance probability. We combined a dataset of forest disturbances detected from space with in-situ forest management records, allowing us to differentiate between different types of disturbances for the Canton of Graubünden, Switzerland, in the years 2005-2018. The resulting dataset of over 28’000 attributed disturbance patches (corresponding to a disturbed forest area of ca. 23’600 ha) was combined with information on topography, forest structure, and historical forest cover. A machine-learning approach was used to investigate the non-linear and interacting relationships between potential drivers and disturbance occurrence. Natural disturbances (especially windthrow and bark beetle outbreaks) were most common at lower elevations, on shallow and south-facing slopes, and in even-aged, spruce-dominated stands with a closed canopy. Forests established in the 20th century were significantly more susceptible to natural disturbances than forests that were already present before 1880, which may be due to the uniform age and vertical structure of secondary forests, as well as legacy effects of former agricultural use. On the other hand, forest management more often took place in forests present before 1880. Management interventions (such as thinning) in turn increased the susceptibility to natural disturbances in the short term. This finding emphasizes the need to balance short-term increases in disturbance susceptibility with long-term benefits in forest resilience when planning management interventions in mountain forests. Our findings highlight the importance of considering multiple interactive drivers, including management and land-use history, for understanding forest disturbance regimes.

Keywords: disturbance regime, forest dynamics, land-use history, spatial modelling, machine learning

6.1 Introduction

Forests provide important ecosystem services, such as regulating the global carbon cycle, supplying renewable resources, and providing habitat to a wide variety of species. In mountain regions, forests provide protection from natural hazards, such as avalanches, shallow landslides, and rockfall, which is essential to mountain communities (Moos et al., 2018). In the European Alps, forest cover has increased during the last century (Bebi et al., 2017; Loran et al., 2016; Mietkiewicz et al., 2017), which contributed to an increase in forest carbon stocks (Bolliger et al., 2008) and natural hazard protection (Sebald et al., 2019). However, past land use has legacy effects on forest structure (Bebi et al., 2017), tree species composition (Chazdon, 2008; Thom et al., 2019), and soil characteristics (Brudvig et al., 2013), all of which may influence forests' susceptibility to natural disturbances (Munteanu et al., 2015; Seidl et al., 2011b) and their capacity to provide ecosystem services (Chazdon, 2008; Sutherland et al., 2016; Thom et al., 2019). For instance, forest expansion creates a more homogeneous landscape (Kulakowski et al., 2011; Mietkiewicz et al., 2017), which can facilitate insect outbreaks (Raffa et al., 2008) and increase the risk of natural disturbances (Turner et al., 2013). Hence, there is a need to consider the legacies of past land use when quantifying the susceptibility of forests to increasing disturbances.

Forest canopy mortality has increased in Europe over the last 40 years (Senf et al., 2020, 2018). The Alps have seen a growing rate of bark beetle outbreaks and large-scale windthrow events (Seidl et al., 2014b; Usbeck et al., 2010). Increasing disturbance rates may jeopardize not only the forests' role as carbon sinks (Pugh et al., 2019; Seidl et al., 2014b; Yu et al., 2019), but also their capacity to provide protection from natural hazards (Sebald et al., 2019; Vacchiano et al., 2016). Forest disturbances also affect the aesthetics of the landscape (Sheppard and Picard, 2006), its value for recreation (Flint et al., 2012), and biodiversity (Thom and Seidl, 2016). Lastly, disturbances increase the variability of the supply of renewable biomass and pose a challenge for long-term planning in forest management (Albrich et al., 2018). Natural disturbances have therefore become a key concern for forest managers (Kulakowski et al., 2017; Nikinmaa et al., 2020). Understanding the spatial and temporal dynamics of disturbances and the factors that affect a forests' susceptibility to disturbance can help define priorities for intervention (Seidl et al., 2018) and integrate risk into forest management decisions (Hanewinkel et al., 2011). However, our understanding of disturbances is still incomplete, especially in landscapes with strong management legacies, such as many mountain forests in Europe.

The climatic, topographic and stand factors that drive the occurrence of disturbances and forest susceptibility have been studied extensively (Hanewinkel et al., 2011; Seidl et al., 2011a). The occurrence of forest disturbances is mainly driven by climatic drivers, such as storm winds (Krejci et al., 2018; Seidl et al., 2011b; Wohlgemuth et al., 2008), heavy snowfall (Hlásny et al., 2011), or drought and high temperatures that facilitate bark beetle development (Faccoli, 2009; Stadelmann et al., 2013) and forest fires (Conedera et al., 2011; Pezzatti et al., 2010). When analysing spatial patterns of disturbances, climatic factors can be exacerbated by topography. For example, bark beetle outbreaks are more frequent on drier, south-exposed slopes (Stadelmann et al., 2014), while a complex topography can constrain disturbance size (Senf and Seidl, 2018). Forest susceptibility to disturbance also depends on stand characteristics, such as species composition, particularly the proportion of bark beetle host trees (e.g., Norway spruce, *Picea abies* (L.) Karst.) (e.g. Krejci et al., 2018; Netherer and Nopp-Mayr, 2005; Temperli et al., 2013), stand age, tree height, density, and growing stock (Díaz-Yáñez et al., 2017; Radl et al., 2017; Seidl et al., 2011b; Stadelmann et al., 2013).

Empirical research on spatial drivers of disturbances in managed forests is often limited to individual disturbance events or short time periods (Seidl et al., 2011a). Dendrochronological research of long-term disturbance dynamics, in turn, has mostly focused on primary (unmanaged) forests (Čada et al., 2020; Janda et al., 2017; Panayotov et al., 2015). Research relating disturbance dynamics to past and present management thus mostly relies on process-based simulations (Seidl et al., 2018; Temperli et al., 2017, 2013; Thom et al., 2018), which have found that both the legacies of past land use (Thom et al., 2018) and current management strategies have a strong effect on forest disturbance dynamics (Seidl et al., 2018). Information on historical land use and management is, however, rarely available for empirical studies of disturbance dynamics. A study in the Carpathian mountains found a higher disturbance rate in forests established after 1860 compared to "old" forests (Munteanu et al., 2015). These "new" forests may be more susceptible to natural disturbances due to their homogeneous species composition and uniform age structure (Munteanu et al., 2015; Seidl et al., 2011b), as a high disturbance rate in recent years has also been observed in primary and unmanaged spruce stands that developed after major disturbances 19th century (Čada et al., 2016; Janda et al., 2017; Panayotov et al., 2015). However, a higher disturbance rate in "new" forests could also be the result of different management strategies (e.g., clear cuts of plantations after a 70-120-year rotation). Since Munteanu et al. did not differentiate between anthropogenic and natural disturbances, or control for the influence of forest structure, these effects remain unresolved.

In this study, we aim at improving our understanding of mountain forests' susceptibility to natural disturbances, particularly how susceptibility is influenced by management and land-use legacies. To this end, we combined remotely-sensed disturbance data with in-situ forest management information to derive a large dataset of forest disturbances for the Canton of Graubünden in Switzerland (covering a forest area of 210'000 ha) for the years 2005-2018. This dataset was combined with historical maps of forest cover and land use, and a machine-learning approach was used to quantify the non-linear and interacting effects of (i) site and stand characteristics, (ii) historical land use, and (iii) recent forest management on the susceptibility of forests to both natural and anthropogenic disturbances. We hypothesized that while stand and site characteristics are important drivers of natural disturbance risk, susceptibility to both natural and anthropogenic disturbances would be strongly influenced by past land use and management.

6.2 Methods

6.2.1 Study area

Graubünden is the largest Canton of Switzerland, covering 7'105 km^2 in the southeast of the country. It is a mountainous region that includes the upper Rhine and Inn catchments, with elevations ranging from 260 to 4049 m a.s.l. and a mostly inner-alpine climate. Traditionally, the landscape has been shaped by mountain agriculture, but many former pastures have been abandoned during the 20th century. Land abandonment and afforestation have contributed to an increase in forest cover (Loran et al., 2016) of over 30 % between 1880 and 2000 (Ginzler et al., 2011). Today, almost 30 % of the canton is forested (Abegg et al., 2020). Most of the forests in Graubünden are conifer-dominated, with spruce as the most common species. At high elevations, spruce gives way to larch (*Larix decidua* L.) and pines (*Pinus cembra* L., *Pinus mugo* Turra), while at lower elevations, Scots pine (*Pinus sylvestris* L.) is dominant on some of the driest sites. European beech (*Fagus sylvatica* L.) and other broadleaved species as well as silver fir (*Abies alba* Mill.) occur to a limited extent in valleys with a less continental climate. The upper treeline is at around 1800 meters a.s.l. in the northern part of the Canton and almost 2400 m a.s.l. in the inner-alpine Engadin valley. Around 60% of the forests in Graubünden are protective forests, which protect people and infrastructure from natural hazards such as avalanches, rockfall, and shallow landslides (Kanton Graubünden, 2018). Forest management mostly takes place in the form of small-scale interventions, many of which are aimed at maintaining the forests' resilience and protection capacity (Temperli et al., 2017). Common natural disturbances in the region include windthrow, such as the storm Vaia in 2018 (Kanton Graubünden, 2018), snow breakage, and bark beetle outbreaks (Bebi et al., 2017). Snow avalanches also play an important role in forest dynamics (Kulakowski et al., 2011), while forest fires are less frequent but of increasing importance (Pezzatti et al., 2016).

6.2.2 Disturbance dataset

The analysis was based on a spatially explicit dataset of forest disturbances derived from Landsat time series (Senf and Seidl, 2020). The map gives information about the year of the most severe disturbance per pixel at 30 m resolution over the period 1986-2018 (the product is openly available for forests across Europe for the years 1986-2016 at http://doi.org/10.5281/zenodo.3924381). In case of multiple disturbances at the same location, only the most severe disturbance is detected. The remote sensing product currently does not contain information about the disturbance agent (e.g. windthrow or bark beetle outbreak), nor does it differentiate between natural and anthropogenic disturbances. We therefore combined the Landsat-based data with forest management information from the Cantonal Office for Forest and Natural Hazards (AWN, 2019). Available as a spatially explicit database from 2005 onwards, it contains information about forest management interventions, including sanitary cuts after natural disturbances and planned interventions for wood harvesting and protection forest management.

The raster of satellite-detected disturbances was converted into polygons, where spatially continuous disturbances from the same year were considered as a distinct disturbance patch, and overlaid with management records (see Figure 6.1). A satellite-detected disturbance was assigned to a recorded event when it occurred within a distance of up to 200 m (to account for mapping inaccuracies, with priority given to closer events) and +/- 1 year of the recorded event (since some disturbances and management interventions are only recorded the following year). In addition, we used the swissfire database (Pezzatti et al., 2010) and the StorME record of natural hazard events (FOEN, 2019a) to attribute disturbances to fire or avalanches, respectively. In ambiguous cases, that is where a disturbance event detected from satellite data overlapped with multiple recorded disturbances, the most likely disturbance agent was determined manually based on the size and shape of the disturbed area and the event descriptions in the management records. When a natural disturbance was followed by salvage logging, the disturbance event was assigned to the original cause of the disturbance. A disturbance cause could be assigned to 75 % of the disturbances detected in the satellite time series, whereas 25 % correspond either to unreported natural disturbances or false positives (see Table 6.2). This resulted in a spatially explicit dataset of forest disturbances attributed to individual disturbance agents, distinguishing avalanches, bark beetles, forest fires, snow breakage, windthrow, other natural disturbances, and anthropogenic disturbances for the whole Canton Graubünden for the years 2005-2018. Anthropogenic disturbances include harvesting and other silvicultural interventions not caused by natural disturbances.

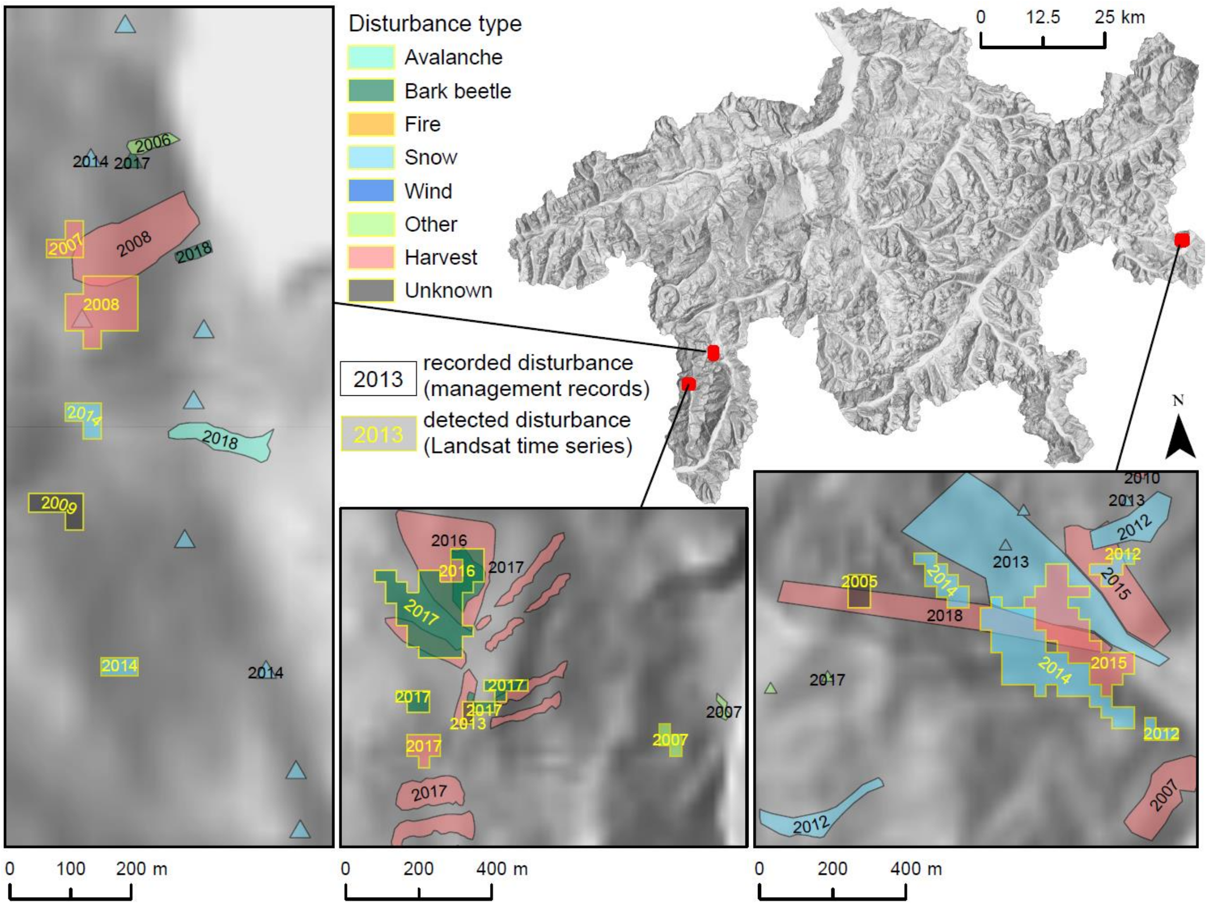

Figure 6.1: A hillshade map of the Canton of Graubünden (swisstopo) with close-ups showing both satellite-detected disturbances (yellow labels) and management records (black labels). Triangles indicate approximate locations of natural disturbance damages from the forest management records.

6.2.3 Modelling

In order to model the spatial factors that affect disturbance risk, we compared the 28’002 disturbed areas (“presence”) with 30’000 randomly sampled non-disturbed forest locations (“absences” with an area of 0.28 ha, corresponding to the median patch size of natural disturbances, see Table 6.2) across the whole study area. Then, a random forest classifier (Breiman, 2001) was used to classify disturbed vs. non-disturbed locations based on spatial predictors (see Table 6.1).

The predictors were selected based on disturbance drivers commonly reported in the literature, and included topographic site descriptors (calculated from a DEM, swisstopo) and in-situ forest structural variables from a stand map (canopy cover, species composition, vertical structure, see Table 6.1). In addition, two digitalized historical maps were used to investigate the effect of land-use history. The so-called Siegfried maps were a series of topographic maps drawn at the 1:25’000 scale in most of Switzerland and 1:50’000 in the Alps, where the first map was created in the years 1872-1908, and the last in 1917-1944 (Loran et al., 2016). Based on forest cover information from these maps, we differentiated between three classes of land-use history: (i) forests that were present before the first Siegfried map (ca. 1880), (ii) forests established in the time between both historical maps (ca. 1880-1920) and (iii) forests established after the last Siegfried map (ca. 1920). Furthermore, spatially explicit data about tree heights was available in the form of a canopy height model from 2015. In order to make use of this predictor, we focused the main part of our analysis on disturbances that occurred between

2016 and 2018 (3'668 disturbance patches). As an additional predictor, we included a variable describing whether a management intervention (including thinning, harvesting, salvage logging, and measures to promote regeneration) occurred during the previous 11 years (2005-2015).

Table 6.1: Description of the predictors used in the analysis of disturbance risk, with the values found in the case study area. The mean (and standard deviation) are shown for continuous variables, while the frequency of categories is shown for factor variables. Variables shown in bold were selected for the final models.

Predictor variable	Description	Values	Data source
Elevation	Digital elevation model (25m-resolution)	1447 (363) m a.s.l.	DHM25 (swisstopo, 2004)
Slope	Slope angle	29 (10) °	
Aspect	4 classes: North, East, South, West.	North 28 %, East 23 %, South 21 %, West 27 %	
Topographic exposure	Calculated as the difference in elevation to mean of a focal window (5 x 5 cells of 25m-resolution), ranging from negative values (concave) to positive (convex).	0.2 (5) m	Guisan et al., 2017; Stadelmann et al., 2014
Cover	Canopy cover (0-100 %)	70 (14) %	AWN, 2019b
Spruce	Share of Norway spruce in the stand, from 0 (none) to 100 (pure spruce stand).	62 (35) %	
Broadleaves	Share of broadleaves in the stand.	9 (22) %	
Dominant species	Categorical variable indicating the dominant tree species.	Broadleaf: 5 % Spruce: 52 % Other conifer: 37 % Mixed: 7 %	
Structure	2 classes: even-aged and uneven-aged as categorized by experts from the Cantonal Office for Forest and Natural Hazards.	Even: 60 % Uneven: 40 %	
Species composition	Share of deciduous trees in the canopy cover, derived from remote sensing	18 (25) %	Swiss NFI (Waser et al., 2017)
Land-use history	3 classes: Pre-1880: present before 1872-1908 Post-1880: established after 1872-1908 and before 1917-1944 Post-1920: established after 1917-1944	Pre-1880: 63 % Post-1880: 10 % Post-1920: 27 %,	Siegfried maps (1872-1908 and 1917-1944), (Loran et al., 2016)
Canopy height	Mean canopy height in 2015, derived from a stereo-imaging digital surface model at a 1 m resolution.	16 (5) m	Ginzler and Hobi, 2015
Height variability	Standard deviation of the 2015 canopy height model.	5 (3) m	
Management	Binary variable indicating whether there was a recent management intervention in the years 2005-2015.	Yes: 21 % No: 79 %	AWN, 2019a

A random forest model was fitted for natural and anthropogenic disturbances separately, as well as for each individual type of natural disturbance, both for the period 2016-2018 and for the whole period (2005-2018, without the predictors canopy height and management). Random forest is a machine learning algorithm where the classification is based on an ensemble of decision trees (Breiman, 2001). The imbalanced distribution of classes (i.e. many more absences than presences) may introduce a bias towards the more represented absences in the classifier, which aims to minimize the overall error rate (Chen et al., 2004). To deal with this, an equal number of data points was sampled from both classes for each classification tree in the random forest.

Two indicators were used to quantify the importance of variables in the random forest models. The "Mean Decrease Gini" expresses the total decrease in node impurities (measured with the Gini index) when a variable is used for splitting, averaged over all classification trees (Breiman, 2001). Since the "Mean Decrease Gini" can be biased towards variables with a wide range or higher number of classes (Strobl et al., 2007), we also calculated a permutation-based variable importance, which measures how much the accuracy of the model is decreased by permutations in each predictor (Genuer et al., 2015). Among correlated predictors (Pearson correlation > 0.4), such as different descriptors of species composition (see Table 6.1), only the variable with the highest importance was used in the final model. The effects of the predictor variables and interactions between them were further explored using partial dependence plots, where predicted probabilities are calculated for each value of a predictor variable (or each combination of multiple variables), while varying all the other variables in the model (Friedman, 2001; Greenwell, 2018). The individual partial dependence plots thus depict the marginal effect of each variable, which can help identify non-linear effects, while partial dependence plots with multiple variables can illustrate interactions between variables. In order to be able to compare the effects of predictors among different types of disturbances, the same combination of predictors was used for all disturbance agents.

To evaluate the models' quality, we performed a tenfold split calibration-validation of each model, where a subset of 80 % of the data was used for training and 20 % for validation, and calculated the corresponding area under the receiver operating curve (ROC). The ROC is generated by plotting a model's true positive against its false positive rate at different thresholds of the probability of presence. The area under the curve (AUC) is thus an indicator of model performance that measures how well a model can distinguish between presences and absences, independent of the probability threshold used for assigning a data point as present (Hosmer and Lemeshow, 2000).

To verify the robustness of the variable effects found in the random forest models, we also fitted a binomial generalized linear model (Venables and Ripley, 2002) and a gradient boosting machine classifier (Friedman, 2001; Greenwell et al., 2019) for each disturbance type with the same predictor variables, calculated the corresponding AUC and analysed the variable importance of each model. The gradient boosting approach is similar to the random forest, but the trees are built sequentially, where each new tree aims to minimize the errors of the previous trees (Friedman, 2001; Greenwell et al., 2019). The variable importance in the gradient boosting machine is expressed as the relative contribution of each variable to the overall performance of the classifier. The binomial generalized linear model is a logistic regression, where the degree of association between each variable and the response is expressed through the estimated coefficients. All the analyses were carried out in R (R Core Team, 2019).

6.3 Results

The combination of the Landsat-based disturbance map with the management records as well as the fire and natural hazard databases resulted in the identification of 28'002 individual disturbance patches for the years 2005-2018 (see Figure 6.2), with a mean disturbance patch size of 0.85 ha and an average of 1'647 ha of disturbed area per year.

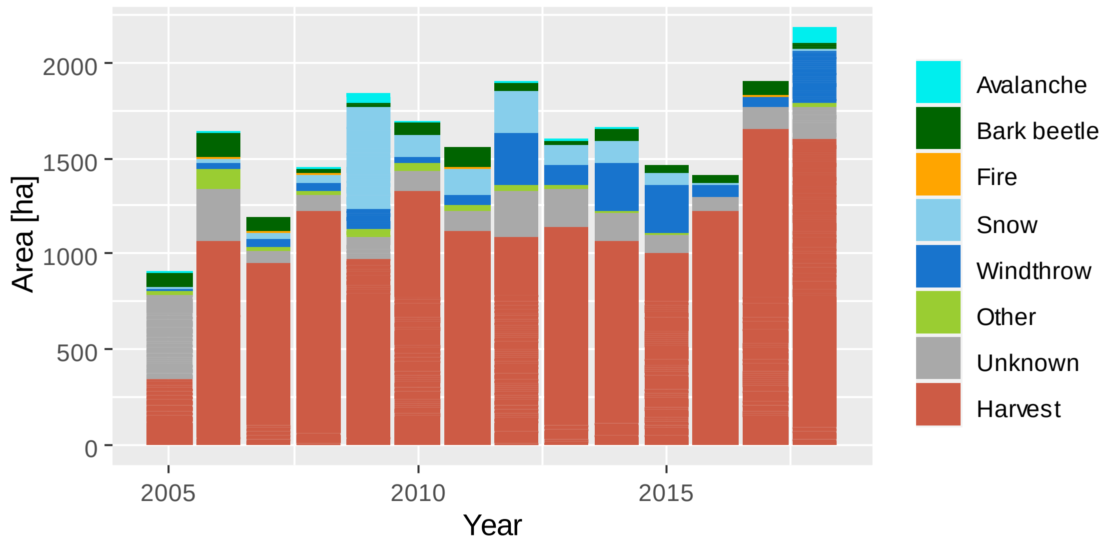

Figure 6.2: Time series of disturbances in the Canton of Graubünden between the years 2005 and 2018. The dataset includes disturbances detected from Landsat timeseries and forest management records in the Canton of Graubünden, where the disturbance agent is assigned based on forest management records as well as information on natural hazards (StorME) and forest fires (swissfire).

Overall, 58 % of forest management records (including sanitary cuts due to natural disturbances and anthropogenic interventions) were detected as disturbances in the Landsat-based disturbance map. Among all disturbances in the Landsat-based disturbance map, 25 % could not be assigned to any disturbance recorded in the management data, the natural hazard or the forest fire database. This suggests a commission error of approximately 25 % in the Landsat product, although some of these events may be natural disturbances that were not recorded in the forest management dataset.

Table 6.2: Overview of the number of disturbances and their patch size per type for years 2005 – 2018. The dataset includes disturbances detected from Landsat timeseries, forest management records, StorME and swissfire datasets in the Canton of Graubünden. The column "undetected" indicates the percentage of recorded disturbances (natural and management-related) that were not detected in the remote sensing product, while the row "unknown" shows the disturbances detected in the time series that were not recorded in the management data.

Type	**number**	**patch size [ha]**					**undetected**
		mean	**sd**	**median**	**5th percentile**	**95th percentile**	
Harvest	16'226	1.03	1.89	0.45	0.08	3.96	43 %
Avalanche	163	1.25	3.71	0.45	0.09	3.50	19 %
Bark beetle	1'628	0.49	1.15	0.19	0.05	1.89	54 %
Fire	86	0.86	1.44	0.36	0.09	3.33	7 %
Snow	1'647	0.85	4.00	0.27	0.05	2.70	34 %
Windthrow	2'232	0.77	2.10	0.27	0.05	2.88	42 %
Other	446	0.88	2.03	0.36	0.05	4.10	34 %
Unknown	5'574	0.40	0.48	0.27	0.09	1.08	-

The random forest models of different disturbance types reached AUC values of around 0.8 for the years 2016-2018 (see Table 6.3), which indicates good model performance (Hosmer and Lemeshow, 2000). The exception are disturbances with very few observations, such as forest fires and snow breakage events. The directionality of effects, that is whether disturbance susceptibility increases or decreases with a predictor variable, was consistent when running the random forest model for the years 2005-2018, as well as with the gradient boosting and generalized linear models (see Appendix C for all model performances and variable importance). The effects reported herein are thus robust to variation in the input data, as well as variations in the modelling approach.

Table 6.3: Performance of the random forest models (AUC – area under the receiver operating curve) across different types of disturbances for the period 2016-2018. N indicates the number of disturbance events, where 80% were used to calibrate and 20% to validate the models in a tenfold split calibration-validation procedure.

Disturbance	**n**	**AUC**
All natural	1164	0.79
Avalanche	20	0.82
Bark beetle	358	0.81
Fire	11	0.76
Snow	41	0.75
Windthrow	397	0.83
Harvest	2504	0.80

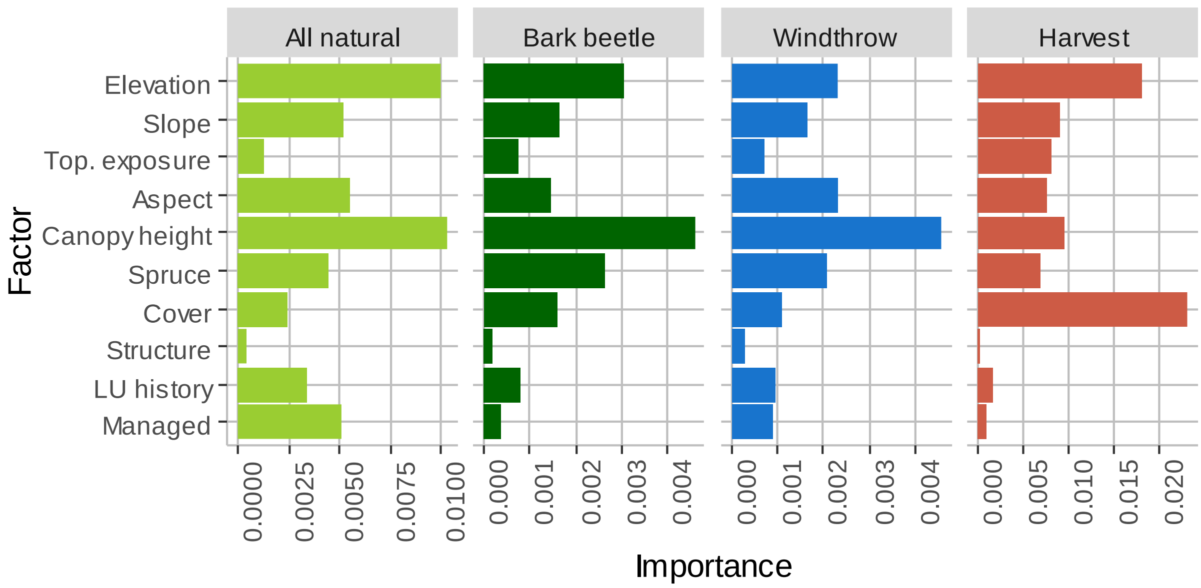

Figure 6.3: Permutation-based variable importance in the random forest models for all natural disturbances, bark beetle, windthrow, and harvest (the most common types of disturbances in the region) in the years 2016-2018. The absolute values of the importance measure are not comparable due to the different sample sizes in each model. Other indicators of variable importance are shown in Appendix C (Figure C.1 and Table C.2). For variable definitions, we refer to Table 6.1.

The strongest predictors of natural disturbance susceptibility are canopy height and topographic factors (Figure 6.3). All of the modelled disturbance agents are more likely to occur at lower elevations (except avalanches) and on south- and east-facing slopes (Figure 6.4). Susceptibility decreases sharply on steep slopes above ca. 35° (except for avalanches and forest fires). Topographic exposure has a strong non-linear effect on disturbance risk, where sites with a neutral exposure (i.e., neither convex nor concave topography) are most susceptible. Spruce-dominated stands show a higher susceptibility to natural disturbance than mixed stands, particularly in the case of bark beetle outbreaks. Taller canopies also correspond to a higher risk of disturbance for all disturbance agents (except avalanches). This effect is particularly strong for windthrow, but levels off at canopy heights >25 m (see Figure 6.4). Bark beetle outbreaks are more common in even-aged stands, whereas uneven-aged (i.e. layered) stands are more exposed to windthrow. Overall, however, the effect of vertical structure on susceptibility is weak compared to other stand characteristics.

We found a strong interaction between species composition and canopy cover. In stands with a high proportion of spruce, a higher canopy cover results in a higher natural disturbance susceptibility, whereas in stands of other species, susceptibility decreases with canopy cover (see Figure 6.5). The high natural disturbance susceptibility of closed-canopy spruce stands is particularly pronounced in forests established after ca. 1920. These stands are more susceptible to natural disturbances than forests established earlier even when controlling for stand and site characteristics (Figure 6.4). Although the importance of land-use history in predicting disturbance susceptibility is low compared to topographic factors and species composition, its effect is consistent across different types of natural disturbances (windthrow, bark beetle, and avalanches, as well as snow breakage and fire when analysing the whole time period 2005-2018, see Appendix C, Figure C.2), and across different topographic conditions. In stands established between 1880 and 1920, the disturbance susceptibility was lower than in stands established after 1920, and was lowest in areas that were forested before 1880.

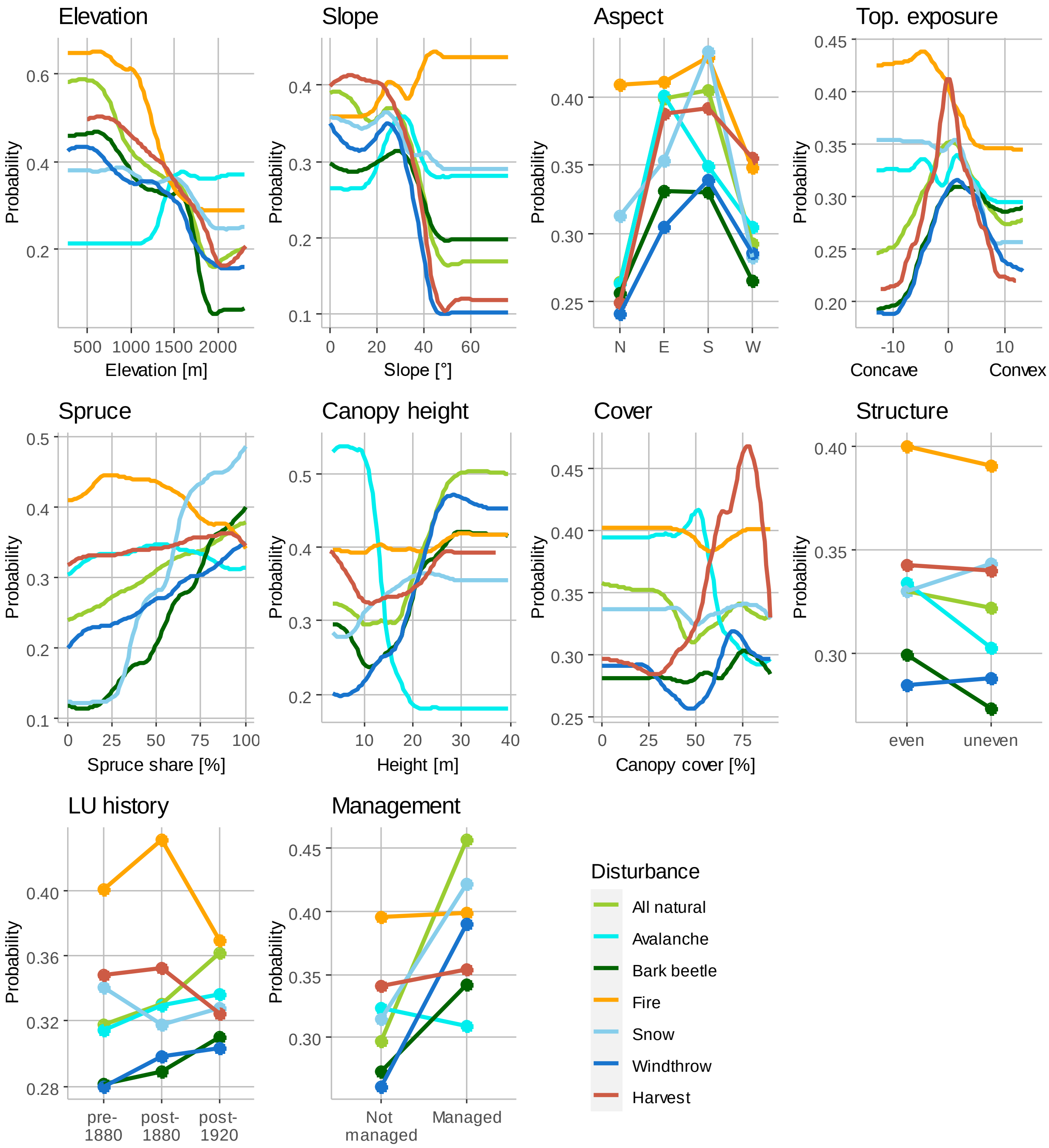

Figure 6.4: Smoothed partial dependence plots of the random forest model of disturbance probability for different disturbance agents for the years 2016-2018. The x-axis shows the values of the predictor and the y-axis indicates relative disturbance probabilities. Note that the scale of the axis differs between plots to better visualize the effects of individual predictors. Partial dependence plots for all disturbance agents and the whole time period (2005-2018) are shown in the Appendix C, Figure C.2).

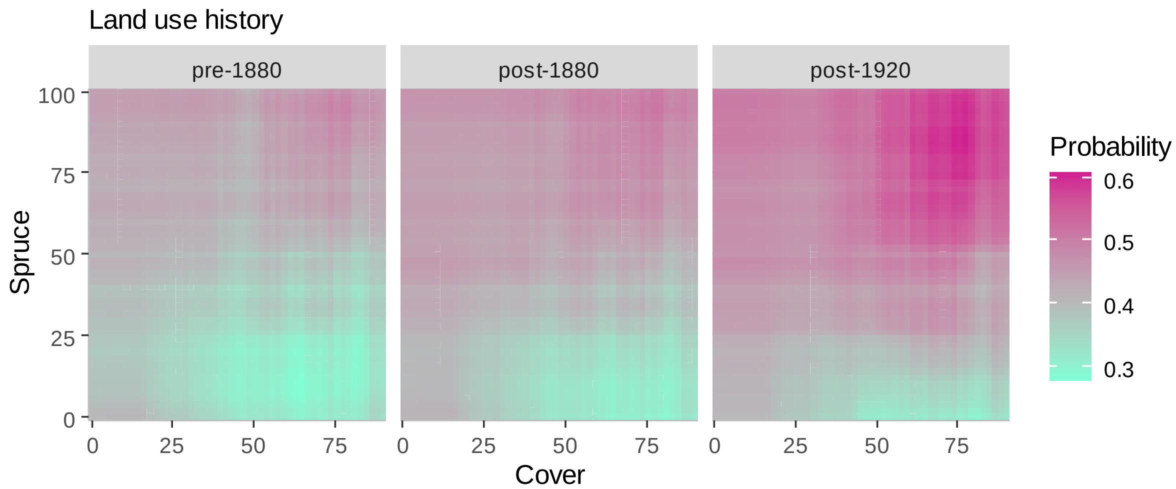

Figure 6.5: Interaction between canopy cover, spruce share, and land-use history class in the random forest model of relative natural disturbance probability between 2005 and 2018.

In contrast to natural disturbances, anthropogenic disturbance (harvesting) is more common in forests that were established before 1920, particularly in dense stands, whereas canopy height, vertical structure and fraction of spruce have a smaller effect. In terms of topography, harvesting follows a similar spatial pattern to natural disturbance, and occurs more often at lower elevations and south- and east-facing slopes below 40°. Canopy cover is a more important predictor of anthropogenic than of natural disturbances, where forests with a cover of around 75 % are most likely to be harvested.

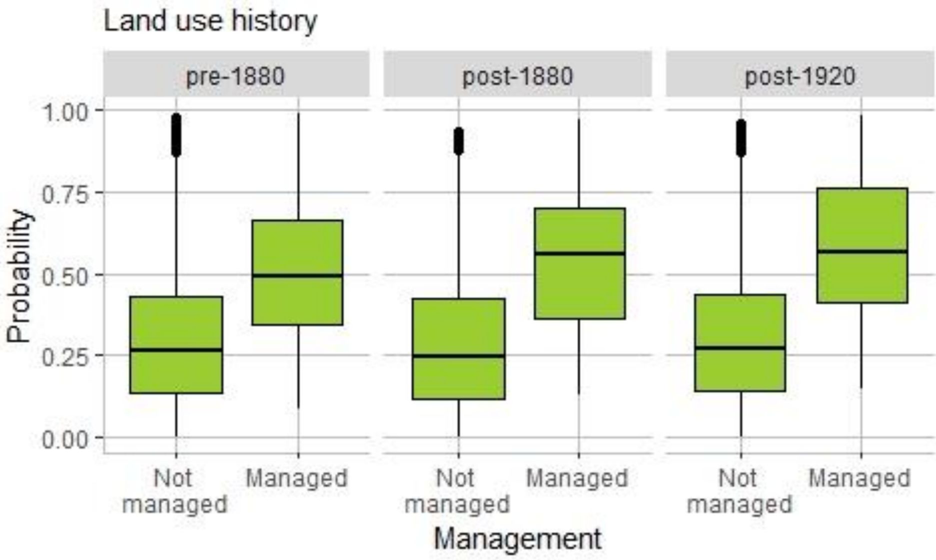

Figure 6.6: Comparison of natural disturbance probability in managed and unmanaged stands per land-use history class, based on predicted values of the random forest for all natural disturbances between 2016 and 2018, where the hinges of the boxplot correspond to the 25th and 75th percentiles of predicted probabilities over all presence and absence points used in the analysis.

When analysing disturbances that occurred between 2016 and 2018, we found that forests that had been managed (e.g., thinned) during the previous eleven years were more likely to experience another disturbance than forests that remained untreated in the previous period (see Figure 6.6). The relationship between recent management and disturbance susceptibility was particularly strong for windthrow and less pronounced for anthropogenic disturbances (Figure 6.4).

6.4 Discussion

6.4.1 Spatial predictors of disturbance susceptibility

Our results reaffirm the important role of topography, which effects a site's microclimate, in determining the susceptibility to forest disturbances (Hanewinkel et al., 2011; Stadelmann et al., 2014). Forests at lower elevations, on shallow, south- and east- facing slopes are more at risk of windthrow, snow breakage, and bark beetle outbreaks. While it is well known that warmer and drier sites are more suitable for the development of bark beetles (Netherer et al., 2015; Netherer and Nopp-Mayr, 2005) and the occurrence of forest fires (Conedera et al., 2011), the consistent patterns across different disturbance agents indicate that warmer and drier conditions also make forests more susceptible to other types of natural disturbances. These conditions are especially critical for Norway spruce, which has a low tolerance to drought (Vitali et al., 2017), and are likely to be further exacerbated by future climate warming (McDowell et al., 2020; Seidl et al., 2014b). Anthropogenic disturbances (harvesting and other silvicultural interventions) are also more likely at lower elevations and on gentle slopes, which reflects the better accessibility of these sites.

Among stand characteristics, canopy height is the most important predictor of natural disturbance susceptibility. This is unsurprising, as taller trees are more likely to experience damage from windthrow and snow breakage (Díaz-Yáñez et al., 2017; Seidl et al., 2014a). Trees are likely to reach large heights in dense stands, where competition for light is strong. A higher canopy cover thus contributes to higher disturbance susceptibility (Netherer and Nopp-Mayr, 2005; Radl et al., 2017). Our findings confirm this effect for spruce-dominated forests, but not in stands with a heterogeneous species composition (Figure 6.5).

6.4.2 Land-use legacies

Our results show that secondary forests (established during the 20th century) are more susceptible to natural disturbances than forests that were already present during the 19th century. While most of the management in post-1920 stands is related to sanitary cuts as a response to natural disturbances (Figure 6.4), stands established before1920 are more likely to be actively managed (Bebi et al., 2017). The more frequent harvesting in pre-1880 stands with a high canopy cover (Figure 6.4) may reflect the prevailing forest management strategy, which prioritizes the initiation of regeneration in dense forests (AWN, 2018).

We note that the land-use history class does not necessarily correspond to stand age, as forests established prior to 1880 may have a more heterogeneous age structure than secondary forests established after 1920, which were often initiated in one uniform age cohort. Bebi et al. (2017) analysed the difference in structure between pre- and post-1880 forests in NFI plots across Switzerland, and found that "new" forests do not only have a lower total growing stock, but are also vertically more homogeneous. In unmanaged mountain spruce forests in Central and Eastern Europe, uniform stands established after large disturbance events in the mid-19th century are now experiencing a new pulse in disturbances (Čada et al., 2016; Janda et al., 2017; Panayotov et al., 2015). In our study, homogeneous spruce stands established only 80-100 years ago are most susceptible to disturbances. These stands have often already experienced considerable self-thinning, with severe competition, high levels of stress and high mortality (Krumm et al., 2012). Small gaps due to self-thinning can make these dense stands with short crowns and high height-diameter ratios even more susceptible to disturbance (Panayotov et al., 2016, 2015).

Besides the uniform age structure of forests established during the 20th century, disturbance susceptibility may be influenced by other effects of land-use legacy. For similar stand characteristics, our results indicate that forests established on former agricultural land after 1920 are more susceptible to natural disturbances than forests that were already present at the end of the 19th century (see Figure 6.5). Post-agricultural forest soils have been found to have a lower soil water capacity, lower nitrogen and soil organic matter, and higher phosphorus content than old forest soils (Brudvig et al., 2013). In addition, the presence of pathogenic fungi may be higher in spruce plantations (Holuša et al., 2018). All of these factors may exacerbate forests' vulnerability to drought and make them more susceptible to other natural disturbances. Although the large-scale historical forest cover data used in this study does not contain information on historical management practices, differentiating between afforestation and forest encroachment on former agricultural lands would help to disentangle the more specific legacy effects.

The higher susceptibility of forests established during the 20th century to natural disturbances is particularly relevant as secondary forests are increasing worldwide through forest expansion and afforestation, while old forests are being lost due to land use change, harvest and disturbances in many parts of the world (McDowell et al., 2020). Old forests are better at providing a wide range of ecosystem services, and have higher levels of biodiversity (Sutherland et al., 2016; Thom et al., 2019). While the data in our study area indicate that areas already forested during the 19th century are less susceptible to natural disturbances, more structurally diverse old forests may be also better at maintaining ecosystem services after disturbances (e.g. with younger trees in lower layers of the canopy taking over after canopy disturbance). This suggests that for a resilient provision of ecosystem services, maintaining old forests should be prioritized over new afforestations (Körner, 2017). When new forests are established, their management should prioritise resilience (i.e., by promoting species' and structural diversity) in order to maintain their provision of ecosystem services in the long-term.

6.4.3 Forest management implications

Intensifying forest management, e.g. through shorter rotation periods and intensified thinning regimes, has often been proposed as a way to mitigate the risk of natural disturbances in forests (Seidl et al., 2018; Zimová et al., 2020). However, our results indicate that prior forest management interventions may increase the forests' susceptibility to natural disturbances. This effect may be influenced, in part, by an autocorrelation in management records, where previously managed stands are more likely to be monitored and thus have a higher chance for disturbances to be recorded. However, we found a positive effect of recent management on disturbance susceptibility even when considering all non-anthropogenic satellite-detected disturbances, including events not reported in the management records. An opening in the stand due to felling may reduce local sheltering effects and the support that trees gain from their neighbours (Hale et al., 2012; Schelhaas et al., 2007), making them more susceptible to subsequent disturbances. In order to prioritize management interventions, it is thus crucial to identify situations when positive long-term effects of interventions on forest resilience are greater than the detrimental effects immediately after interventions.

While the available data did not allow for an analysis of long-term effects, our work provides some important indications on how forest management can promote structural and species diversity and decrease the risk of subsequent natural disturbances (Seidl et al., 2018). Our data suggest that management interventions in dense, homogeneous spruce stands would be most helpful at an early stage, before strong competition begins and tree crowns become relatively short (i.e. before the stem-exclusion phase, Bebi et al., 2013). Although such early measures that promote structural and species diversity are often not cost-effective in the short term (Temperli et al., 2017). However, positive effects of such interventions on diversity and disturbance risk may be much greater compared to interventions in later stages of stand development, when even-aged cohorts of trees are already susceptible, and an intervention may increase the risk of a disturbance instead of reducing it.

In this study, we only addressed one aspect of resilience, i.e. forests' resistance to disturbance. Other important aspects of resilience include the capacity of a system to maintain its function or rapidly return to a desired state after disturbance (Folke et al., 2004), as well as its capacity to adapt to change (Elmqvist et al., 2019). Over the long term, disturbances in vulnerable spruce-dominated stands can create more favourable conditions for other species (Zielonka et al., 2010), thus facilitating forests adaptation to climate change (Thom et al., 2017). Our study suggests that forest management may need to focus more on ensuring the required provision of ecosystem services, rather than attempting to reduce disturbance risk (Seidl et al., 2018). For example, while sanitary cuts after natural disturbance are a common practice aimed at reducing the risk of further bark beetle outbreaks, leaving woody debris in the forest may in fact help to maintain the protection function after disturbance (Teich et al., 2019; Wohlgemuth et al., 2017), as well as supporting biodiversity (Wermelinger et al., 2017). A better understanding of spatial patterns of disturbance susceptibility as well as ecosystem service supply and demand (Stritih et al., 2019a) can help differentiate between areas where disturbance risk reduction is required, and those where embracing the natural disturbance regime may be more beneficial (Seidl et al., 2018).

6.4.4 Limitations

In this study, we used a Landsat-based disturbance product and in-situ forest management records to derive a large spatially explicit dataset of natural and anthropogenic disturbances, which allowed us to investigate the drivers of different types of disturbances. However, this dataset has certain limitations. The detection of disturbances through remote sensing is limited to disturbances large enough to have a significant impact on the canopy at the scale of a Landsat pixel (30 m). This is reflected in the omission rate, where over 40 % of reported management interventions (e.g., thinnings) were not detected in the satellite data (see Table 6.2). Some small-scale disturbances that were not detected or reported may therefore be missing from our analysis, particularly in older and heterogeneously structured forests, where small-scale gap dynamics are typical (Panayotov et al., 2015).

The limitations of satellite data for detecting and identifying disturbances highlight the importance of complementing remote sensing with in-situ information (Senf et al., 2018). However, the mapping of forest management by practitioners is not always spatially accurate and, in some cases, only approximate point information is recorded for events. This creates uncertainty in matching the recorded management information to satellite-detected disturbances. As spatially explicit forest management records become more common, similar analyses may be possible with fewer uncertainties and over longer time scales in the future. In addition, it is important to note that while our dataset compiles the occurrence and agent of a disturbance, it does not contain information about the severity of the disturbance (e.g., percent tree mortality), which would be useful to better characterize the dominant disturbance regimes.

6.4.5 Conclusions

In this study, we found that besides well-known factors such as topography and species composition, land-use legacies and recent management interventions affect the susceptibility of mountain forests to natural disturbances. In particular, closed spruce stands established after 1920 are more susceptible to natural disturbances than areas that were already forested during the 19th century. Our results also indicate that management interventions increase a stands' susceptibility to disturbance in the short term, highlighting the importance of considering trade-offs when managing mountain forests for resilience. In areas where a stable provision of ecosystem services is a priority, e.g. in protective forests, management interventions should take place early, before the stand reaches susceptible levels of canopy height and cover, since later management interventions may increase disturbance susceptibility. These findings also underscore the need to consider the interactions between site and stand conditions, land use and management history, and between different disturbance agents to improve our understanding of forest disturbance regimes.

6.5 Acknowledgements

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7 Paper IV: Addressing disturbance risk to mountain forest ecosystem services

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Abstract

Ecosystem service (ES) mapping has been developed with the aim of supporting ecosystem management, but ES maps often lack information about uncertainty and risk, which is essential for decision-making. In this paper, we use a risk-based approach to map ES in mountain forests, which are experiencing an increasing rate of natural disturbances, such as windthrow, bark beetle outbreaks, and forest fires. These disturbances affect the capacity of forests to provide essential ecosystem services, such as protection from natural hazards, wood production, and carbon sequestration, thus posing a challenge for forest management. At the same time, disturbances may also have a positive effect on certain services, e.g. by improving habitats for species that rely on dead wood. We integrate forests' susceptibility to natural disturbances into probabilistic Bayesian Network models of a set of ES (avalanche protection, carbon sequestration, recreation, habitats, and wood production), which combine information from remote sensing, social media and in-situ data, existing process-based models, and local expert knowledge. We use these models to map the level of the services and the associated uncertainties under scenarios with and without natural disturbances in two case study areas in the Swiss Alps. We use clustering to identify bundles of risk to ES, and compare the patterns of risk between the non-protected area of Davos and the strictly protected area of the Swiss National park with its surroundings. The spatially heterogeneous pattern of risk to ES reflects topographic variability and the forest characteristics that drive disturbance susceptibility, but also the demand for ecosystem services. In the landscape of Davos, the most relevant risks to ES are related to decreases in the protection against avalanches and carbon sequestration, as well as some risk to wood production and recreation. In the strictly protected Swiss National Park, the overall level of ES risk is lower, with an increase in habitat quality under the disturbance scenario. This risk-based approach can help identify stands with high levels of ES that are particularly susceptible to disturbances, as well as forests with a more stable ES provision, which can help define priorities in forest management planning.

Keywords: risk, natural disturbances, forest management, protected areas, uncertainty, Bayesian Networks

7.1 Introduction

Ecosystems globally are undergoing change at an unprecedented rate (IPBES, 2019; IPCC, 2018), exposing many of the ecosystem services (ES) they provide to risks related to changes in land use (Foley et al., 2005), climate, and an increasing frequency of extreme events (IPCC, 2014). This challenges the provision of services that are essential for human well-being (IPBES, 2019), and generates a high level of uncertainty for ecosystem managers (Polasky et al., 2011).

Mountain ecosystems provide essential ES to both local and global populations (Grêt-Regamey and Weibel, 2020), but are also sentinels of climate change (Pepin et al., 2015) and particularly vulnerable to extreme events (Klein et al., 2019b). In the Alps, mountain forests provide crucial protection from natural hazards (such as avalanches, rockfall, and landslides), as well as storing carbon, providing timber and energy resources, places for recreation, and habitats for rare and charismatic species, which are valued by a wider society (Schirpke et al., 2019b). In recent years, the dynamics and management of Alpine forests have been increasingly driven by natural disturbances, such as windthrow, bark beetle outbreaks, and forest fires (Seidl et al., 2014b; Usbeck et al., 2010), and these events are expected to become more frequent due to climate change (Anderegg et al., 2020; Yu et al., 2019). Disturbances can transform forests from carbon sinks into carbon sources (Anderegg et al., 2020; Pugh et al., 2019) and contribute to an instable provision of timber and energy (Albrich et al., 2018). In addition, disturbances can affect forests' capacity to provide protection from natural hazards (Sebald et al., 2019; Vacchiano et al., 2016), and affect landscape aesthetics (Sheppard and Picard, 2006) and recreational value (Flint et al., 2012). At the same time, disturbances can also have a positive effect on biodiversity (Thom and Seidl, 2016). The expected intensifying disturbance regime will thus pose important new challenges for forest managers (Kulakowski et al., 2017; Nikinmaa et al., 2020), and the degree to which forest managers should interfere in the forests' natural disturbance regime is increasingly disputed (Müller et al., 2019; Thorn et al., 2020). Combining information about disturbance risk with ES assessment could therefore help to identify priority areas for intervention or non-intervention and support forest management decisions (Lecina-Diaz et al., 2021b; Seidl et al., 2018).

In other fields that deal with high levels of uncertainty, such as finance or hazard management, the concept of risk is routinely used to inform decisions under uncertainty by combining impacts with probabilities (Dow et al., 2013). In modern portfolio theory, risk is calculated by multiplying asset returns with their variance (Alvarez et al., 2017) and allows for portfolio managers to optimize their returns under uncertainty. This approach has been translated to ES, for example to investigate optimal strategies for forest owners under a payments for ES scheme (Matthies et al., 2015). However, since not all ES values can be expressed in monetary terms, it is often difficult to compare measures of returns for different types of ES (Alvarez et al., 2017). In addition, the portfolio manager for whom to optimize is not always clearly defined, especially in case of public goods, making it challenging to implement portfolio management for ES.

In hazard management, risk assessments evaluate the probability and the impact of hazards, and provide a basis for decisions about acceptable vs. intolerable levels of risk (Dow et al., 2013). However, although the ES framework has been developed with the aim of supporting decision-makers (Daily et al., 2009), risk is rarely explicitly addressed in ES assessments (Dong et al., 2018; Hein et al., 2015). Recently, Lecina-Diaz et al. (2021) combined forest fire hazard, susceptibility, adaptive capacity, and ES supply to map risks in Catalonia, while Pártl et al. (2017) combined information on various hazards with ES provision to identify hotspots of ES risk in Czechia. Attempts have also been made to include risks to

ES supply in ecological risk assessments in China (Dong et al., 2018; Xu et al., 2016). However, the level of risk to ES depends on their value to people, which is determined not only by the potential supply of ES, but also by the demand for ES. The local demand for ES can by influenced by specific management regimes, such as protected areas. Protected areas affect the level of ES provision (Hanna et al., 2020; Mina et al., 2017), as well as the demand for and access to ES (Schirpke et al., 2020a). For example, publicity and information provided to visitors in protected areas can affect people's choices (Millhäusler et al., 2016) and perception of the landscape (Backhaus et al., 2013; Crouzat et al., in review). To provide information about risks to ES that is relevant for decision-makers, it is therefore important to include information about the demand for ES (Mandle et al., 2020).

Mapping ES supply and demand has been used to support ecosystem management and landscape planning by identifying hotspots and trade-offs or synergies between different ES that consistently occur together (i.e. "bundles") (Raudsepp-Hearne et al., 2010; Saidi and Spray, 2018; Tallis and Polasky, 2009). However, maps of ES are often created at a broad spatial scale, which does not correspond to the scale relevant for applications in ecosystem management (Spake et al., 2017). Many ES mapping approaches are based on coarse ecosystem categories such as land cover (Eigenbrod et al., 2010), neglecting the spatial structure within these categories (Spake et al., 2017; Sutherland et al., 2016). The increasing availability of remote sensing can facilitate more detailed ES assessments (Cord et al., 2017), but ES assessments are still associated with high uncertainties related to data, models, and the inherent variability of ecosystems (Stritih et al., 2019a; Willcock et al., 2018).

Bayesian Networks (BNs) are an increasingly popular tool to model ES (Gonzalez-Redin et al., 2016; Smith et al., 2018) due to their capacity to integrate both quantitative and qualitative information (such as expert knowledge), and to explicitly address uncertainties (Kelly (Letcher) et al., 2013). The probabilistic structure of BNs is particularly well suited for modelling systems with high levels of uncertainty, and for risk assessments (Grêt-Regamey and Straub, 2006; Kleemann et al., 2017; McDonald et al., 2016), where it is important to consider not only the most likely outcomes, but also extreme events. BNs have thus been used for risk-based evaluations of ES under future scenarios (Grêt-Regamey et al., 2013a), to assess uncertainties in ES assessments (Smith et al., 2018), and to disentangle different sources of uncertainty (Stritih et al., 2019a). Therefore, BNs also have the potential to evaluate specific risks to ES, such as forest disturbances, while taking into account their interactions with other uncertainties in ES assessments.

In this study, we assess the spatially explicit risks to mountain forest ES due to natural disturbances and compare the risks to ES between the non-protected landscape of Davos and the strictly protected Swiss National Park with its surrounding. To model a set of mountain forest ES, we use Bayesian Networks that combine different types of information about ES supply and demand, and integrate the associated uncertainties. These probabilistic models are used to map the ES under scenarios with and without natural disturbances to identify areas where the ES may be particularly at risk due to disturbance. In addition, we use clustering to identify bundles of ES risk and discuss how these could be used to identify management priorities.

7.2 Methods

7.2.1 Case study areas

We assessed the risk to forest ES due to natural disturbances (windthrow, bark beetle outbreaks, forest fires, avalanches, and snow breakage) in two case study areas in the south-eastern part of the Swiss Alps, the tourism resort of Davos and the Swiss National Park (SNP) with its surroundings (see Figure 7.1). The town of Davos is a well-developed urban and touristic centre, located in the central part of the main valley at an elevation of 1550 m a.s.l.. The rest of the main valley and the three side valleys in the region are relatively rural, with a few scattered settlements and a landscape still strongly dominated by mountain agriculture. Overall, the case study area of Davos covers an area of 254 km^2 and an elevation range from 1250 to 3146 m a.s.l.

The region of the lower Engadin and Val Müstair has a similar topography to Davos, with elevations from 1019 to 3410 m a.s.l. and a traditional agricultural landscape characterized by historic villages and the steep-flowing river Inn. The region includes the Swiss National Park (SNP), which was established in 1914 as the first national park in the Alps and the only national park in Switzerland. The park is designated as a category Ia nature reserve (highest protection level - strict nature reserve, IUCN). Today, the park covers an area of 170 km^2 and forms the core zone of the UNESCO Biosphere Reserve Engiadina Val Müstair, which also includes the regional nature park Biosfera Val Müstair and a part of the municipality of Scuol.

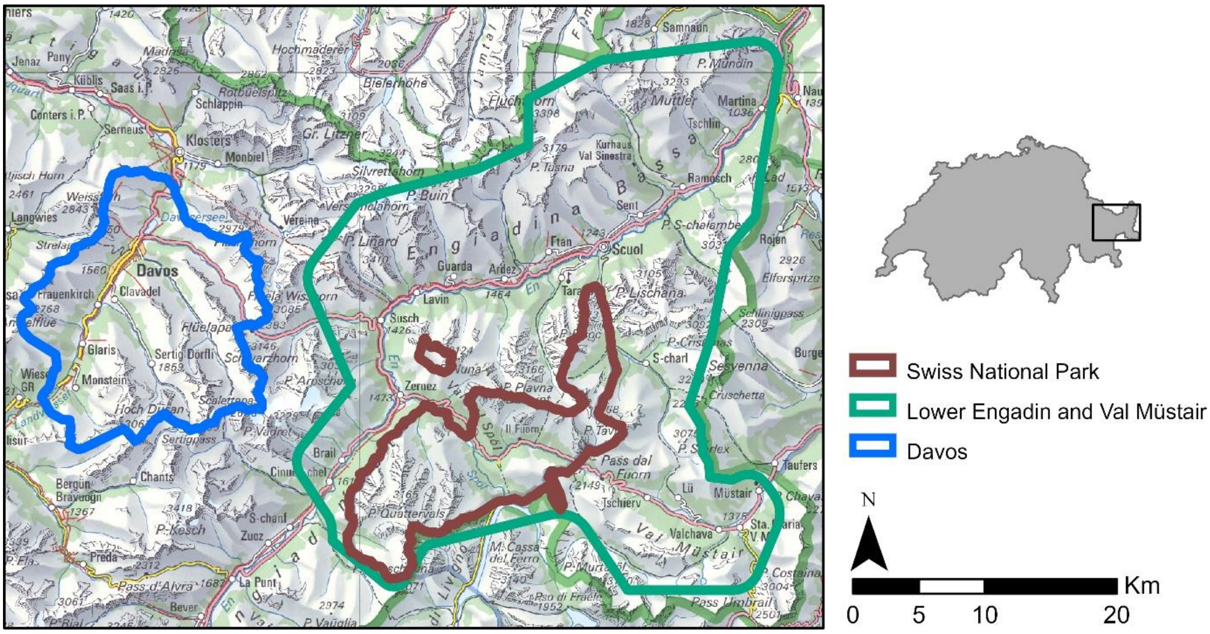

Figure 7.1: Overview of the case study areas (National topographic map 1:500'000, swisstopo).

In both regions, most of the forests are conifer-dominated, and the treeline occurs between 2100 and 2400 m a.s.l.. In these mountainous areas, one of the most important ES provided by forests is protection from natural hazards, such as avalanches (Grêt-Regamey et al., 2008). In the SNP, no interventions in the forest are allowed, while most management outside of the park takes place in the form of small-scale interventions (Temperli et al., 2017). Due to the difficult mountainous terrain, wood production is currently not profitable in most forests in the region, and many forest management interventions are primarily aimed at maintaining the forests' protection capacity. In addition, forest managers also aim to maintain habitats for priority species such as capercaillie (AWN, 2018). Moreover, recreation is an important ecosystem service in Davos (Grêt-Regamey and Kytzia, 2007), the SNP and the surrounding region (Backhaus et al., 2013; Crouzat et al., in review).

7.2.2 Assessing risk with Bayesian Networks

Risk is defined by the *probability* of a hazard and the *magnitude* of its impact (IPCC, 2018), where the magnitude of natural disturbance impacts depends on the *exposed value* of ecosystem services and their *susceptibility* to disturbances (Lecina-Diaz et al., 2021b). To address the *probability* of natural disturbance impacts on ES, we use probabilistic Bayesian Network models of ES. Bayesian Networks (BNs) are graphical models, consisting of nodes representing variables and links that represent dependencies between nodes (Jensen, 2001; Kjaerulff and Madsen, 2013). Each node has a finite set of possible states (qualitative states such as land cover, or discretized quantitative states such as canopy height). The links between nodes are quantified in conditional probability tables, which contain the probability distribution of the "child" nodes for each combination of states of its "parent" nodes.

The BN models of ES combine information about ecosystem structure and function, demand for ecosystem services, and disturbance effects (see conceptual representation in Figure 7.2), while taking into account the uncertainty in each component (Stritih et al., 2019a). Since each conditional probability table in the network can be defined individually, the BN models can integrate different types of information, e.g. by "learning" from data, process-based models, or expert knowledge (Borsuk et al., 2004). To combine quantitative (e.g. tonnes of carbon) and qualitative variables (e.g. landscape attractiveness), all of the final ecosystem service values were expressed in four levels (no service, low, medium, high level). For quantitative variables, the discretization into levels was defined based on quantiles of the mean predicted value.

When we run the BNs with spatially explicit evidence, the output consists of a probability distribution of the ecosystem service for each pixel of the study area. To take into account the *probability* and *magnitude* of the ES, we summarize the probability distribution by calculating the expected value $E[X] = \sum_{i=0}^{N} p_i \cdot i$, where i represents the index of the state (0 - no service, 1 - low, 2 - medium, 3 - high level of ES) and p_i is the probability of state i (Landuyt et al., 2015).

The output probability distribution integrates various sources of uncertainty, including data and model uncertainty, epistemic uncertainty in expert knowledge, as well as natural variability. To extract only the risk related to natural disturbances, we therefore calculate the specific disturbance risk as $Risk(dist) = E[ES_{dist.}] - E[ES_{no\ dist.}]$, where $E[ES_{no\ dist.}]$ is the expected value of ES under a scenario without distrurbances and $E[ES_{dist.}]$ is the expected value under a disturbance scenario (see Figure 7.2). Negative values indicate a loss of ES, while positive values indicate an improvement in ES.

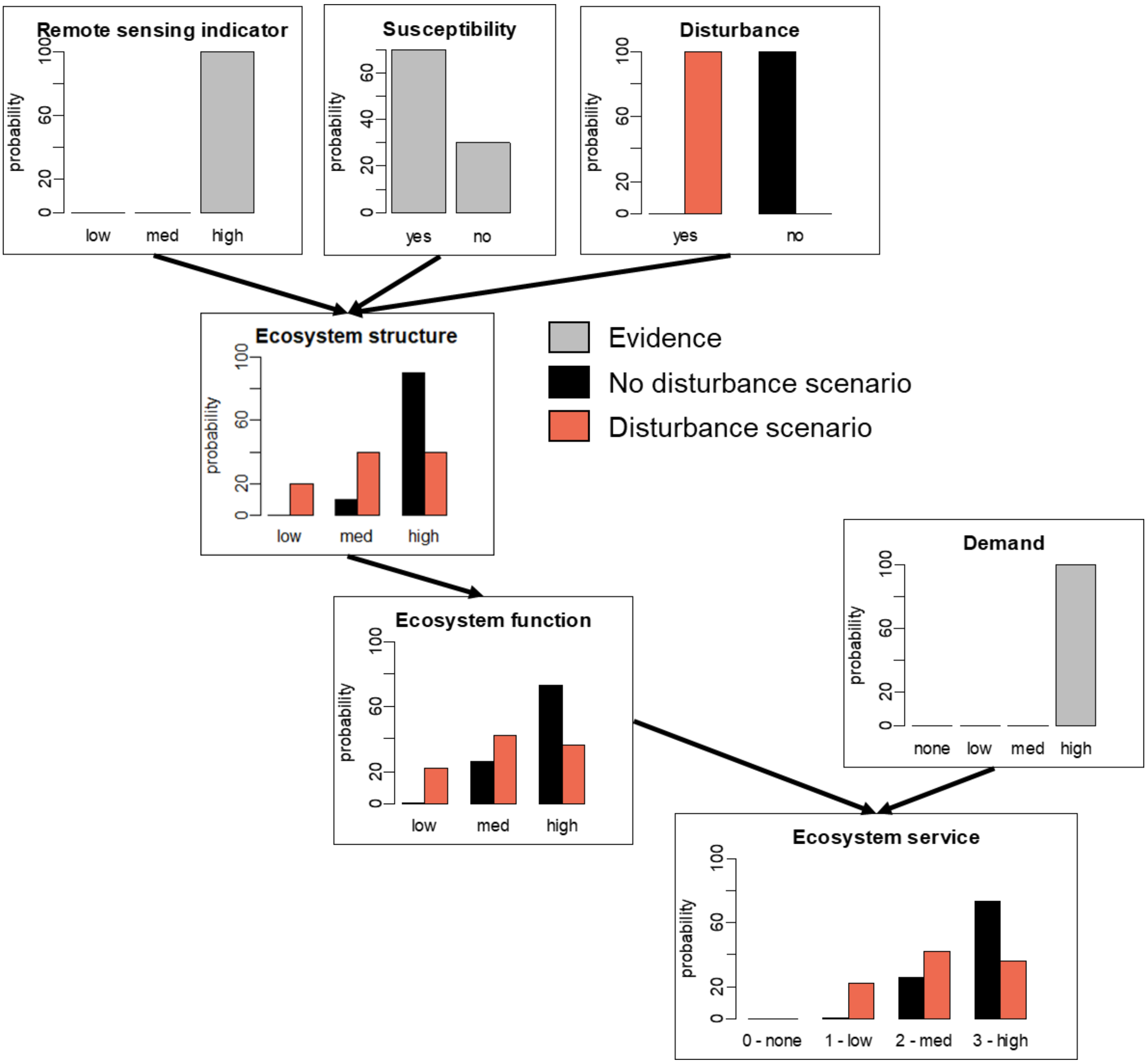

Figure 7.2: Conceptual representation of a Bayesian Network of an ecosystem service, where each box shows a node with its probability distribution over possible states. Evidence has been set for the nodes "Remote sensing indicator", "Demand", and "Susceptibility", where the evidence for susceptibility is based on probabilities derived from modelling of natural disturbances in the region (Stritih et al., 2021). For the other nodes, the posterior probability distributions under a disturbance and no-disturbance scenario are shown. Risk related to disturbances is calculated as the difference between the expected values of the "Ecosystem service" node under the disturbance and no-disturbance scenario.

7.2.3 Exposed values – ecosystem services

We modelled five ecosystem services: carbon sequestration, wood production, avalanche protection, recreation, and habitats. The models of ES were based on remote sensing inputs as proxies of ecosystem structure, including a classification of vegetation types derived from Sentinel-2 images (European Space Agency, 2016, see details in Appendix D, Table D.1), and a canopy height model (Ginzler and Hobi, 2015), as well as a digital terrain model (swissALTI3D, swisstopo, 2015). Ecosystem structure was linked to ecosystem functions and services based on process-based models and in-situ data (for carbon sequestration, wood production, and avalanche protection, see Table 7.1), and based on literature and expert knowledge (for recreation and habitats). Below, we briefly describe the individual ES models, while the details of all the models are shown in the Supplementary material (Appendix D). We used the

BN software Netica to develop the models (Norsys, 2010), and then ran the BN models spatially at a 100m-resolution using gBay, an online tool for BNs with geodata (Stritih et al., 2020).

Table 7.1: Summary of ecosystem service models, with type of models used and the data used as inputs (RS indicates the remote sensing inputs). The details of each model are provided in Appendix D.

Ecosystem service	**Model type**	**Input data**
Carbon sequestration and Wood production	Process-based	RS: vegetation type, crown cover, canopy height Land-use history (historical maps) Elevation, slope (DTM, swissALTI3D) Dead wood amount Distance to roads (swissTLM3D, swisstopo, 2020) Protected area Harvesting costs, wood prices
Avalanche protection	Process-based	RS: vegetation type, crown cover, gap width Elevation, slope, curvature, terrain roughness (DTM, swissALTI3D) Dead wood Buildings, roads, protection barriers (swissTLM3D) Process-based avalanche simulations Snow height distribution
Habitats	Literature-based	RS: vegetation type, crown cover, canopy height Neighbourhood forest cover Distance to forest cover, distance to grazing area Land-use history Dead wood Elevation, slope (DTM, swissALTI3D) Distance to roads, road density, hiking paths (swissTLM3D) Protected area
Recreation	Expert-based	RS: crown cover Points of interest (Open Street Map, 2020) Viewshed of mountain peaks Accessibility: roads, ski lifts, hiking paths, bus stops (swissTLM3D)

For *carbon sequestration*, in-situ data from the cantonal forest inventory of Graubünden (AWN, 2018b) were used to “learn” the relationship between canopy height and the stock of aboveground biomass, and to estimate forest growth rates based on site and stand characteristics. The growth rates were also used to estimate the amount of wood available for *wood production* (Grêt-Regamey et al., 2013a), and its value was calculated based on wood prices and harvesting costs. The model for *avalanche protection* was based on the BN described in Stritih et al. (2019), where forests can prevent avalanche releases and have a braking effect on avalanche flows, while the demand for avalanche protection is determined by the infrastructure and people at risk.

Recreation was modelled based on the accessibility and landscape attractiveness, where the most important factors determining the attractiveness of the landscape for recreation (topography and view, places of cultural importance, and wildlife observation potential) were determined by experts from the SNP and tourism organizations from the surrounding communities (Crouzat et al., in review). The spatial pattern of recreation was validated using the locations of the Flickr pictures as a proxy for the actual use of recreation areas (Langemeyer et al., 2018; Wood et al., 2013).

Biodiversity supports the provision of other ecosystem services, but also has an intrinsic value in itself for many people (Mace et al., 2012), and is recognized as a priority in national policy (FOEN, 2012) and by local forest management (AWN, 2018). We therefore modelled the *Habitats* of three regionally important species: capercaillie (*Tetrao urogallus* L.), an indicator species for structurally diverse mountain forests (Suter et al., 2002), the three-toed woodpecker (*Picoides tridactylus* L.), a keystone species in forests with substantial amounts of dead wood (Bütler et al., 2004a; Roberge and Angelstam, 2006), and red deer (*Cervus elaphus* L.), a charismatic species that attracts visitors to the SNP (Millhäusler et al., 2016). The models for each species were based on existing literature from the region and validated using observation data (Info fauna, 2018; Vogelwarte, 2018, see Table 7.2), and the final value of habitats combined all three species' habitats with an OR-operator (e.g. if an area is highly suitable for any of the species, the level of the habitat service is high).

Table 7.2: Validation of the expert- and literature-based models for habitats and recreation. The AUC (area under the receiver operating curve) is a measure of model performance, calculated as the area under the curve of true positives (presences) vs. false positives (random absence points) at different thresholds of presence probability. AUC values above 0.8 indicate good model performance.

Model		**AUC**	**Validation data**
Habitats	Three-toed woodpecker	0.849	Observation data (Vogelwarte, 2018)
	Red deer	0.815	Observation data (Info fauna, 2018) and grazing damage (forest management data, AWN, 2019)
	Capercaillie	0.877	Forest management plan – capercaillie habitat (AWN, 2018)
Recreation		0.852	Flickr photo locations

7.2.4 Susceptibility to natural disturbances

Each ES model includes the potential effects of natural disturbances on the service. The probability that a stand is affected by a disturbance is determined by its susceptibility, which is affected by site and stand characteristics, management and land-use history, as modelled based on a dataset of disturbances in the region in Stritih et al. (2021). In case of a disturbance, tree mortality (estimated based on forest management records) and decay of dead woody debris affect carbon sequestration levels, while salvage logging after disturbances influences both the amount of harvest and the types of wood products. Reduced forest cover and new gaps created by disturbances can limit forests' avalanche protection capacity, although this can be partly mitigated by snags and downed dead wood (Teich et al., 2019; Wohlgemuth et al., 2017). A higher amount of dead wood improves habitat suitability for the three-toed woodpecker, but may have a small negative effect on the perceived landscape attractiveness (Rewitzer et al., 2017).

7.2.5 Identifying bundles of ES risk

To summarize the information about risk related to different ES and identify areas with similar levels of risk (i.e., bundles of risk), we performed a cluster analysis on all the forest pixels in the study areas using the cluster package in R (version 2.1.1, Maechler et al., 2021; R Core Team, 2019). First, the most suitable number of clusters was identified using a bootstrapped calculation of the gap statistic (Tibshirani et al., 2001), and then clustering was performed with the k-medoids algorithm, a robust alternative to k-means (Kaufman and Rousseeuw, 1990).

7.3 Results

The maps of ES value (Figure 7.3) show a high level of spatial heterogeneity within mountain forests, as well as differences between both study areas. The spatial pattern of the expected value of carbon sequestration mainly reflects forest structure, with larger stocks of wood and higher growth rates in favourable growing conditions at lower elevations, such as in the Lower Engadin valley. Wood production is closely linked to carbon sequestration, and is only limited by accessibility in some remote locations. In most of the forests, harvesting is carried out using a cable system, and high harvesting costs lead to a low value of wood production, with low spatial variability. Inside the SNP, no harvesting is allowed, so the wood production value is zero (Figure 7.3).

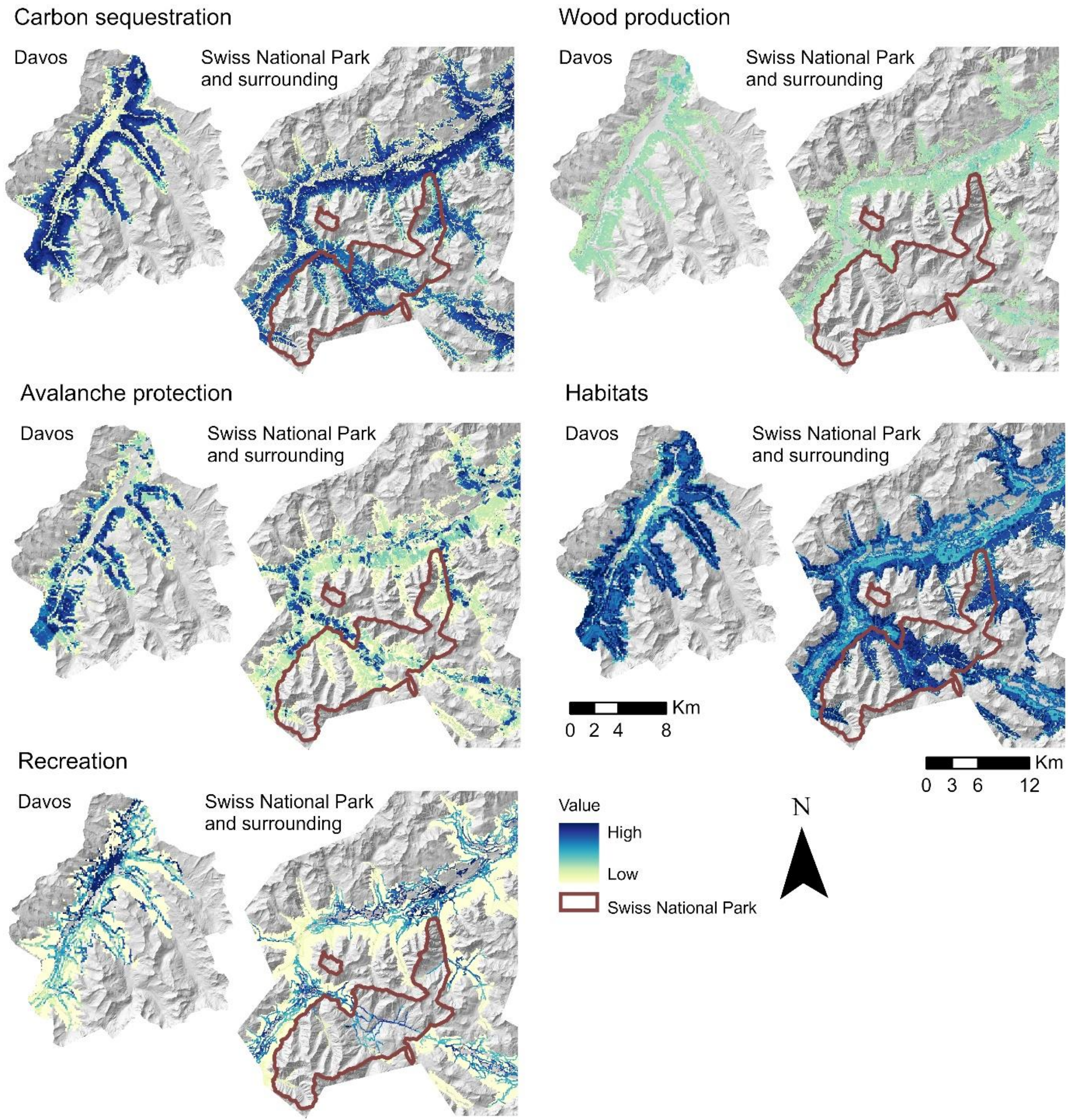

Figure 7.3: Map of the expected value of five ecosystem services in the area of Davos and the Swiss National Park with the surrounding lower Engadin and Val Müstair.

Most of the forests in both regions are suitable habitats for at least one of the modelled species, and slightly more suitable inside the national park due to the lower level of anthropogenic disturbance. In contrast, the spatial patterns of recreation and avalanche protection are largely driven by demand. The expected value of recreation is mainly determined by accessibility, with higher values near towns and roads, and a lower value in more remote areas. In the SNP, recreation is limited to hiking paths, as visitors are not allowed to leave the trails. Inside the park, there are some forests important for avalanche protection above the main road crossing the park, but overall, the demand for avalanche protection is low. The value of avalanche protection is higher outside the park, particularly on the slopes above towns and villages (Figure 7.3). The forests with the highest avalanche protection value are dense evergreen forests on steep slopes, which would have a high probability of avalanche releases in case there was no forest.

Most of the modelled ES show a decrease in expected value under the disturbance scenario (Figure 7.4). The risk of a loss of ES is largest for carbon sequestration, and there is a correlation between the expected value of the service and the associated risk (see correlations in Appendix D, Table D.2). However, at high levels of carbon sequestration, there is a wide variability of risk, which reflects differences in forests' susceptibility to natural disturbances. At higher elevations and in open forests, the susceptibility to disturbances is lower. In addition, salvage logging is not common in inaccessible areas and absent in the SNP, and the dead wood remaining in these stands decays slowly, meaning that the immediate loss of carbon stored in these ecosystems is low in comparison to forests at lower elevations. For avalanche protection, we also find a clear correlation between the expected value of the service and risk due to disturbances, where forests that provide more avalanche protection are also more susceptible to disturbances. The risk for avalanche protection is mostly lower in the SNP and higher outside the park.

For the other modelled ES, the magnitude of changes in the expected value of ES under the disturbance scenario is lower (Figure 7.4). The risk for wood production is correlated with risk for carbon sequestration (see Appendix D, Table D.3), but not clearly related to the expected value of wood production. While the volume of wood production would increase on the short term in case of disturbance due to salvage logging, the lower prices of salvaged wood result in a lower value of wood production in most areas. However, since the expected value of wood production is already low under the disturbance scenario, this change is small (Figure 7.4). The expected value of habitats shows small increase under the disturbance scenario, related to the increased availability of dead wood, which is particularly important for the three-toed woodpecker. This increase is more likely in the SNP, where no salvage logging takes place, while the risk to habitats is close to zero in most areas outside the park. The increase in habitat suitability in the park contributes to a higher probability of wildlife sightings and thus a small increase in the expected value of recreation under the disturbance scenario. Outside the park, disturbances have a small negative impact on the attractiveness of the landscape for recreation.

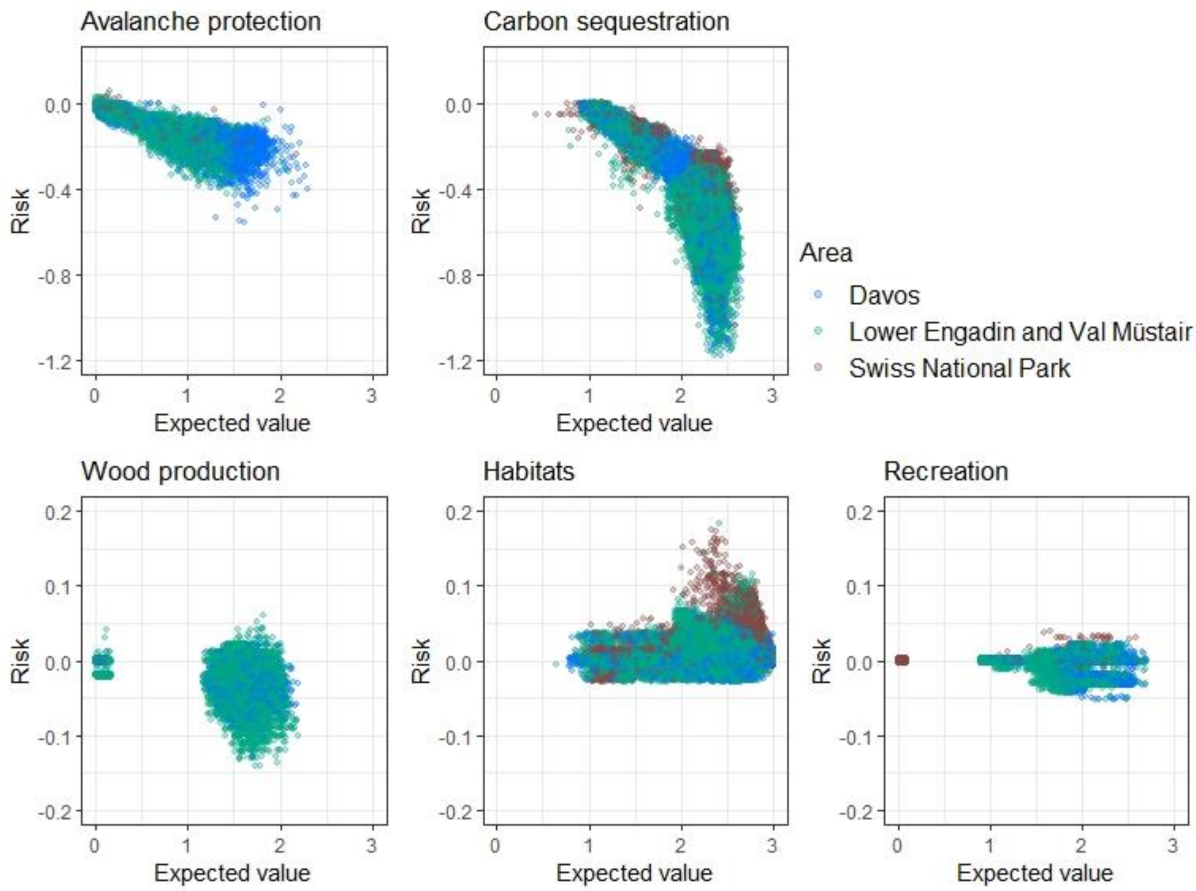

Figure 7.4: Risk to ES due to natural disturbances (i.e. difference between expected value in disturbance and no-disturbance scenario) vs. expected value for different ES. Points represent forested pixels, and expected values are categorized from 0 (no ES) to 3 (high ES value).

The cluster analysis identified 6 main clusters of ES risks (see Figure 7.5). Clusters 1-3 represent areas where multiple forest ES are at risk due to disturbances. In cluster 1, carbon sequestration, wood production and avalanche protection may all decrease under a disturbance scenario, while a small increase in habitat quality can be expected. Cluster 2 includes areas with some risk to recreation, mostly near towns and recreational infrastructure. Forests with lower risk to avalanche protection and carbon sequestration are included in cluster 3, which is most widespread on the north-facing slope of the Lower Engadin valley (north of the SNP, see Figure 7.5). Cluster 4, with the largest improvement in habitats and a low risk for carbon sequestration and avalanche protection, can only be found inside the SNP. Cluster 5 represents areas with a low risk to carbon sequestration and small improvement in habitats, mostly in more remote areas and in the national park, while cluster 6 includes areas near the treeline with low risk to all modelled ES.

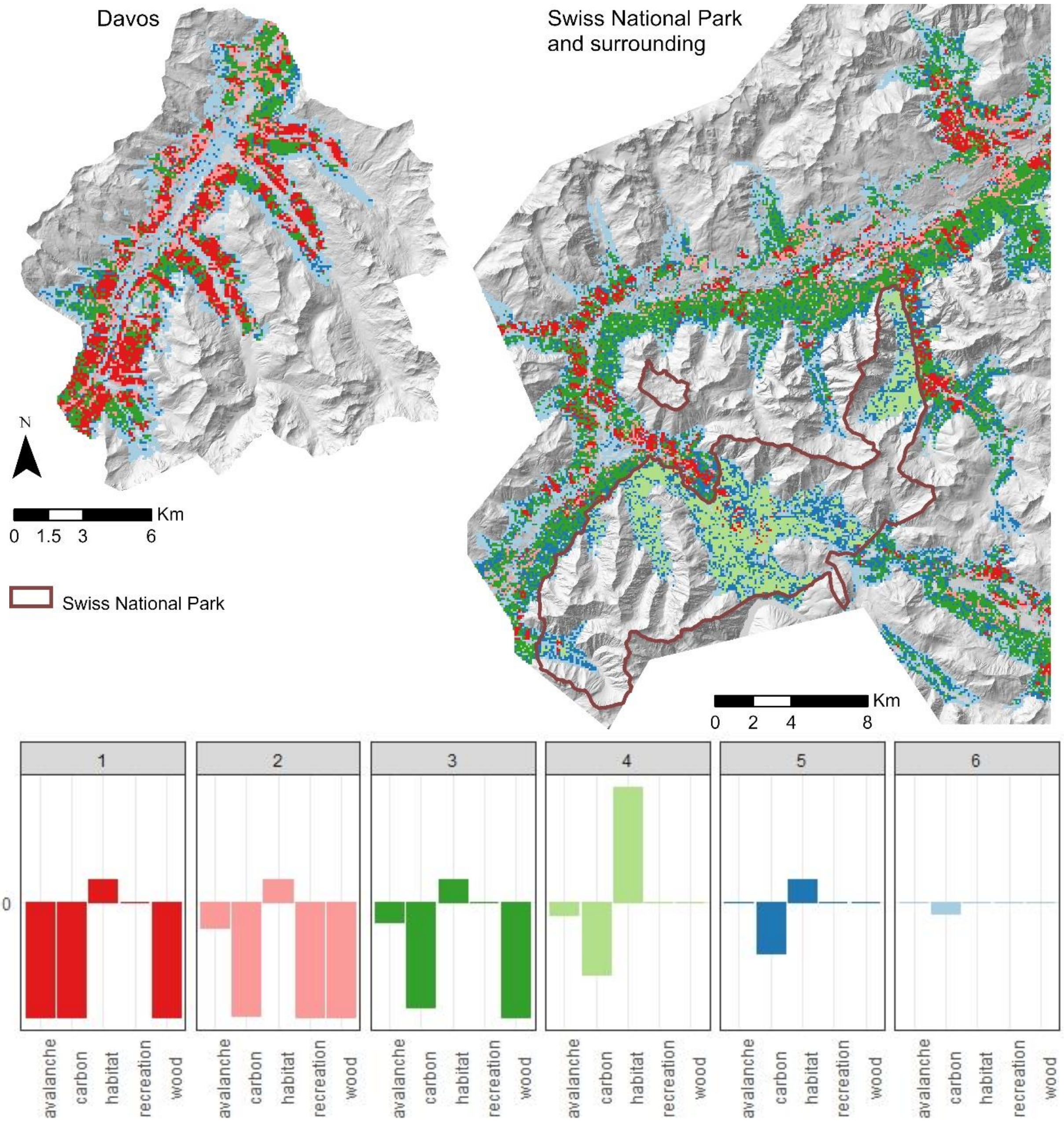

Figure 7.5: Map of the clusters based on risk to ES, and their characteristics, where the bar height indicates the median risk for each ES (avalanche protection, carbon sequestration, habitats, recreation, wood production) due to disturbances (scaled to the maximum change for each ES for better readability). A negative value indicates a loss of ES, while positive values indicate an increase in ES.

7.4 Discussion

7.4.1 Natural disturbance effects on ecosystem services

The increasing rate of natural disturbances is likely to affect ES in mountain forests, but their effect is heterogeneous in space and across different types of ES. In part, the disturbance impact is driven by factors that determine forests' susceptibility to disturbances, such as topography, stand structure and land use history (Stritih et al., 2021). However, it also depends on the way that disturbed forests are managed and perceived by people.

Natural disturbances and the extent of salvage logging after such disturbances affects all of the modelled ES. In this study, we assumed that some salvage logging takes places in most accessible forests outside the SNP, which results in a clear distinction of disturbance effects inside and outside of the national park. Salvage logging is usually carried out to utilize at least part of the wood of dead or damaged trees before they decay, and to mitigate the risk of subsequent bark beetle outbreaks (Müller et al., 2019). However, the quality of wood is often lower compared to regular harvests, and large-scale disturbances can result in an oversupply and low wood prices (Schelhaas et al., 2003). The profitability of salvage logging is therefore low, particularly in areas with high harvesting costs such as the Swiss Alps (Temperli et al., 2017). On the other hand, when dead wood remains in the stand after disturbances, it provides important habitats for the three-toed woodpecker as modelled in this study, but also for many other birds, plants, insects, and fungi (Thorn et al., 2020). In dry, inner-alpine valleys and at high elevations, such as in the SNP, the slow decomposition of woody debris (Vanderhoof et al., 2013) may buffer the loss of carbon after disturbances, although dead wood decay and thus long-term effects on ES are associated with high levels of uncertainty (Schmid et al., 2016).

Besides supporting biodiversity, dead wood can also contribute to maintaining forests' capacity to protect from natural hazards, such as avalanches or rockfall after disturbances (Teich et al., 2019; Wohlgemuth et al., 2017). This is particularly important as our results indicate a high risk in most areas with a high value of avalanche protection. Some of the structural characteristics that support avalanche protection (i.e. dense evergreen stands) also make forests more susceptible to natural disturbances, indicating a trade-off between the current protection effect and the long-term stability of protection forests (Temperli et al., 2020).

Previous research has shown that forest disturbances are often perceived as having a negative effect on landscape aesthetics and recreation (Flint et al., 2012; Rewitzer et al., 2017; Ribe, 2009; Sheppard and Picard, 2006; Thom and Seidl, 2016). A survey carried out in the SNP in the 1990s showed that some visitors expressed a negative perception of dead wood in the park, as it was perceived as "untidy" (Hunziker, 1997). However, due to the park management's effort to inform visitors about the ecological importance of dead wood, as well as changing visitor demographics, a repeated survey found that visitors perceived dead wood as neutral or even positive (Backhaus et al., 2013).

Here, we modelled the short-term effects of natural disturbances, the most immediate and already visible effect of climate change in mountain forests (Kulakowski et al., 2017). However, on the long-term, climate change is likely to have other effects on mountain forests, such as an upward shift in the treeline, which may lead to an increase in carbon sequestration and avalanche protection (Grêt-Regamey et al., 2013b). On a longer time scale, feedback loops between management and disturbances are important for the long-term provision of ES. For example, the long-term protection capacity of forests after disturbances will depend on the speed of regeneration, which in turn may be influenced by the intensity of ungulate browsing (Brüllhardt et al., 2015; Wohlgemuth et al., 2017). While forest management interventions can increase disturbance susceptibility on the short term (Stritih et al., 2021), interventions that increase species- and structural diversity may decrease the risk of disturbances in the long term (Seidl et al., 2018). In addition, retaining dead wood can help maintain some ES after disturbances, but may increase the risk of subsequent bark beetle infestations (Seidl and Rammer, 2017; Stadelmann et al., 2014).

To take these long-term processes into account, a useful approach may be to couple the ES models with dynamic vegetation models at the landscape scale (Seidl et al., 2014a; Temperli et al., 2020). Such process-based models would also allow to consider climate effects in more depth, but contain also considerable uncertainties (Petter et al., 2020), which could be integrated in the BN-approach by running multiple simulations with varying parameters. At the same time, the ES models can also be used to identify important variables that should be modelled over time. For example, although dynamics of dead wood are usually not explicitly modelled in dynamic vegetation models (Petter et al., 2020), our results indicate that dead wood plays an important role in forest ES. A combination of ES models and dynamic vegetation models could improve predictions of future ecosystem services, and allow us to address the long-term adaptive capacity of forests, which is an important aspect of forest vulnerability (Lecina-Diaz et al., 2021b).

In addition to long-term changes in forest structure and dynamics, the demand for forest ES may exceed also the current bounds of variability in the future. Such changes may include an increased use of renewable biomass for energy (Thees et al., 2020) or changes in exchange rates that influence visitation rates in Switzerland (Millhäusler et al., 2016). Furthermore, people's preferences may also change over time as societal values develop (Voinov et al., 2014), adding a further component of uncertainty about long-term changes in ES (Brunner et al., 2017).

7.4.2 Bundles of ES risk and implications for management

By mapping not only the value of ES, but also the associated risks, additional valuable information can be added to traditional ES-bundle analyses. Our results show a correlation between the expected value and risk to ES for carbon sequestration and avalanche protection, indicating a trade-off between the level and stability of ES provision. This type of trade-off has also been identified in simulation-based studies of forest ES dynamics (Albrich et al., 2018; Temperli et al., 2020). However, this relationship is not homogeneous in space, and less pronounced for other ES. Mapping the risks to ES is therefore important information for forest managers under a changing disturbance regime, who face decisions about where to control and where to embrace the effects of natural disturbances (Kulakowski et al., 2017; Seidl et al., 2018).

Based on the cluster analysis of ES risks, we can identify not only priority areas with a high risk to ES (e.g. cluster 1, Figure 7.5) but also areas with a more stable provision of several ES (clusters 5 and 6). While high risk indicates areas where interventions may be needed to ensure the demanded level of ES provision, areas of stable provision are important in terms of the insurance value of ecosystems (Baumgärtner and Strunz, 2014). Ecosystem management based on risk to ES may therefore differ from management based on the current value of ES.

Decisions about risk management depend not only on the quantified risk, but also on the risk perception of people affected. For different ES users, some risks may be more important than others, depending on who is affected (Blennow et al., 2014). For example, a loss of protection from natural hazards would have a much more direct effect on the local population compared to a loss of carbon sequestration. In addition, the perception of risk is not necessarily linear – rather than the average expected change, it may be more important to ensure that the provision of ES does not fall below a certain threshold (Shah and Ando, 2015). While questions about risk perception and priorities should be addressed together with affected stakeholders (Blennow et al., 2014), explicitly evaluating the risks and uncertainties in ES assessments can support informed discussions about risk management decisions.

7.4.3 Protected and non-protected areas

Our results indicate a strong effect of strict protection on ES and risks to ES. Overall, we find a lower level of risk in the strictly protected Swiss National Park compared to both the surroundings of the park (Lower Engadin and Val Müstair), and the more densely used area of Davos. While the forests of Davos provide a wider range of ES, the provision of these services is at risk in some parts of this study area under an intensifying disturbance regime. Forest managers are therefore faced with high uncertainty regarding issues such as the long-term effectiveness of disturbed forests for natural hazard protection and their perception by visitors. In contrast, the lack of human intervention in the SNP results in a higher quality of habitats and a potential increase of ES under the disturbance scenario. It is important to note that we only modelled the habitats of three species and weighted all the species equally. Although the capercaillie and three-toed woodpecker are considered to be indicator species for species-rich forests (Roberge and Angelstam, 2006; Suter et al., 2002), other species may be negatively affected by natural disturbances (Thom and Seidl, 2016), and a different prioritization of species might affect the modelling results.

The differences between protected and non-protected areas are driven by regulations (e.g. lack of salvage logging and limited recreation outside of hiking trails), but also by differences in demand for ES, such as the smaller amount of infrastructure at risk of avalanches inside the park, and different visitor preferences. Therefore, the differences are more pronounced for services with a local demand (e.g. avalanche protection) than for services with a global demand (e.g. carbon sequestration).

In many protected areas, the concept of ES is not explicitly addressed in management plans (Palomo et al., 2014). In the case of the Swiss National Park, the park managers have a federal mandate to let natural processes take their course, enable research in an undisturbed ecosystem, and to educate visitors (Haller, 2014). In contrast to many other protected areas worldwide that aim to foster both conservation and sustainable development (Dudley, 2008), these clear management objectives limit the need for decisions about trade-offs between ES in the SNP. Nonetheless, assessments of ES can help demonstrate the importance of such protected areas (Kettunen et al., 2008), such as the insurance value of ecosystems in the park, where the risk to ES is low compared to non-protected areas. In addition, information about ES dynamics and risk in the absence of human intervention can provide valuable information for managers of non-protected areas (Hanna et al., 2020).

7.4.4 Conclusions

In this study, we assessed the spatially heterogeneous risk to mountain forest ES posed by natural disturbances. By mapping bundles of risk to ES, we can identify areas with high ES value and high risk, as well as areas with a stable provision of ES, and this type of information can serve as a basis for risk-based decisions about ecosystem management. Although many uncertainties remain about mountain forest dynamics under a changing climate, our results show that retaining dead wood in the stand can help mitigate the effects of natural disturbances on forest ES. When comparing mountain forests in the non-protected area of Davos with those in the strictly protected Swiss National Park, our findings indicate a lower risk to ES in the protected area. These differences are largely driven by differences in demand for ES, highlighting the need to include demand in assessments of risk to ES.

7.5 Acknowledgements

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8 Synthesis

The aim of this thesis was to advance risk-based ES assessments in the context of mountain forest management under uncertainty. In the following sections, I summarise the key findings of the thesis, address their policy relevance and scientific impact, and suggest an outlook for further research.

8.1 Summary of key findings

In this thesis, BN models were developed to integrate different types of information on a set of mountain forest ES, including avalanche protection, carbon sequestration, habitats, recreation, and wood production. Using this probabilistic approach, the ES, their uncertainties, and specific risks due to natural disturbances were mapped in the regions of Davos and the strictly protected Swiss National Park with and its surroundings. Below, the main results are summarised in reference to the research questions presented in Chapter 3.

i. *What are the major sources of uncertainty in forest ecosystem service assessments and to what extent can uncertainties be reduced using remote sensing?*

Models of ES include uncertainties related to the input data used to map ecosystem structure (e.g. classification and measurement errors in remote sensing products) and parameter uncertainties in the empirical or process-based models that link ecosystem structure to ecosystem functions. When data or models are not available, assessments rely on expert knowledge, which is also associated with some uncertainty. We developed methods to integrate all these uncertainties into probabilistic BN models, where the uncertainties are propagated to the model output and the overall uncertainty about the modelled ES can be quantified, as demonstrated for the example of avalanche protection in **Paper I**.

To disentangle the different sources of uncertainty, evaluate their influence on the model output, and identify knowledge gaps, an innovative approach of stepwise sensitivity analysis was developed to plot the flow of information in the model. This analysis showed that uncertainty about avalanche protection is largely related to the inherent variability of the natural hazard process and the uncertainty in the links between ecosystem structure and functions (**Paper I**). Although using several remote sensing inputs (e.g. LiDAR-based canopy height) can improve the accuracy of mapping ecosystem structure and can address the spatial variability within land-cover categories, this only has a small effect on reducing the overall uncertainty in the ES assessment. Therefore, to fully utilise the potential of remote sensing in ES modelling, it should be used not only to map ecosystem structure but also as calibration and validation data to further improve models of ecosystem processes, functions, and services. Nevertheless, in situ data are essential. Whereas satellite data were used for mapping forest disturbances in **Paper III**, in situ information from forest managers was needed to add information about disturbance agents to the remote sensing product.

ii. *How can uncertainties be included in spatially explicit models of socio-ecological systems?*

By running BNs in a spatially explicit way, for each pixel in a raster, uncertainties in models of socio-ecological systems can be mapped (**Paper I**). However, in such a pixel-based approach, spatial relationships, such as neighbourhood effects, or processes at different scales are usually neglected. To address this issue, we developed an online tool called gBay that couples spatial BNs with geoprocessing scripts. Considering neighbourhood effects helped reduce uncertainties in the avalanche protection model (**Paper II**).

Although BNs are increasingly used in socio-ecological modelling, few tools for spatial BNs are accessible to users. The gBay tool is therefore openly available online, along with guidelines for the development and use of BN models. In the frame of the ECOPOTENTIAL project, BNs have been used to model ES and land-use change in several PAs in Europe (Stritih et al., 2019b).

iii. Which factors influence the risk to mountain forest ecosystem services due to natural disturbances?

By analysing the spatial patterns of natural disturbances in **Paper III**, we found that forests' susceptibility is influenced by current site and stand characteristics as well as by land-use history and management. Spruce forests at warmer sites are particularly susceptible to disturbances, an effect that is likely to be exacerbated by climate change. Furthermore, forests established on former agricultural land during the 20^{th} century are more susceptible to disturbances than 'older' forests, and forest management interventions exacerbate disturbance risk on the short term.

Natural disturbances have diverse effects on different ES (**Paper IV**), from the high risk of a loss of regulating services (carbon sequestration and avalanche protection) to potential increases in habitat quality. The spatial patterns of risk to ES are affected by forests' susceptibility to disturbances and by differences in demand for ES.

iv. How can knowledge of risk help manage forest ecosystem services?

By integrating spatially explicit information about the supply of and demand for ES and the susceptibility to disturbances, we were able to map the spatially heterogeneous risk to ES due to natural disturbances (**Paper IV**). This allows us to identify areas of high risk and high demand for ES, priority areas for forest management where interventions may be needed to secure sufficient provision of ES under a changing disturbance regime, and areas where interventions may exacerbate disturbance risk.

By comparing the strictly protected Swiss National Park with managed landscapes outside the park, we were able to examine various aspects in which management affects the risk to ES. Non-managed forests in the Swiss National Park provide fewer ES than forests outside the park, but their ES are less at risk and may even improve under a changing disturbance regime. On the short term, dead wood remaining in the stand after disturbances plays an important role in buffering the loss of ES due to tree mortality, an effect that should be considered in decisions about salvage logging. Differences in people's perceptions of and demand for ES also have an important effect on the risk to ES.

Areas with high provision of ES are often associated with high risk, especially for regulating services, indicating a trade-off between short-term ES benefits and the long-term stability of the provision of ES. Risk-based ES assessments can therefore support management strategies that aim for the sufficient provision of ES under a range of possible outcomes rather than optimising ES under the most likely scenario.

8.2 Limitations and outlook

8.2.1 Addressing dynamics

Forest dynamics include processes that take place at different time scales, such as the legacy effects of historic land use and short-term effects of management interventions on forests' susceptibility to disturbances (**Paper III**), as well as the interactions and feedbacks among these processes. A major limitation of BNs is their static nature, which means that these feedbacks and dynamic processes cannot be directly modelled in a BN. We can partly overcome this limitation using iterative BNs, where each time step is represented by a copy of the network and outputs from one time step are inputs into the next, as demonstrated in **Paper II**. However, this time-slicing approach has some limitations. Because all the uncertainties in the model are propagated through each time step, this can result in a very wide probability distribution after some iterations. A very uncertain prediction that conflates epistemic and aleatory uncertainties is not likely to be informative and may be difficult to interpret – for example, to identify spatial patterns in the model outputs.

Another approach to address dynamics is to couple BNs with other types of models that are better suited for dynamic modelling, such as agent-based models or dynamic vegetation models. BNs have already been combined with agent-based models, for example, to simulate land-use decisions (Sun and Müller, 2013) or flows of ES (Johnson et al., 2012), where the agents' characteristics are sampled from the output distribution of a BN. In the next time step, the outcomes of the agents' behaviours and interactions are used to update the BN. A similar approach could be used to combine BNs and dynamic vegetation models, where spatially explicit simulations of forest dynamics could serve as an input to BN models of ES, and BN outputs could inform some modules of dynamic vegetation models with high levels of uncertainty, such as natural disturbances. To account for uncertainties in process-based models, ensemble modelling – running the simulations with various model formulations – would also be useful (Huber et al., 2020). However, the increasing complexity of such integrated, dynamic BN models could make it more difficult to calibrate and validate the models and for users to understand and trust them (Bruce G. Marcot and Penman, 2019).

The BN approach developed in this thesis can also support dynamic modelling efforts without explicit model integration. Analyses of uncertainty and sensitivities, such as those demonstrated in **Paper I**, can help identify the most important variables that need to be addressed in dynamic models to make useful predictions of future scenarios. For example, the results of **Paper IV** show that salvage logging and dead wood dynamics significantly affect the provision of ES after disturbances (see also Figure 8.2) but are rarely addressed in simulation models (Petter et al., 2020), indicating a gap that should be addressed in future research. In addition, to improve dynamic model predictions, EO products could be used either as a source of calibration and validation data (Petter et al., 2020; Plummer, 2000) or by continuously updating predictions as new observations become available (Ma et al., 2017).

8.2.2 Looking for leverage

With growing awareness about the severity of the climate and biodiversity crises, research on socio-ecological systems is increasingly focused on how to leverage transformations towards sustainability (Chan et al., 2020; O'Brien, 2018). Under high level of uncertainty, fostering the resilience of systems to cope with (often unexpected) perturbations (Seidl, 2014) and stay on desired pathways (Elmqvist et al., 2019) is crucial. Levers and leverage points (i.e. where to intervene to change a socio-ecological system

(Chan et al., 2020; Meadows, 1999)) have mainly been discussed in the context of large-scale societal transformation (Chan et al., 2020; O'Brien, 2018). However, the concept of leverage points could also be useful at a smaller scale, where many decisions about the management of socio-ecological systems take place.

Bayesian networks are a useful tool to explore the effects of different interventions on the modelled system. Once the network has been compiled, one can interact with it by setting evidences to certain nodes and observing their effect on the probability distributions of other nodes, which is one reason for the popularity of BNs in the participatory modelling context (Voinov et al., 2018). In addition, it is relatively simple to calculate the sensitivity of target nodes to findings on other nodes (Marcot, 2012), which can be used to identify variables with a strong influence on the system. This type of analysis could be used to identify leverage points – that is, where to intervene to change a system. Below, I illustrate how sensitivity analysis could help identify leverage points for increasing the resilience of forest ES to natural disturbances. In this context, leverage points are characteristics of the system, where an intervention could help maintain the ES in the face of disturbances.

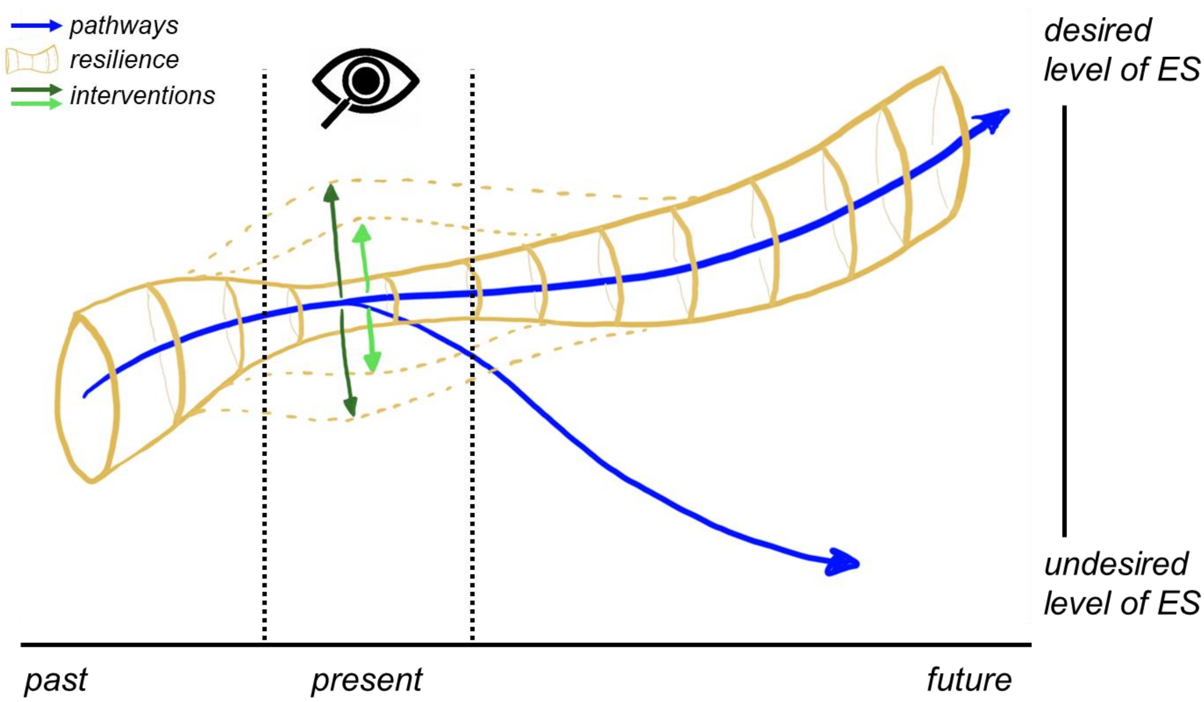

Figure 8.1: Conceptual representation of resilience, adapted from Elmqvist et al. (2019). Blue arrows represent pathways, and the resilience of the desired pathway is represented by the width of the 'tunnel' around it – that is, the tolerance of the system to disturbances and its capacity to continue to develop while maintaining the desired ES. The analysis focuses on one point in time, where the system can shift to an undesired pathway in case of a perturbation if the resilience is low. The green arrows represent interventions that can increase the resilience of the system.

An influence analysis (Marcot, 2012) was performed for two regulating ES (avalanche protection and carbon sequestration) under a scenario with a high probability of disturbance. The analysis was performed for two locations near Davos with a similar slope and elevation but different conditions in terms of forest structure, aspect, and land-use history as well as terrain roughness and level of demand for avalanche protection. First, evidences were set to describe the specific conditions at each location (see Table 8.1). Then, evidences on nodes that could potentially be modified by management interventions (such as salvage logging or changes in species composition) were individually modified. The influence of these nodes was calculated as the change in the posterior probability distributions of the target ES nodes using the Kullback-Leibler distance as a measure of differences between distributions (Kjaerulff and Madsen, 2013). In addition to the strength of the influence of each node, the direction of effects was evaluated – that is, does a higher value of this node have a positive or negative effect on the ES under the disturbance scenario.

Table 8.1: Characteristics of two forest stands, for which the sensitivity analysis of ES is shown in Figure 8.1.

Location	A	B
Elevation [m a.s.l.]	1850	1850
Slope [°]	35	35
Aspect	South	North
Land-use history (forested since…)	Post-1920	Pre-1880
Terrain	Smooth	Rough
Species composition	Spruce	Mixed
Crown cover	Dense	Scattered
Structure	Even	Uneven
Avalanche protection demand (frequent scenario)	High	Low
Avalanche protection demand (extreme scenario)	High	High

Overall, carbon sequestration is more sensitive to the influence of selected nodes (expressed by higher values of influence in Figure 8.2) than avalanche protection, which is more uncertain due to natural variability (as discussed in **Paper I**). Nonetheless, an increase in crown cover would have a positive effect on avalanche protection even under an increased probability of disturbances. Increased terrain roughness (e.g. due to lying dead wood) also has a positive effect on avalanche protection, and salvage logging in the event of a disturbance would therefore have a negative effect. Harvesting has a negative effect on carbon sequestration, although this effect is more pronounced at location B, which is less susceptible to natural disturbances. In addition, the use of harvested products (i.e. for energy or stem wood) has a strong influence on the carbon budget.

This analysis shows that the sensitivity of ES to potential intervention depends on the local context. Because the forest at location B is less susceptible to disturbances (due to the forest structure, aspect, and land-use history, see Table 8.1) than that at location A, the influence of variables that further affect susceptibility (e.g. vegetation type and canopy height) is lower. Because of the higher terrain roughness at location B, the probability of an avalanche release is lower; therefore, a protection barrier to prevent releases would not have the same effect at location B as at location A. In addition, it is important to note that the effects of many variables are non-linear and may have either a positive or a negative effect on the ES. For example, the share of spruce in the species composition increases the probability of a high provision of ES but also the probability of a loss of ES because of a higher susceptibility to natural disturbances. Salvage logging can have a positive or negative effect on carbon sequestration, depending on whether the salvaged wood is used for fuel or timber products, and on the decay rates of dead wood.

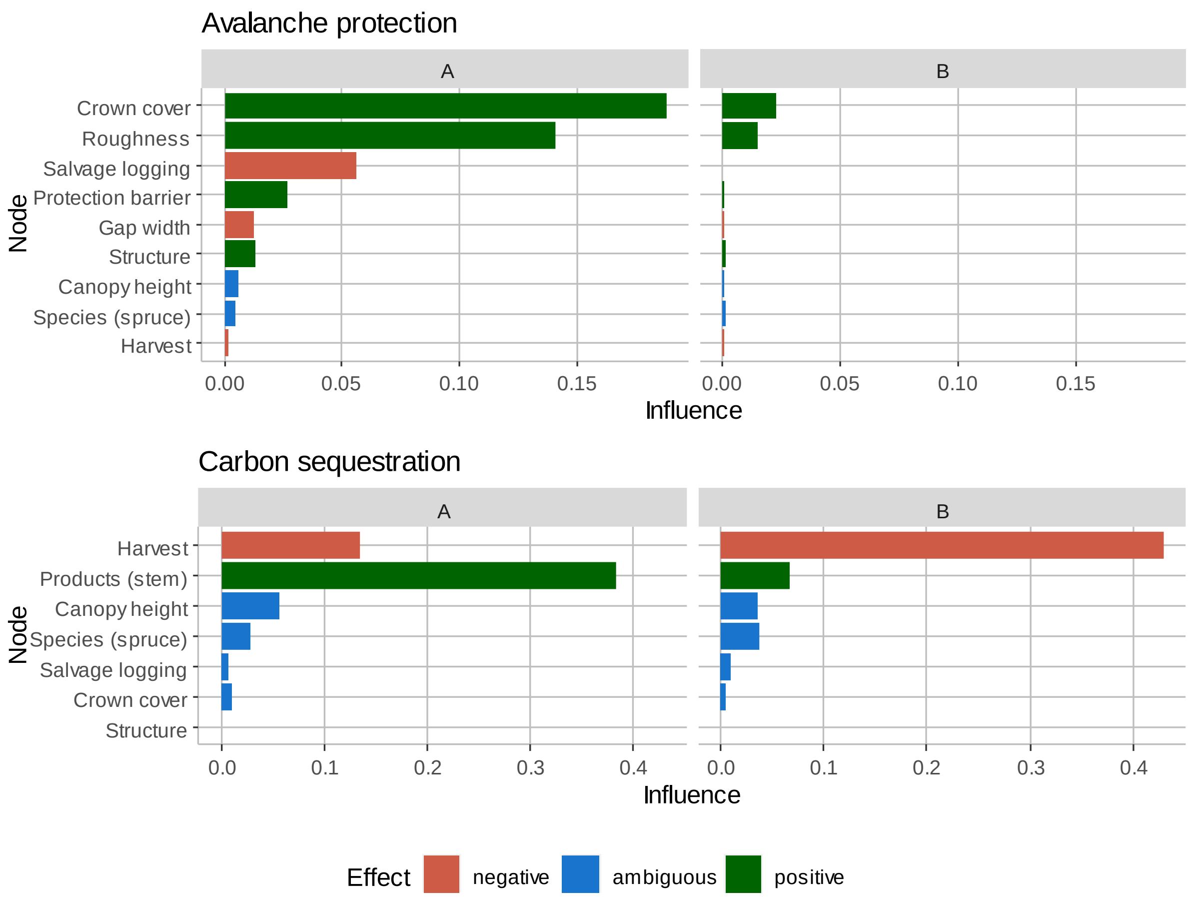

Figure 8.2: Influence of a subset of nodes (that can potentially be influenced by forest management) on two ES (avalanche protection and carbon sequestration) under a disturbance scenario for the two locations described in Table 8.1. The sensitivities are coloured based on the direction of effects on ES, where 'ambiguous' means that the variable can have either a positive or a negative effect on the ES level depending on the state of the other variables in the system.

Such analyses of sensitivities over different forest types and ES could be combined with spatially explicit bundles of risk to ES (**Paper IV**) to develop a typology of forest areas based on their level of risk, potential leverage points, and the degree to which they can be steered towards a more resilient provision of ES. This information could help forest managers prioritise interventions in areas of high risk, where interventions can be more effective. Similar analyses with other models of socio-ecological systems could be used to investigate the leverage potential of different types of variables, including those that relate to the political or personal spheres (O'Brien, 2018), such as regulations, incentives, behaviours, or values.

8.2.3 Including people's perceptions of ecosystem service values and risks

In recent years, there is a growing understanding within the ES community about the importance of considering a plurality of worldviews, beliefs, and value systems that determine how we value nature (Díaz et al., 2018), including intrinsic, instrumental, and relational values (Arias-Arévalo et al., 2017; Díaz et al., 2015). The ES modelled in this thesis mostly have an instrumental value (recreation, avalanche protection, carbon sequestration, and wood production), whereas habitats are assumed to have an intrinsic value. However, the value of ES also has a relational dimension. For example, people's recreational experiences can contribute to the feeling of being connected to nature, whereas the use of local wood products can support a feeling of local identity (Schröter et al., 2020). Although the valuation of ES was not a primary focus of this thesis, and people's perceptions were only explicitly included in the model for recreation (**Paper IV**), such values could be included through a participatory process involving diverse stakeholders and would help to inform any potential decisions about trade-offs between different ES (Martín-López et al., 2014).

Similar to the diverse values related to ES, people also have diverse perceptions of risk. Risk perceptions are shaped by available information, experiences, trust in experts and institutions, and socio-cultural and personal factors, and these perceptions determine people's preparedness to address these risks (Wachinger et al., 2013). Attitudes towards risk also affect decision-making. Whereas 'rational' decision-makers in portfolio management may seek to optimise returns while minimising variance (Markowitz, 1952; Matthies et al., 2015), more cautious decision-makers may prefer to ensure that none of the managed assets (or in this case, ES) fall below a certain threshold (Polasky et al., 2011; Shah and Ando, 2015). If risk-based ES assessments are to be used for decision-making, it is important to determine the tolerable levels of risk for affected stakeholders (Dow et al., 2013) and how these risks are distributed among different groups of people (Blennow et al., 2014). For example, risks to carbon sequestration may be more acceptable to local stakeholders, as its impacts are distributed over the global population, than risks to avalanche protection, which more directly affect a smaller group of people.

Participatory approaches can help understand people's values in relation to nature (Martín-López et al., 2014) as well as their perceptions of risk (Bustillos Ardaya et al., 2019). For example, in collaboration with Italian researchers, we used an online survey and participatory mapping to assess people's perceptions of flood risks on the Tagliamento river (Scaini et al., in review) as a first step in a participatory process of risk management. The results of this survey showed that many people would like to see a stronger integration of flood protection and conservation, highlighting the need for ecosystem-based solutions and the importance of considering multiple ES in risk management.

8.3 Relevance and impact

8.3.1 Scientific impact

Although the research in this thesis is focused on the ES provided by mountain forests in the Swiss Alps, it has a broader relevance to the scientific community with its contribution to advancing the methodology of BN modelling in the context of socio-ecological systems and to making spatial BNs more accessible to a wider range of users.

In the frame of the ECOPOTENTIAL project, BNs were used to address various issues related to ES, from predicting land-use change in the Sierra Nevada, collaborative modelling of ES with stakeholders in Doñana, analysing trade-offs between ES in the Dutch Wadden Sea and the Danube Delta, and mapping whale watching in the Pelagos marine sanctuary. All of these applications have been supported by the guidelines for BN modelling that are openly available on the gBay platform (**Paper II**) and now form part of a Toolbox for decision support (ECOPOTENTIAL Deliverable 7.3, Stritih et al., 2019). By providing open access to a tool for spatial BNs and by informing users on techniques of BN development and use, we make such models more accessible. This is particularly important in the context of participatory research, where the transparent graphical structure of BN models can facilitate the participatory modelling process (Voinov et al., 2018), and as a tool for explicitly addressing uncertainty and risk in socio-ecological models.

On the methodological side, I have developed methods for integrating various types of information (remote sensing, process-based models, and expert knowledge) and their associated uncertainties in BNs. This is particularly useful for analysing model uncertainties and identifying knowledge gaps, as shown in **Paper I**, where the flow of information was visualised for a model of avalanche protection. Many models of socio-ecological systems are associated with high levels of uncertainty and a lack of calibration and validation data (Schulp et al., 2014a), and under time constraints, modellers face decisions and trade-offs about where to focus their efforts (Vorstius and Spray, 2015). In such situations, analyses of information gaps can help prioritise further research.

The analysis of uncertainties showed that a large part of the uncertainty about regulatory services in mountain forests is related to the occurrence of avalanches and other natural disturbances. Natural disturbances are increasingly recognised as an integral part of forest dynamics (Kulakowski et al., 2017) but are also seen as a threat to the carbon sequestration potential of forests under a changing climate (Anderegg et al., 2020). Disturbance regimes are also affected by forest management and land-use change (McDowell et al., 2020), but empirical data required to investigate these interactions at the landscape scale are often lacking (Canelles et al., 2021). Using a large dataset of forest disturbances that combines remote sensing and in situ information, we were able to analyse how land-use legacies and forest management affect disturbance susceptibility (**Paper III**), contributing to a better understanding of disturbance dynamics in mountain forests.

To understand the impacts of changing disturbance dynamics, understanding their effects on forest ES is important, and a growing number of studies simulate ES under an intensifying disturbance regime (e.g. Albrich et al., 2018; Mina et al., 2017). In **Paper IV**, we demonstrated an approach to integrate disturbance risk in ES models. Besides providing relevant information for forest managers, this approach helps to identify critical variables that affect the interactions between disturbances and ES, which can inform future monitoring and modelling efforts.

8.3.2 Relevance for ecosystem management, planning, and policy

The research presented in this thesis is closely linked to the ongoing challenges for ecosystem management in the study areas: the Swiss Alps. As such, the findings have practical implications for decision-makers in forest management and PA management as well as for the planning of nature-based solutions for DRR.

Ecosystem-based solutions for disaster risk reduction (Eco-DRR) are increasingly prioritised by planners who recognise the potential of green infrastructure, which is often more cost-efficient and sustainable than technical solutions and provides additional benefits in the form of other ES (Estrella and Saalismaa, 2013). Ecosystem-based solutions are therefore promoted in policy documents, such as the United Nations' Sendai framework for DRR (UNISDR, 2015a). Protection forests are an important component of Eco-DRR in mountain regions (Moos et al., 2018). The avalanche protection model developed in this thesis integrates different types of available information (state-of-the-art process-based models, remote sensing, and expert knowledge) to map forests' protective function, which can help identify forests that play an important role for Eco-DRR, as well as areas where other structural or non-structural protective measures are needed. A better understanding of avalanche protection and the associated risks and uncertainties can thus support the planning of Eco-DRR in mountain regions. To make these findings more accessible to experts and practitioners working on Eco-DRR, the findings of **Paper I** will be integrated in a handbook about protection forests as ecosystem-based solutions for risk reduction in mountain regions (GR4A, in prep.), which is currently being compiled in the frame of Green Risk 4 Alps, a European Interreg project.

Natural disturbances are a particularly pressing topic not only for forest managers in the Canton of Graubünden, where the areas studied in this thesis are located, but also in forest management across temperate and boreal forests worldwide (Sommerfeld et al., 2018). The work related to natural disturbances in this thesis was conducted in collaboration with the Cantonal Office for Forest and Natural Hazards in Graubünden (AWN), who provided data and feedback on the findings about forest susceptibility to natural disturbances (**Paper III**). In addition, they have shown interest in pursuing the modelling of disturbance risk to ES to inform practical decisions in forest management. The findings of this thesis contribute to the ongoing discussions in forest management about salvage logging (Müller et al., 2019) and add to the existing evidence about the value of leaving dead wood in the forest after disturbances to maintain or even enhance the provision of ES (**Paper IV**; Leverkus et al., 2020; Thorn et al., 2020). In addition, the findings of **Paper III** highlight the importance of timing in management interventions that aim to increase forests' resilience to natural disturbances. Because interventions in dense stands can exacerbate their susceptibility to disturbances, interventions aimed at increasing resilience by promoting species- and structural diversity should take place early in a stand's development (i.e. before the trees are under stress from competition). In the context of the broader challenge of maintaining or increasing forests' carbon sink to mitigate climate change, our findings highlight the need to prioritise the maintenance of structurally rich, 'older' forests over establishing new plantations that are more susceptible to natural disturbances.

Together with other outputs of the ECOPOTENTIAL project that I have been involved in (Crouzat et al., in review.; Guerra et al., 2019; Hummel et al., 2017; Wanke et al., 2019), this work supports the management of PAs by improving our understanding of ES in PAs and bridging the gap between ES research and PA management. In particular, we have analysed the mismatch between scientists' and PA managers' perceptions of the relevant ES and threats to ES in PAs (Hummel et al., 2017) and proposed an approach for a bottom-up definition of essential variables that should be monitored by EO to support PA management (Guerra et al., 2019). We have also used participatory mapping to better understand the actual use of cultural ES in and around PAs (Crouzat et al., in review), which can help support visitor management in PAs. Finally, in the context of calls to protect at least 30 % of the Earth's surface by 2030 (Dinerstein et al., 2019), this work highlights the specificities of ES supply, demand, and risk in PAs as well as their insurance value.

Beyond the specific context of mountain forests, the approaches presented in this thesis can support decisions in ecosystem management, spatial planning, or conservation in other socio-ecological systems. With a better understanding of uncertainties, decision-makers can select the most robust management alternatives – that is, those that perform well across a range of future conditions – rather than the optimal alternative under a 'best-guess' scenario (Maier et al., 2016). Addressing risk in ES assessments also allows planners to differentiate areas with a high level of risk to ES from those where the ES levels are more stable. Identifying areas of high uncertainty can help prioritise further research in the areas where reducing uncertainty would be most helpful for future decisions, and models can be updated as new information becomes available. Furthermore, evaluating risks to different ES can allow for discussions about the acceptable level of risk for specific ES and for optimising the provision of ES within the boundaries of tolerable risks. Knowledge about risks and uncertainty can therefore contribute to more robust decisions in ecosystem management and policy.

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10 Appendices

Appendix A: Supplementary information to Paper I - Quantifying uncertainties in earth observation-based ecosystem service assessments

A.1: Overview of network nodes

Table 10.1: Description of nodes in the Bayesian Network, their states, and methods use to quantify their conditional probabilities.

Node	Description	States	CPT method	Source
Input nodes - remote sensing				
Land cover classification	Classification	Evergreen forest, deciduous forest, non-forest	Confusion matrix	Random forest classification with combination of LiDAR, aerial CIR images and Sentinel2
Crown cover (measured)	Measured cover of vegetation above 3 m	10 states: 0 - 100 [%]	Normal distribution around actual state	LiDAR (Lastools (Isenburg, 2016)), error estimated based on Moeser et al. 2014
Roughness (measured)	Measured terrain roughness	9 states: 0 - 1	Fuzzy definition of categories based on ground truth	Derived from LiDAR-based DTM (Sappington et al., 2007)
Gap width (measured)	Width (along contour lines) of non-forested area [m]	9 states: 0 - 8000 [m]	Normal distribution around actual state	Derived from LiDAR-based CHM
Building (detected)	Presence of a building detected	Boolean	Confusion matrix	Building extraction from LiDAR (Lastools)
Curvature	Planar slope curvature	7 states: -45 - 5		Derived from LiDAR-based DTM
Slope	Slope angle	8 states: 0 - 90 [°]		From LiDAR-based DTM
Elevation	Elevation [m a.s.l.]	7 states: 1500 - 2900		Derived from LiDAR-based DTM
Input nodes - avalanche hazard data				
Max new snow height	Annual maximum new snow height, which determines the avalanche release scenario	9 states: 0 - 2 [m]	Gumbel distribution of maximum new snow height, Davos, Fluelastrasse	(Salm et al., 1990; SLF, 2017b)
Velocity 300	Maximum velocity under the 300 year scenario	9 states: 0 - 60 [m/s]		RAMMS (Christen et al., 2010) model output

Velocity 30	Maximum velocity under the 30 year scenario	10 states: 0 - 60 [m/s]		RAMMS model output
Nodes representing ecosystem structure				
Crown cover	Cover of vegetation above 3 m	10 states: 0 - 100 [%]	Fuzzy logic definition of categories	
Crown cover (class)	Category of forest density	Dense, scattered, open, non-forest		
Roughness (class)	Category of terrain roughness	Rough, knobby, smooth		
Land cover	Actual land cover class	Evergreen forest, deciduous forest, non-forest	Based on ground truth plots	
Gap width	Width (along contour lines) of non-forested area [m]	9 states: 0 - 8000 [m]		
Potential release prevention	Potential of forest to prevent an avalanche release	Boolean	Logistic model	(Bebi et al., 2001)
Potential detrainment	Capacity of forest to remove snow from avalanche flow	12 states: 0 - 120 [Pa]	Expert knowledge (four-point estimation)	(Feistl et al., 2014; Teich et al., 2014)
Nodes representing the hazard process				
Release	Probability of an avalanche release	Boolean	Fuzzy logic	(Veitinger et al., 2016)
Release height	Height of snow released in the event of an avalanche	10 states: 0 - 3 [m]	Logical combination of "Release" and "Max new snow height", corrected for "Slope"	(Salm et al., 1990)
Velocity	Maximum avalanche flow velocity	9 states: 0 - 60 [m/s]	Defined by scenarios, with uncertainty estimated based on simulations with varying input parameters	RAMMS (Christen et al., 2010)
Max pressure	Maximum avalanche pressure	4 states: = 0 - 300 [kPa]	Derived from velocity, with uncertainty estimated based on simulations with varying input parameters	RAMMS
Nodes representing ecosystem functions				
Release prevented	Probability a release would be prevented by the forest	Boolean	Logical combination of "Release" and "Potential prevention"	
Prevention	Height of snow in prevented avalanche release	11 states: 0 - 3 [m]	Logical combination of "Release prevented" and "Release height"	
Detrainment	Height of snow detrained in forest during avalanche	7 states: 0 - 0.8 [m]	Learning from simulations with varying input parameters	RAMMS

Risk assessment and valuation nodes				
Building	Presence of a building	Boolean		
Building type	Type of building	One-family house, farm building, guesthouse, multi-family house, industrial, infrastructure	Distribution of types from local data	Communal cadastre (Davos, unpublished)
Lethality	Avalanche pressure is lethal	Boolean	Fuzzy logic based on values from literature	Swiss National Platform for Natural Hazards (BAFU, 2015; Planat, 2008)
People per building	Average no. of people per building	6 states: 0 - 20	Fuzzy logic based on values from literature	Swiss National Platform for Natural Hazards
People present	People are present in a building	Boolean	Fuzzy logic based on values from literature	Swiss National Platform for Natural Hazards
Damage	Building is destroyed by avalanche	Boolean	Fuzzy logic based on values from literature	Swiss National Platform for Natural Hazards
Building cost	Cost of destroyed building	6 states: 0 - 10^7 [CHF]	Distribution per type from local data	Communal cadastre (Davos, unpublished)
Damage (cost)	Cost due to damaged building	7 states: 0 - 10^7 [CHF]	Logical combination of "Damage" and "Building cost"	
Cost of human death		Constant: 5*10^6 [CHF]	Constant value from literature	Life Quality Index approach (Merz et al., 1995)
Lethality (cost)		5 states: 0 - 10^8 [CHF]	Logical combination of "Lethality" and "Cost of human death"	
Output nodes				
Provision	Combination of prevented release and detrained snow height	12 states: 0 - 4 [m]	Sum of "Prevention" and "Detrainment"	
Demand	Avalanche risk to people and buildings	5 states: 0 - 1.1*10^8 [CHF]	Sum of "Damage (cost)" and "Lethality (cost)"	

A.2: Implementation of fuzzy logic in the Bayesian Network

We use fuzzy logic (Zadeh, 1965; Zimmerman, 2001) to address linguistic uncertainty to link qualitative categories to continuous variables. In fuzzy logic, membership functions m(y) define the level of membership (between 0 and 1) in a specific class for values of y. For example, we define trapezoidal membership functions of crown cover (Y) for the classes of forest density (X) (see Figure A.1). The thresholds between classes have been defined by experts, whereas the slopes of the membership functions are defined based on the standard deviation of measured crown cover at locations where the forest density was classified in the field (method adapted from Petrou et al., 2013). At the expert-defined threshold of Y = 70 % crown cover, the probability of the forest being classified as "dense" is 0.5, while a forest with 100 % crown cover will certainly be classified as "dense" (P(X = dense) = 1). We use the membership function to define the probability of the class (X) given an observation y, P(X|Y=y), which is proportional to P(Y|X) * P(X).

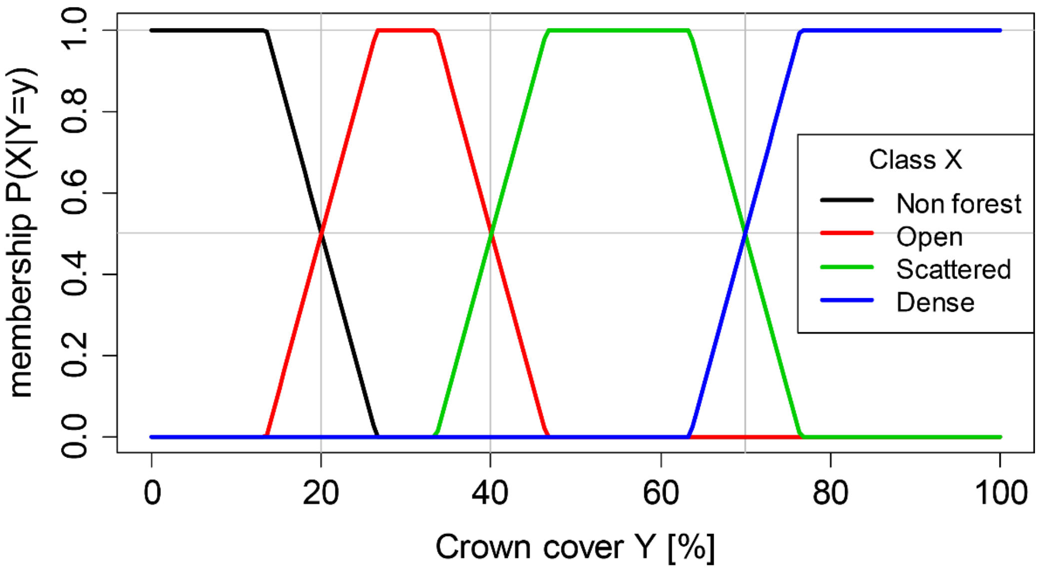

Figure A.1: An illustration of the use of fuzzy logic, where trapezoidal membership functions define the classes of density based on the percentage of crown cover.

A.3: Demand for avalanche protection

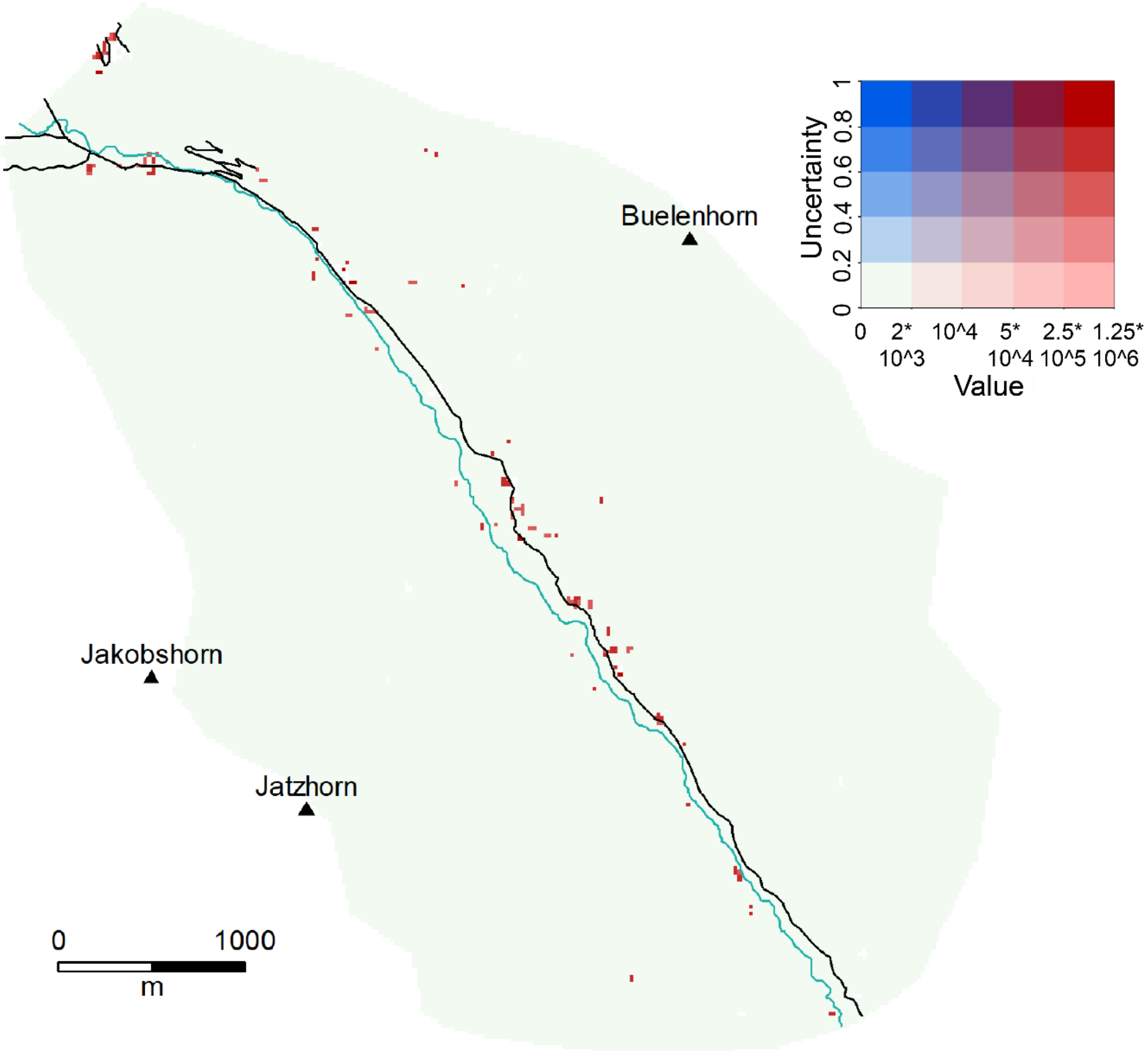

Figure A.2: Map of modelled demand for avalanche protection in the Dischma valley, Davos, Switzerland. Areas with high values correspond to buildings, and the higher values are mostly associated with higher uncertainties (dark red).

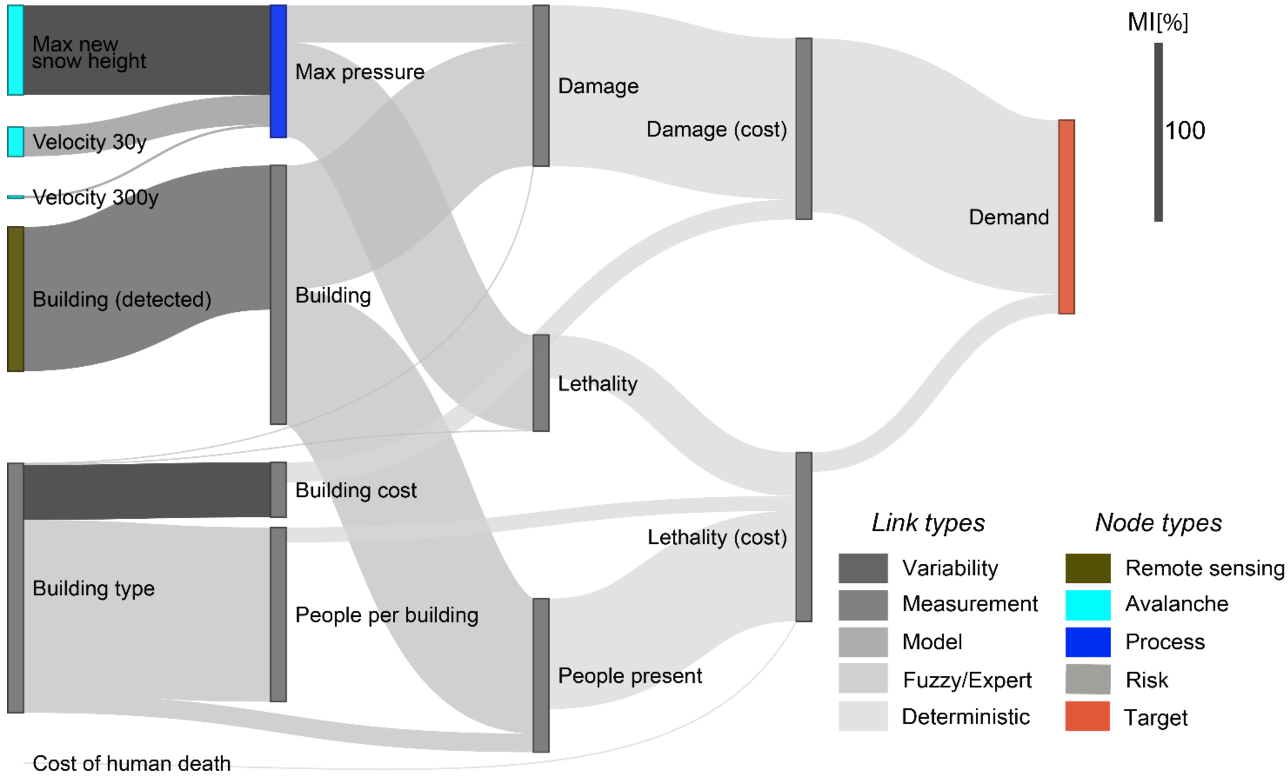

Figure A.3: Sankey diagram of the stepwise sensitivity analysis of the BN for avalanche protection demand, where the width of a link between two nodes corresponds to the relative mutual information (MI %), i.e. the percentage of the entropy on a node that can be reduced by a finding on a preceding node. The nodes are labelled and coloured by the type of variable represented (see Fig. 2), while the link colours represent the types of uncertainty taken into account while quantifying the link in the BN.

A.4: Examples of posterior probability distributions and posterior sensitivities

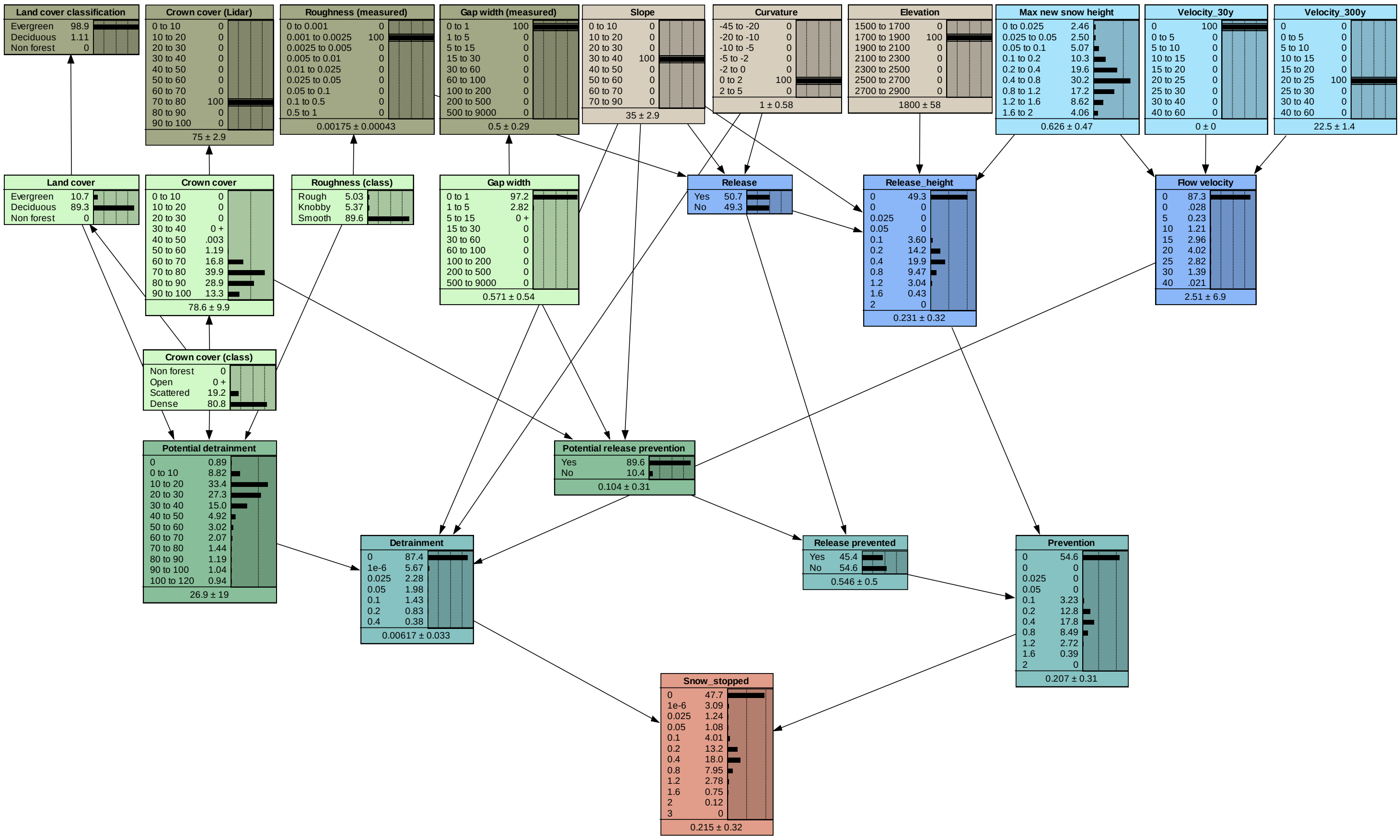

Figure A.4: Example of posterior probability distribution of avalanche protection provision.

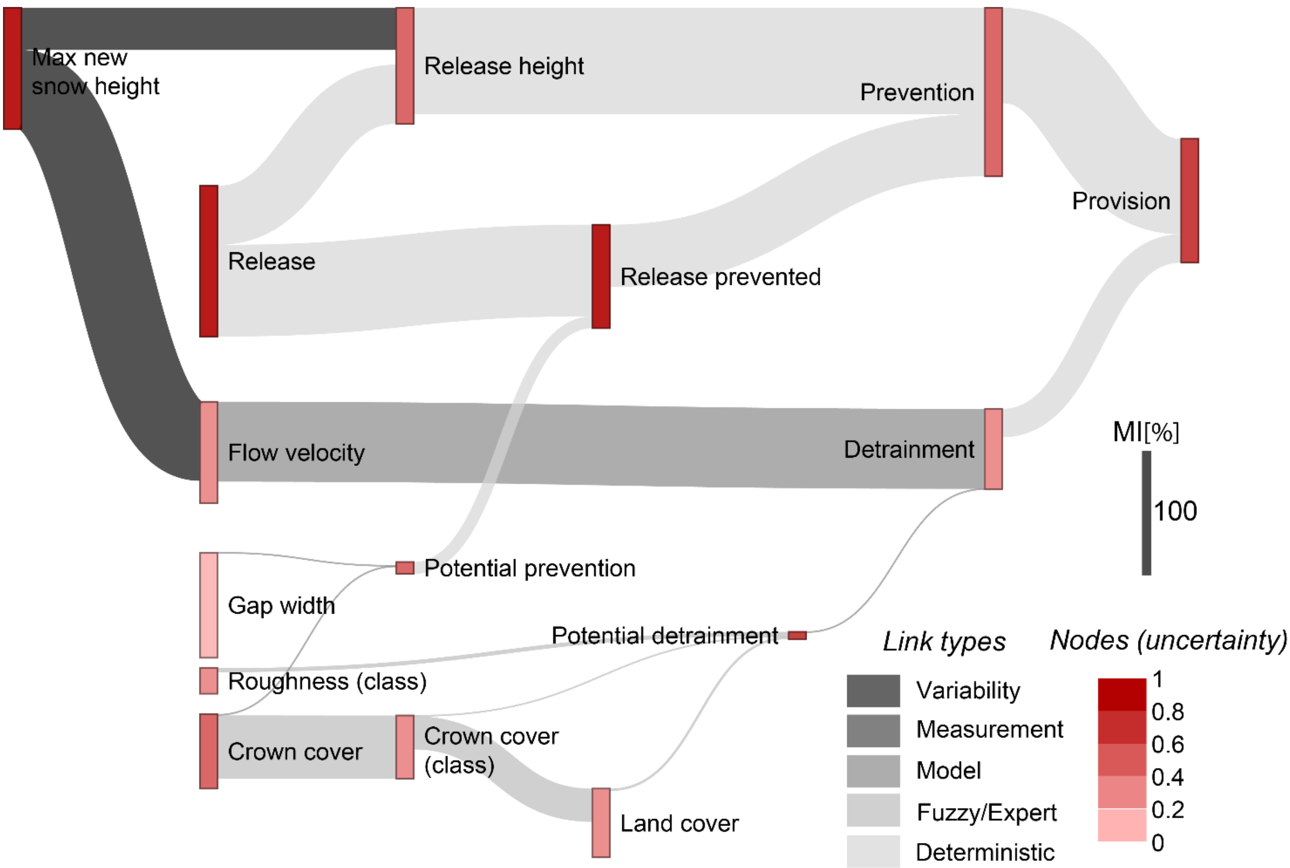

Figure A.5: Stepwise sensitivity analysis for posterior distribution of avalanche protection provision (Figure A.4). Node colours show the uncertainty (entropy) of the nodes, while the links are coloured according to the method used to quantify them.

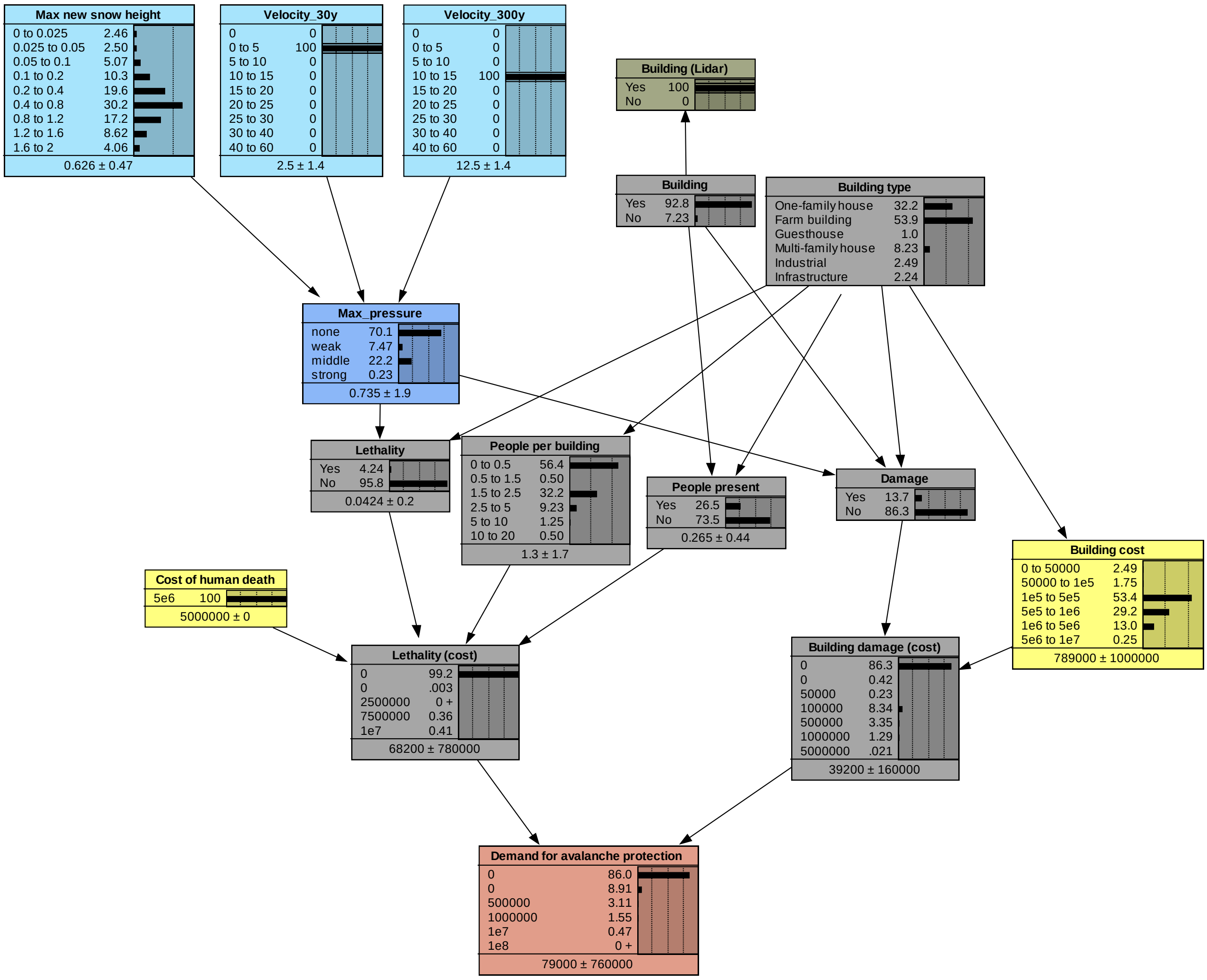

Figure A.6: Example of posterior probability distribution of avalanche protection demand.

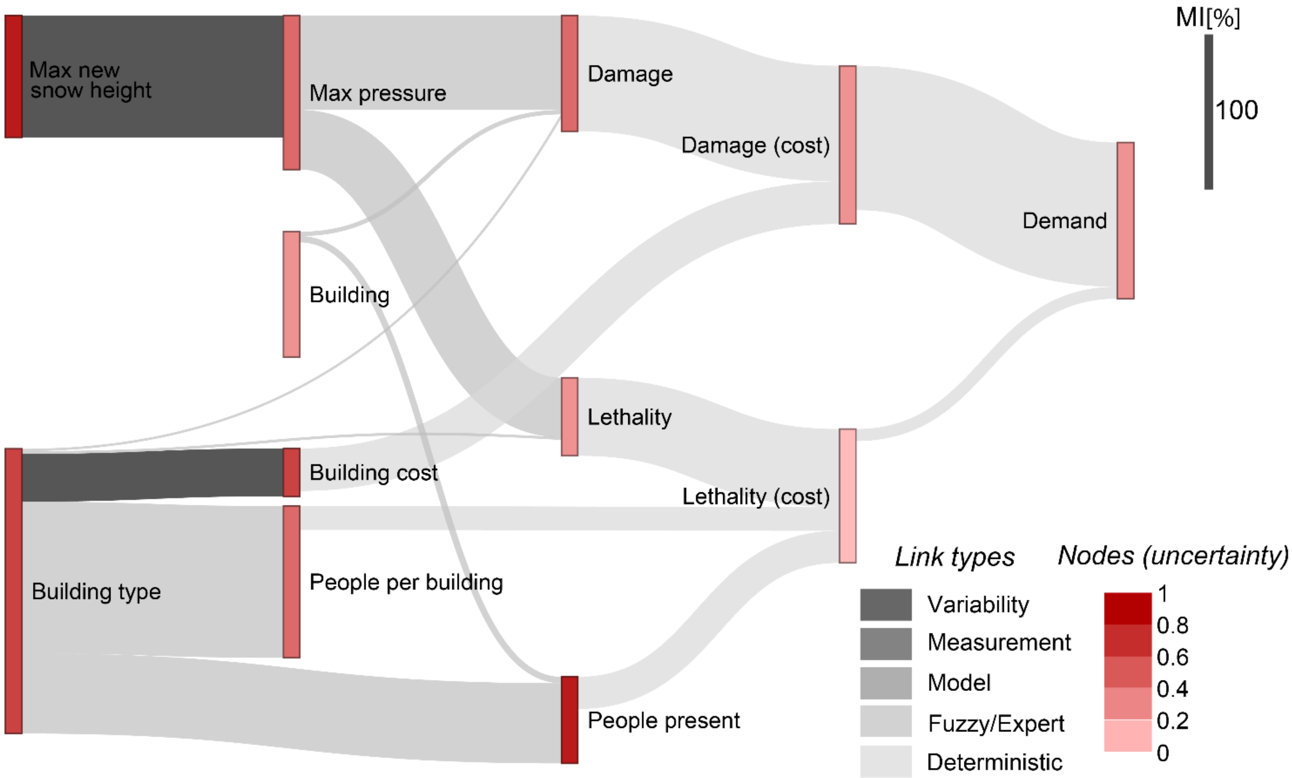

Figure A.7: Stepwise sensitivity analysis for posterior distribution of avalanche protection demand (Figure A.6). Node colours show the uncertainty (entropy) of the nodes, while the links are coloured according to the method used to quantify them.

Appendix B: Supplementary information to Paper II - An online platform for spatial and iterative modelling with Bayesian Networks

B.1: Python scripts

In order to account for spatial interactions and processes and different scales, users can implement a Python script in gBay. In order to be compatible with gBay, the uploaded script file needs to implement a function named 'process' with the following definition:

```
process(GDALDatasetH dataset, list nodes_data, int iteration)
```

The inputs to the process function are:

- GDALDatasetH dataset: contains the metadata of the spatial data being processes (e.g. raster spatial extent, pixel size and projection). gBay uses GDAL to operate with spatial data.
- list nodes_data: contains the data of the nodes that are used as inputs for the geoprocessing script. The node data is stored as a python dictionary with three keys:
    - name: <str>name of the node
    - type: <int> type of the node (PY_DISCRETE / PY_CONTINUOUS (PY_DISCRETE if omitted)
    - data: <list> list of probabilities (between 0 and 100) of each state for each raster cell or object.
- int iteration: the number of the current iteration, which can be used if some inputs should be modified over time.

The ‘process’ function should return a list of nodes with the updated node likelihoods if the output node is discrete, or node values if the node is continuous.

The python script should import the node_utils python module (which contains functions to validate the output and to read and write node information), as well as other packages used by the script (e.g. gdal, scipy)

gBay stores the probabilities of the nodes selected by the user as to be used by the python script, creates the nodes_data list and, runs the ‘process’ function. Then, it runs a function to validate whether the output complies with the nodes_data format, and if it does, it will set the node probabilities as returned by the function. This happens at the beginning of the processing and at the end of each iteration. In case the results are not validated (e.g. the data types are incompatible, or total probability does not add up to 100%), or in case an error occurs in the execution of the script, gBay will print out the error message and ignore the output data.

It may also occur that the results are correctly formatted, but invalid form the BN perspective, e.g. when trying to set a probability of a state that would be impossible according to the node’s CPT and the evidence set on its parent. In this case, gBay will print out an error message from Netica.

B.1.1 Example

Besides the factors affecting future land cover described in Figure 5.1, the transition of meadows to forest may also be affected by the distance to the nearest forest patch. If a node "Distance_forest" is added to the network, its values can be calculated based on the input land cover map directly in gBay using a python script.

```
### Calculates the distance to the nearest cell with a specific state
### (e.g. forest)
### Input: discrete raster of categories (e.g. 0 = meadow, 1 = forest)
### Sets evidence on node continuous node (Distance_forest)

# import required packages
import os
import sys
import numpy
from gdalconst import *
from osgeo import gdal
import math
from node_utils import *
from scipy.spatial import distance
import gdal


# SET FUNCTION PARAMETERS
# name of input node
input_name = "Land_cover_t0"
# number of the state in the input raster that defines the cells
#(e.g. forest), the distance to which we are interested in
state_number = 1;
# name of output node
output_name = "Distance_forest"


# function that finds cells of interest
#(where the state with the highest probability is forest)
def isForest(node, cell):
    return (getStateHighestLikelihood(node, cell) == state_number)

# function that finds distance to the nearest cell of interest
def findCloserForestCell(cell, forest_list, width):

    if (len(forest_list) == 0):
        print "findCloserForestCell: There are no forests in the map."
        return None

    return min(distance.cdist([cell], forest_list, 'euclidean')[0])

# function that writes distance to the output node
def process(dataset,nodes_data,iteration):

    # find the corresponding input node
      #(and write error message if it does not exist)
    node_forest = getNodeByName(nodes_data, input_name)
    if (not node_forest):
        print  "ERROR Node", input_name, "is not in nodes_data"
        return []

    # extract the total number of cells in the raster
    total_cells = dataset.RasterXSize * dataset.RasterYSize ;
```

```
    # get pixel size and print it
    pixelsize = dataset.GetGeoTransform()[1]
    print  "pixelsize:", pixelsize

    # find all the cells which are most likely forests
    forest_cells = [];

    for cell in range(total_cells ):

        if (isForest(node_forest,cell)):
            forest_cells.append(cell);

    print "There are", len(forest_cells), "cells that are forest"

    # create and empty distances array
    distances=[]

    # Transform the forest cells to 2-dimensional array
    forest_coords  =  list(map(lambda  x:  [x  /  dataset.RasterXSize,  x  %
dataset.RasterXSize], forest_cells))

    # calculate distances to nearest forest cell
      # for each cell in the raster
    for cell in range(total_cells):

        if (isNODATA(node_forest, cell)):
            distances.append(PY_NODATA_VALUE)
        elif isForest(node_forest, cell):
            distances.append(0)
        else:
            distances.append(findCloserForestCell([cell                  /
dataset.RasterXSize,    cell    %    dataset.RasterXSize],    forest_coords,
dataset.RasterXSize) * pixelsize)

    # create a continuous node output
    new_nodes_data = [{'name' : output_name, 'type': PY_CONTINUOUS, 'data':
distances}]

    # print some values to check if they are correct
    for i in range(10):
        print "cell:", i, ":" ,  new_nodes_data[0]['data'][i]

    # check if the output has the correct format
    if (validResultData(new_nodes_data, total_cells)):
        return new_nodes_data

    else:
        print ("Some error here: ")
```

B.2: Bayesian Network for avalanche protection

To model the provision of avalanche protection, we used a model adapted from Stritih et al. (2019), see Figure B.1. The model was modified to account for neighbourhood effects in the avalanche release process, where a pixel is only accounted as a potential avalanche release if it is part of a sufficiently large release area. We used a Python script to calculate fuzzy release areas based on release probabilities, as illustrated below. This led to lower uncertainty in the definition of release areas and in the total provision of avalanche protection (see Table B.2)

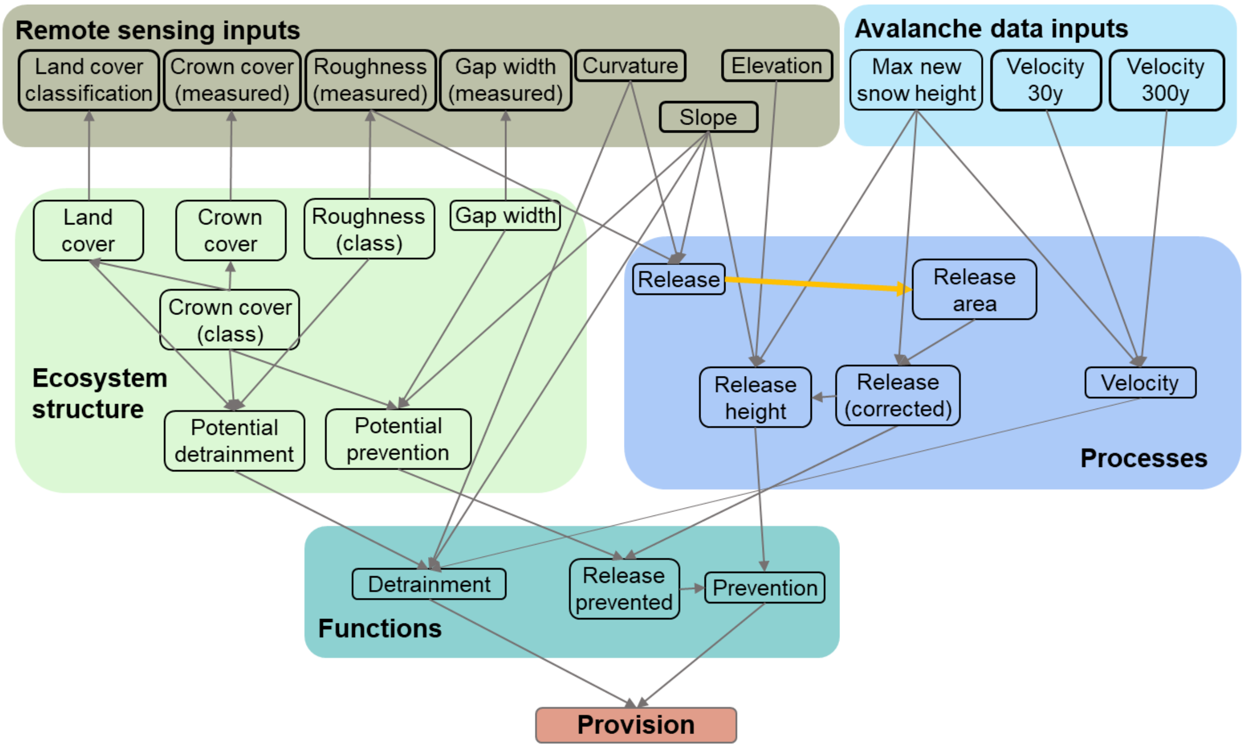

Figure B.1: Bayesian Network used to model the provision of avalanche protection, adapted from Stritih et al. (2019). The BN uses inputs (indicated with a thicker frame) from remote sensing and avalanche data to infer about the ecosystem structure and processes, which determine the detrainment (snow braking in the forest during an avalanche) and prevention functions. These functions are combined to express the total level of avalanche protection provision. The orange arrow indicates where a Python geoprocessing script is used to calculate the size of avalanche release areas from per-pixel release probabilities.

B.2.1 Fuzzy area calculation

The raster (Figure B.2) shows the probability P(release) of each pixel belonging to a release area. A fuzzy release area size is calculated for the pixel shown in red. First, the area is calculated for different threshold probabilities α, where every pixel where P(release) >= α is considered part of the release area. This results in a different size of release area for each probability (Table B.1), from which a cumulative probability distribution can be derived (in this case, the release area is between 4 and 19 pixels). Based on this probability distribution, we can calculate the probabilities of the area belonging to a size class (Figure B.3).

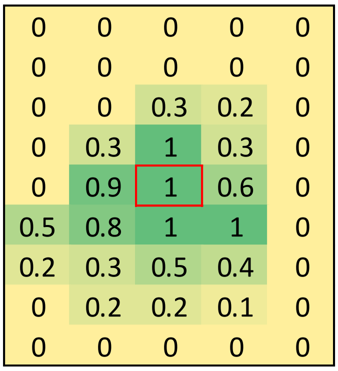

Figure B.2: Example raster of P(release)

Table B.1: Area calculation for different α-values

Threshold probability (α)	Area
0.05	19
0.1	19
0.2	18
0.3	14
0.4	10
0.5	9
0.6	7
0.7	6
0.8	6
0.9	5
0.95	4

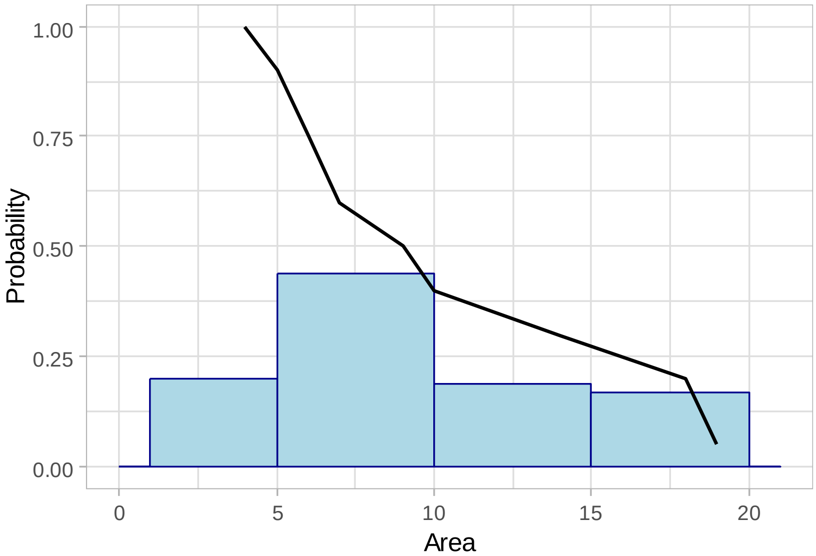

Figure B.3: Resulting cumulative probability distribution of area (black line) and the probability distribution of area in classes (1-5, 5-10, 10-15, 15-20 pixels).

B.2.2 Results: Uncertainty of total provision and release probability with and without accounting for release area size

Table B.2: Mean uncertainty in total provision of avalanche protection and release probability across the whole study area, expressed in coefficient of variation (CV, only for continuous nodes) and entropy index, with and without the correction for release area size (neighbourhood effect).

	without neighbourhood correction		with neighbourhood correction	
Node	**CV (%)**	**Uncertainty**	**CV (%)**	**Uncertainty**
Provision	95	0.089	87	0.083
Release		0.29		0.19

B.3: The "roll-back mechanism" to implement boundary conditions for land-use change

In order to implement boundary conditions in the land-use change model (a minimum limit of extensive, intensive and medium-intensive land use to support the number of cattle in the region), a Python script was implemented in gBay at the end of every iteration. The script checks the number of extensive, medium-intensive and intensive agriculture cells, and if the frequency is below the defined minimum, it converts cells which have the highest probability of being in those categories back to their previous probability distribution ("rolled-back"), until the minimum frequency agriculture has been reached. In case not enough cells of medium-intensive agriculture are available to convert back to intensive agriculture (due to the minimum limit in this land use category), cells from a third category (e.g. forest) are changed back to medium-intensive, and medium-intensive cells are changed back to intensive, in a "double roll-back". The mechanism is illustrated in Figure B.4.

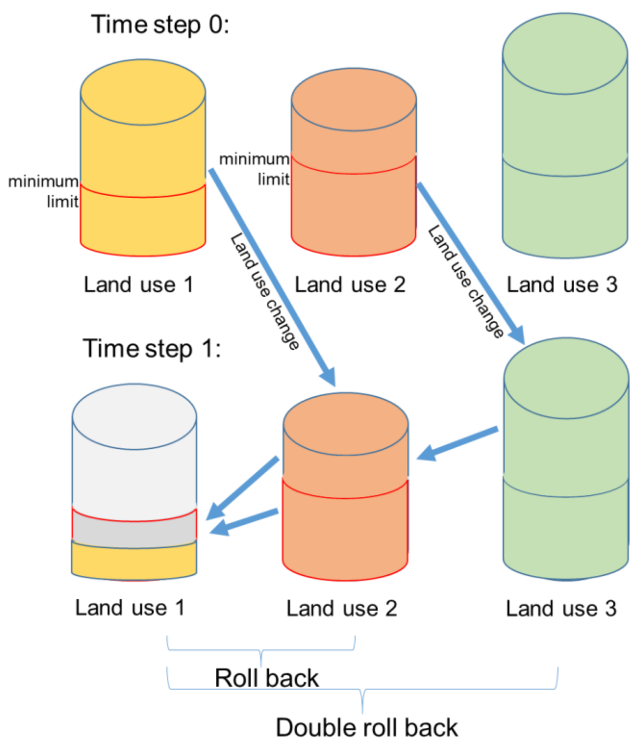

Figure B.4: Representation of the roll-back mechanism to ensure that the minimum frequencies of Land use 1 and 2 are maintained. During the first iteration of the land-use change BN, LU1 is converted to LU2 and LU2 changes to LU3. However, if the frequency of LU1 and LU2 drops below the minimum limit, the roll-back mechanism is implemented to revert cells back to their previous probability distribution, until the minimum is reached.

The conversion matrix (Table B.3) shows how many cells have been transferred to other land-use categories due to the enforced conversion limits, in the production-oriented scenario for iterations (time steps) 2 and 3. In both the hill and mountain region, certain parcels were rolled back. In the hill region, the number in brackets show how cells were initially rolled back from "other" to intensive and in the following from intensive to medium-intensive to fulfil the restrictions (double roll-back).

Table B.3: Rollback mechanism induced by Python script made explicit for the production-oriented scenario in iteration 2 and 3.

ITERATION 2

production-oriented		source land-use category				
Region: Hill		**extensive**	**med-intensive**	**intensive**	**other**	**SUM**
target land-use category	**extensive**				54	54
	med-intensive			797	147	944
	intensive				(112)	0
	other					

production-oriented		source land-use category				
Region: Mountain		**extensive**	**med-intensive**	**intensive**	**other**	**SUM**
target land-use category	**extensive**				9	9
	med-intensive					0
	intensive					0
	other					

ITERATION 3

production-oriented		source land-use category				
Region: Hill		**extensive**	**med-intensive**	**intensive**	**other**	**SUM**
target land-use category	**extensive**				54	54
	med-intensive			112	1400	1512
	intensive				(112)	0
	other					

production-oriented		source land-use category				
Region: Mountain		**extensive**	**med-intensive**	**intensive**	**other**	**SUM**
target land-use category	**extensive**					0
	med-intensive	69544		5558		75102
	intensive					0
	other					

Appendix C: Supplementary information to Paper III - The impact of land-use legacies and recent management on natural disturbance susceptibility in mountain forests

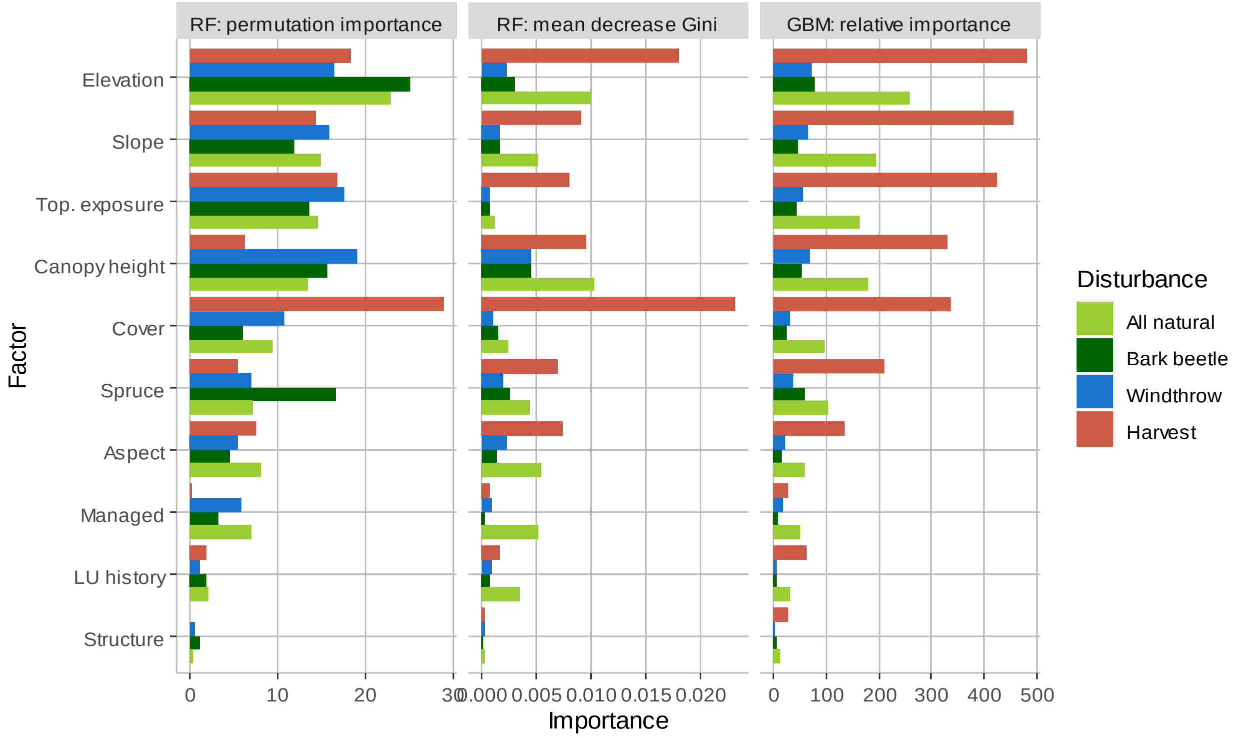

Figure C.1: Three types of variable importance measures (random forest - RF: permutation-based importance and mean decrease Gini; gradient boosting machine - GBM: relative importance) for all natural disturbances, bark beetle, windthrow, and harvest (the most common types of disturbances in the region) in the years 2016-2018. The scales of the difference types of importance measures are not comparable due to the different methods to quantify variable importance.

Table C.1: Performance of the different model types (random forest - RF, gradient boosting machine - GBM, and binomial generalized linear model - GLM) across different types of disturbances and the two analysed time-periods. N indicates the number of disturbance events, where 80% were used to calibrate and 20% to validate the models in a tenfold split calibration-validation procedure.

Time period	Disturbance	n	AUC RF	AUC GBM	AUC GLM
2016-2018	All natural	1164	0.79	0.79	0.77
	Avalanche	20	0.82	0.85	0.82
	Bark beetle	358	0.81	0.82	0.80
	Fire	11	0.76	0.80	0.85
	Snow	41	0.75	0.65	0.74
	Windthrow	397	0.83	0.81	0.81
	Harvest	2504	0.80	0.83	0.73
2005-2018	All natural	6632	0.73	0.76	0.71
	Avalanche	80	0.75	0.74	0.69
	Bark beetle	1037	0.74	0.73	0.71
	Fire	62	0.65	0.65	0.69
	Snow	1116	0.71	0.73	0.68
	Windthrow	1419	0.72	0.70	0.66
	Harvest	11648	0.75	0.79	0.70

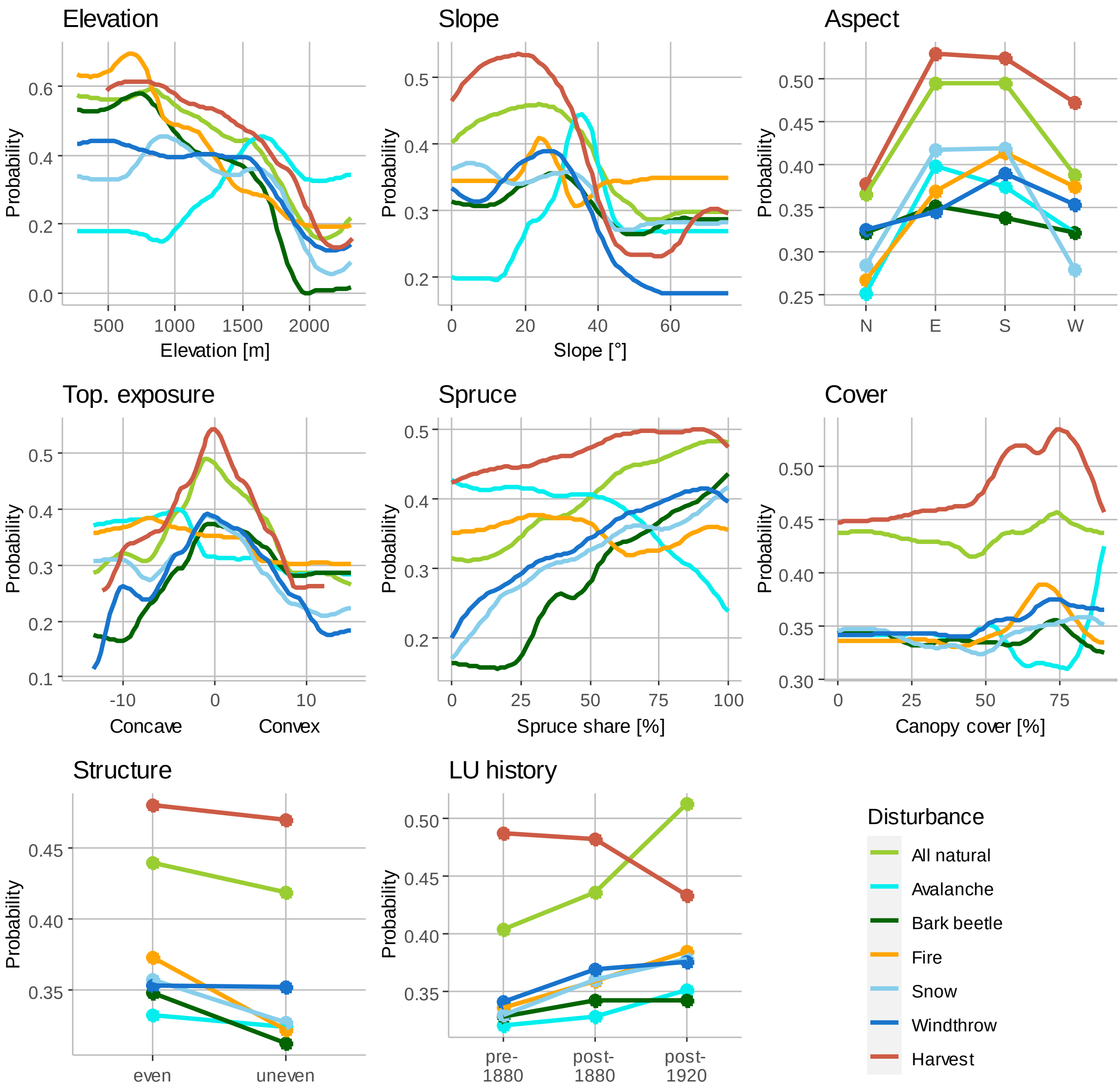

Figure C.2: Smoothed partial dependence plots of the random forest model of disturbance probability for different disturbance agents over the whole time period (2005-2018, without management and canopy height information). The x-axis shows the values of the predictor and the y-axis indicates relative disturbance probabilities. Note that the scale of the axis differs between plots to better visualize the effects of individual predictors.

*Table C.2: Variable importance of all the fitted disturbance probability models: Mean Decrease Accuracy and Mean Decrease Gini for the random forest models, relative variable importance in the gradient boosting machine models and fitted coefficients of the binomial generalized linear models with their significance (***p<0.001, **p<0.01, *p<0.05).*

Period included	Disturbance	Variable	Variable importance	Mean Decrease Gini	GBM relative importance	GLM coefficient	
2016-2018	**All natural**	Elevation	0.0100	257	22.8	0.00	***
		Slope	0.0052	196	14.9	-0.03	***
		TopExp	0.0012	164	14.5	0.01	*
		Aspect	0.0055	62	8.1		
		Aspect (E)				1.04	***
		Aspect (S)				1.15	***
		Aspect (W)				0.39	***
		Canopy height	0.0103	179	13.4	0.08	***
		Spruce	0.0044	105	7.2	0.11	***
		Cover	0.0024	98	9.4	-0.25	
		Structure	0.0004	15	0.5		
		Structure (uneven)				-0.09	
		LU history	0.0034	32	2.2		
		Post-1880				-0.37	**
		Pre-1880				-0.50	***
		Managed	0.0051	52	7.0		
		Managed (yes)				1.28	***
2016-2018	**Avalanche**	Elevation	0.0002	2	15.4	0.00	*
		Slope	0.0000	2	12.6	0.02	
		TopExp	0.0000	1	12.5	-0.04	
		Aspect	0.0000	1	10.2		
		Aspect (E)				2.45	*
		Aspect (S)				2.07	
		Aspect (W)				1.43	
		Canopy height	0.0000	4	27.6	-0.23	***
		Spruce	0.0002	1	6.5	0.01	
		Cover	0.0000	1	9.8	-1.65	
		Structure	0.0000	0	2.2		
		Structure (uneven)				-1.12	*
		LU history	0.0000	0	3.0		
		Post-1880				-0.41	
		Pre-1880				-0.52	
		Managed	0.0001	0	0.2		
		Managed (yes)				1.94	***
2016-2018	**Bark beetle**	Elevation	0.0030	80	25.1	0.00	***
		Slope	0.0016	47	11.9	-0.01	
		TopExp	0.0008	45	13.7	0.02	*
		Aspect	0.0014	18	4.5		
		Aspect (E)				0.95	***
		Aspect (S)				0.81	***

		Aspect (W)				0.30	
		Canopy height	0.0046	53	15.7	0.10	***
		Spruce	0.0026	61	16.5	0.27	***
		Cover	0.0016	26	6.2	-0.17	
		Structure	0.0002	6	1.1		
		Structure (uneven)				-0.35	**
		LU history	0.0008	8	2.0		
		Post-1880				-0.45	*
		Pre-1880				-0.60	***
		Managed	0.0004	10	3.3		
		Managed (yes)				1.78	***
2016-2018	**Fire**	Elevation	0.0005	2	30.1	0.00	***
		Slope	0.0001	1	16.5	0.04	
		TopExp	0.0000	1	6.3	-0.03	
		Aspect	0.0000	1	9.3		
		Aspect (E)				0.05	
		Aspect (S)				0.26	
		Aspect (W)				-17.45	
		Canopy height	0.0001	1	15.3	-0.03	
		Spruce	0.0002	1	11.1	0.02	
		Cover	0.0001	0	2.7	-1.98	
		Structure	0.0000	0	0.3		
		Structure (uneven)				-0.46	
		LU history	0.0000	0	8.3		
		Post-1880				18.48	
		Pre-1880				17.42	
		Managed	0.0000	0	0.0		
		Managed (yes)				-0.55	
2016-2018	**Snow**	Elevation	0.0008	5	15.2	0.00	
		Slope	0.0003	4	15.6	-0.02	
		TopExp	0.0001	5	16.1	-0.04	
		Aspect	0.0002	3	7.2		
		Aspect (E)				0.45	
		Aspect (S)				1.02	*
		Aspect (W)				-0.57	
		Canopy height	0.0005	4	14.5	0.04	
		Spruce	0.0008	8	16.1	0.28	***
		Cover	0.0001	3	8.3	0.49	
		Structure	0.0000	0	0.7		
		Structure (uneven)				0.46	
		LU history	0.0001	1	2.1		
		Post-1880				-0.58	
		Pre-1880				0.24	
		Managed	0.0000	2	4.2		
		Managed (yes)				1.59	***

2016-2018	**Harvest**	Elevation	0.0180	480	18.3	0.00	***
		Slope	0.0090	456	14.4	-0.04	***
		TopExp	0.0081	425	16.9	0.00	
		Aspect	0.0075	137	7.7		
		Aspect (E)				1.17	***
		Aspect (S)				1.11	***
		Aspect (W)				0.78	***
		Canopy height	0.0096	330	6.2	0.03	***
		Spruce	0.0070	210	5.5	0.03	***
		Cover	0.0231	335	28.9	0.85	***
		Structure	0.0003	30	0.0		
		Structure (uneven)				-0.06	
		LU history	0.0017	65	1.9		
		Post-1880				0.62	***
		Pre-1880				0.32	***
		Managed	0.0008	31	0.3		
		Managed (yes)				0.69	***
2016-2018	**Wind**	Elevation	0.0023	72	16.5	0.00	***
		Slope	0.0016	66	15.9	-0.02	***
		TopExp	0.0007	57	17.6	0.03	**
		Aspect	0.0023	23	5.5		
		Aspect (E)				0.84	***
		Aspect (S)				1.41	***
		Aspect (W)				0.63	***
		Canopy height	0.0045	71	19.1	0.13	***
		Spruce	0.0021	37	7.1	0.08	***
		Cover	0.0011	34	10.8	-0.10	
		Structure	0.0003	4	0.7		
		Structure (uneven)				0.23	*
		LU history	0.0010	8	1.1		
		Post-1880				-0.04	
		Pre-1880				-0.38	**
		Managed	0.0009	19	5.9		
		Managed (yes)				2.00	***
2005-2018	**All natural**	Elevation	0.0324	1733	27.9	0.00	***
		Slope	0.0100	1360	10.8	-0.02	***
		TopExp	0.0118	1404	17.6	0.00	
		Aspect	0.0140	302	8.4		
		Aspect (E)				0.70	***
		Aspect (S)				0.71	***
		Aspect (W)				0.14	**
		Spruce	0.0167	753	11.5	0.13	***
		Cover	0.0071	743	17.9	0.17	
		Structure	0.0016	119	0.6		
		Structure (uneven)				-0.21	***
		LU history	0.0112	212	5.3		

		Post-1880				-0.36	***
		Pre-1880				-0.53	***
2005-2018	**Avalanche**	Elevation	0.0008	18	24.5	0.00	***
		Slope	0.0002	16	20.8	0.03	*
		TopExp	0.0000	11	20.0	-0.02	
		Aspect	0.0002	7	9.7		
		Aspect (E)				1.59	***
		Aspect (S)				1.25	**
		Aspect (W)				0.84	*
		Spruce	0.0005	11	11.8	-0.07	*
		Cover	0.0001	9	10.2	0.55	
		Structure	0.0001	1	1.0		
		Structure (uneven)				-0.07	
		LU history	0.0000	2	2.1		
		Post-1880				-0.35	
		Pre-1880				-0.16	
2005-2018	**Bark beetle**	Elevation	0.0069	307	35.8	0.00	***
		Slope	0.0012	182	16.7	0.00	
		TopExp	0.0015	196	19.2	0.02	**
		Aspect	0.0002	55	3.0		
		Aspect (E)				0.25	**
		Aspect (S)				0.15	
		Aspect (W)				-0.06	
		Spruce	0.0066	139	13.4	0.22	***
		Cover	0.0003	107	9.1	0.08	
		Structure	0.0001	17	1.5		
		Structure (uneven)				-0.36	***
		LU history	0.0002	29	1.4		
		Post-1880				-0.02	
		Pre-1880				-0.10	
2005-2018	**Fire**	Elevation	0.0007	18	25.6	0.00	***
		Slope	0.0001	10	21.0	0.01	
		TopExp	0.0000	9	18.4	-0.01	
		Aspect	0.0000	5	8.2		
		Aspect (E)				1.00	*
		Aspect (S)				1.14	*
		Aspect (W)				0.96	*
		Spruce	0.0005	6	11.9	0.02	
		Cover	0.0002	6	11.3	-0.50	
		Structure	0.0000	1	1.5		
		Structure (uneven)				-0.47	
		LU history	0.0000	2	2.0		
		Post-1880				-0.30	
		Pre-1880				-0.56	*

2005-2018	**Snow**	Elevation	0.0032	270	25.6	0.00	***
		Slope	0.0025	212	14.6	-0.01	*
		TopExp	0.0013	229	22.0	-0.01	
		Aspect	0.0016	69	9.6		
		Aspect (E)				0.73	***
		Aspect (S)				0.80	***
		Aspect (W)				-0.09	
		Spruce	0.0027	148	13.7	0.15	***
		Cover	0.0007	128	10.9	0.32	
		Structure	0.0003	19	1.6		
		Structure (uneven)				-0.33	***
		LU history	0.0009	36	2.0		
		Post-1880				-0.03	
		Pre-1880				-0.25	***
2005-2018	**Harvest**	Elevation	0.0421	2873	25.0	0.00	***
		Slope	0.0217	2592	15.9	-0.04	***
		TopExp	0.0206	2482	14.8	0.00	
		Aspect	0.0144	545	7.7		
		Aspect (E)				0.83	***
		Aspect (S)				0.77	***
		Aspect (W)				0.41	***
		Spruce	0.0115	1233	6.0	0.06	***
		Cover	0.0182	1355	28.1	0.25	**
		Structure	0.0011	193	0.1		
		Structure (uneven)				-0.13	***
		LU history	0.0054	370	2.3		
		Post-1880				0.54	***
		Pre-1880				0.46	***
2005-2018	**Wind**	Elevation	0.0035	333	25.3	0.00	***
		Slope	0.0012	288	18.2	-0.02	***
		TopExp	0.0009	297	21.7	0.01	
		Aspect	0.0009	71	4.2		
		Aspect (E)				0.19	*
		Aspect (S)				0.54	***
		Aspect (W)				0.17	*
		Spruce	0.0030	189	14.9	0.13	***
		Cover	0.0014	165	13.4	0.34	
		Structure	0.0004	24	0.3		
		Structure (uneven)				-0.03	
		LU history	0.0014	47	2.0		
		Post-1880				0.02	
		Pre-1880				-0.18	**

Appendix D: Supplementary information to Paper IV - Addressing disturbance risk to mountain forest ecosystem services

D.1: Bayesian Network models

D.1.1 Carbon sequestration and wood production

The BN model for carbon sequestration and wood production was based on (Grêt-Regamey et al., 2013a), but adapted to include remote sensing inputs and in-situ data (see whole network structure in Figure D.1 and a description of all the nodes in Table D.1). We used in-situ data from the cantonal forest inventory of Graubünden (AWN, 2018b) to "learn" the relationship between canopy height and the stock of aboveground biomass, and to estimate forest growth rates based on site and stand characteristics. The level of carbon sequestration was estimated based on changes in aboveground biomass, as is done in the Swiss Greenhouse Gas Inventory (Thürig and Schmid, 2008).

The potential amount of wood production was estimated based on the stem volume increment (Grêt-Regamey et al., 2013a) in areas accessible for harvesting. The value of wood production was calculated based the prices of different wood products and the harvesting costs, estimated according to Bont et al. (2018). The loss of carbon in wood products was estimated according to IPCC guidelines (IPCC, 2006).

In case of disturbances, tree mortality (estimated based on forest management records) and decay of dead woody debris (estimated based on Kahl et al., 2017) lead to a loss of carbon. Instead of regular harvest, salvage logging usually takes place, removing most of the dead wood, except in inaccessible areas and in the Swiss National Park. The amount of salvage logging was estimated based on forest management records (AWN, unpublished). Since the quality of salvaged wood is often lower than in regular harvests, disturbances also influence the distribution of wood products and prices.

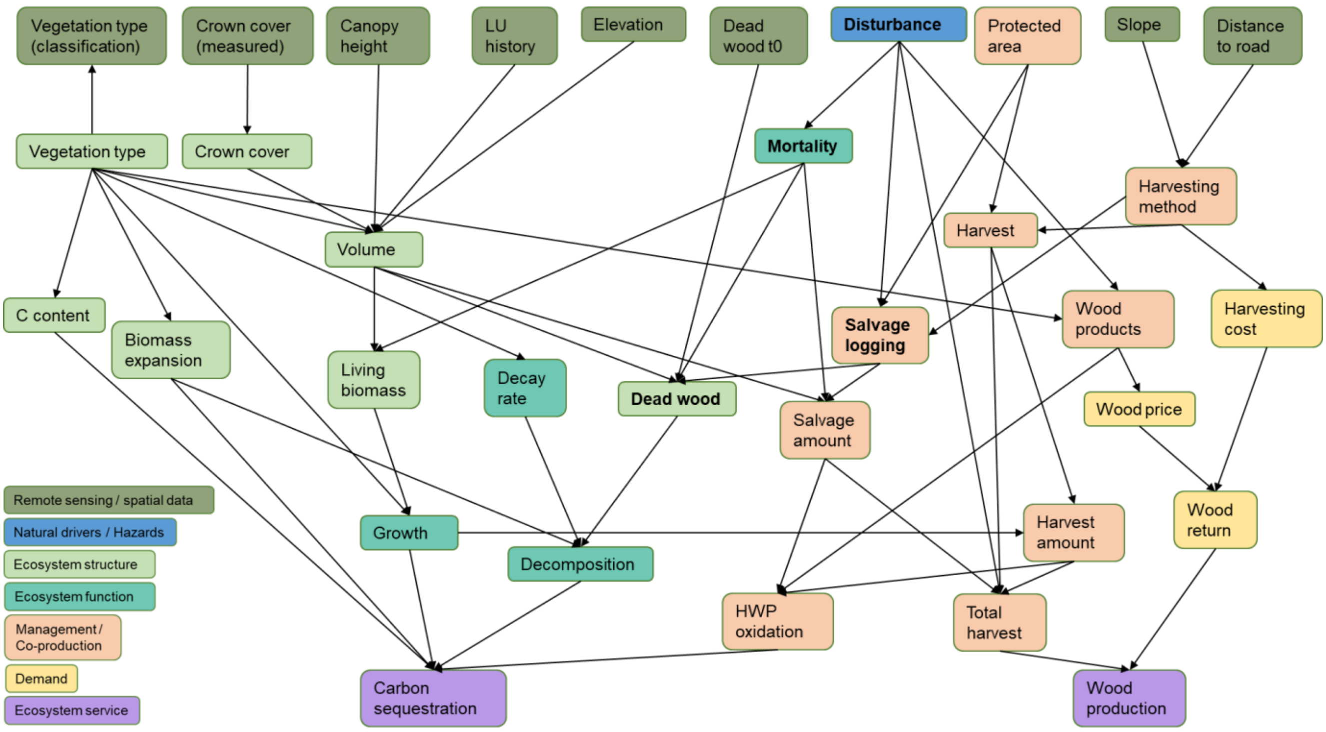

Figure D.1: Structure of the BN for carbon sequestration and wood production. Nodes in bold are influenced by the disturbance BN.

D.1.2 Habitats

We modelled the potential habitats of three species: capercaillie (*Tetrao urogallus* L.), three-toed woodpecker (*Picoides tridactylus* L.) and red deer (*Cervus elaphus* L.). The models of habitat suitability for all three species were developed based on a review of existing literature from the region on their habitat requirements and behaviour. First, the most important spatial variables describing the habitat suitability were selected for each species, and relevant thresholds were identified based on literature. Then, the conditional probabilities were defined, assuming a 100% probability of a high habitat suitability when all the parent nodes are in the most suitable state, and decreasing the probability by 30% for each less suitable factor (assuming an equal weight of all factors for simplicity). The resulting maps of habitat suitability were validated using observation data. The final value of the habitat ES combined all three species' habitats with an OR-operator, i.e. if an area is highly suitable for any of the species, the level of the habitat service is high.

D.1.2.1 Capercaillie

Capercaillie is an indicator species for structurally diverse and undisturbed forests (Suter et al., 2002), and is a priority species for forest managers (AWN, 2018). Important indicators for habitat suitability for capercaillie include the forest type, elevation and slope, and forest structure at different scales (Graf et al., 2009, 2005). In particular, forests with a crown cover of 40-70% and a sufficient cover of ericaceous shrubs are suitable (Graf et al., 2007; Suter et al., 2002). We included both the local crown cover and the forest cover over a 250ha window (Graf et al., 2005). In addition, the species is sensitive to anthropogenic disturbance, so we included a negative effect of road density, harvest, or hiking paths on habitat suitability (Mollet et al., 2008).

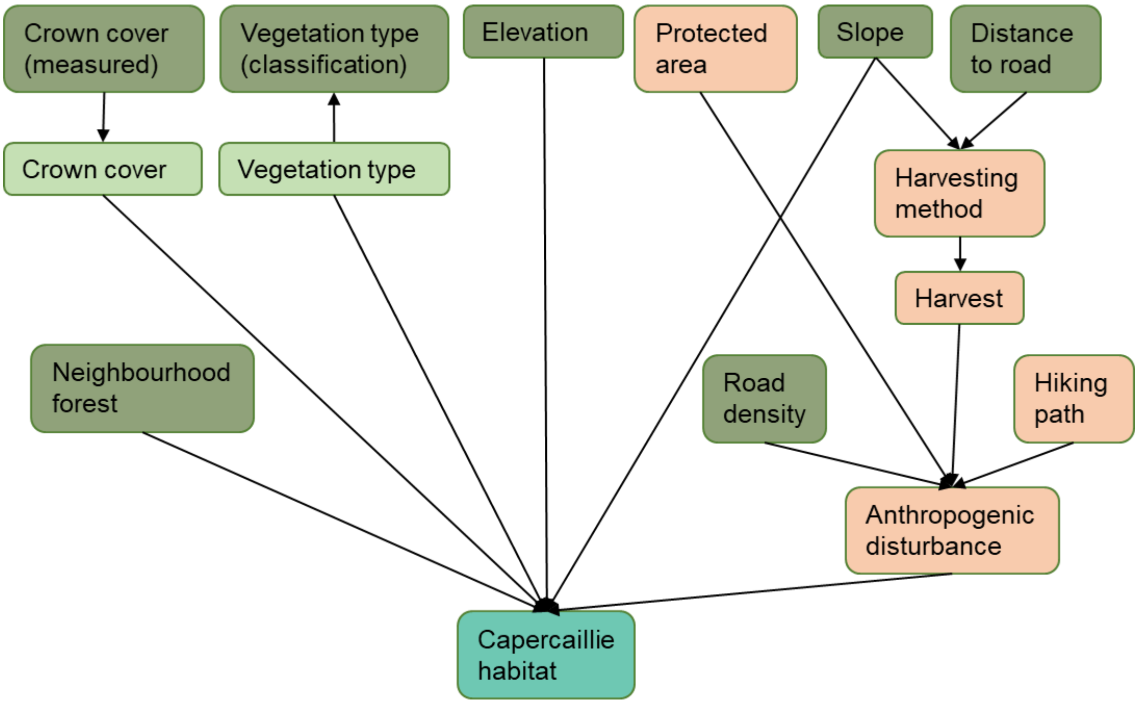

Figure D.2: Structure of the BN for capercaillie habitat.

D.1.2.2 Three-toed woodpecker

The insectivorous three-toed woodpecker is a keystone species providing tree cavities that serve as nesting holes for other species (Pechacek and D'Oleire-Oltmanns, 2004), and an indicator species for forests with substantial amounts of dead wood (Bütler et al., 2004a; Roberge and Angelstam, 2006). Besides the availability of dead wood, habitat suitability for woodpeckers also depends on elevation, and they are less likely to occur in areas with a high road density (Bütler et al., 2004a).

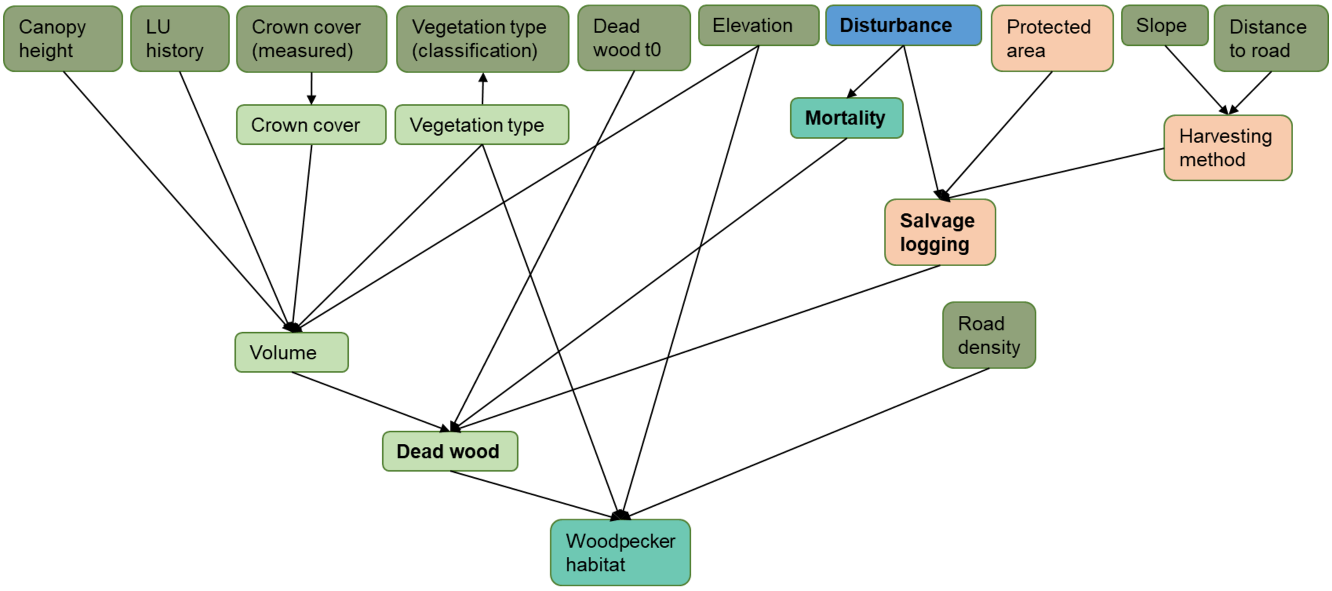

Figure D.3: Structure of the BN for habitat of the three-toed woodpecker. Nodes in bold are influenced by the disturbance BN.

D.1.2.3 Red deer

Red deer is an important charismatic species that attracts visitors to the Swiss National Park (Millhäusler et al., 2016). Red deer mainly graze in grassland (Herfindal et al., 2019), but seek cover in the forest during the day as a predator avoidance pattern (Patrick, 2017). To capture this behaviour, we included the variables "Distance to grazing" and "Distance to cover", and defined the preferred ranges based on observed daily movement patterns of deer in the SNP and surrounding region (Patrick, 2017). While red deer can be disturbed by human presence and avoid trails, they are more likely to stay out in the open and at higher elevations in the SNP, where no hunting takes place (Haller et al., 2002; Patrick, 2017).

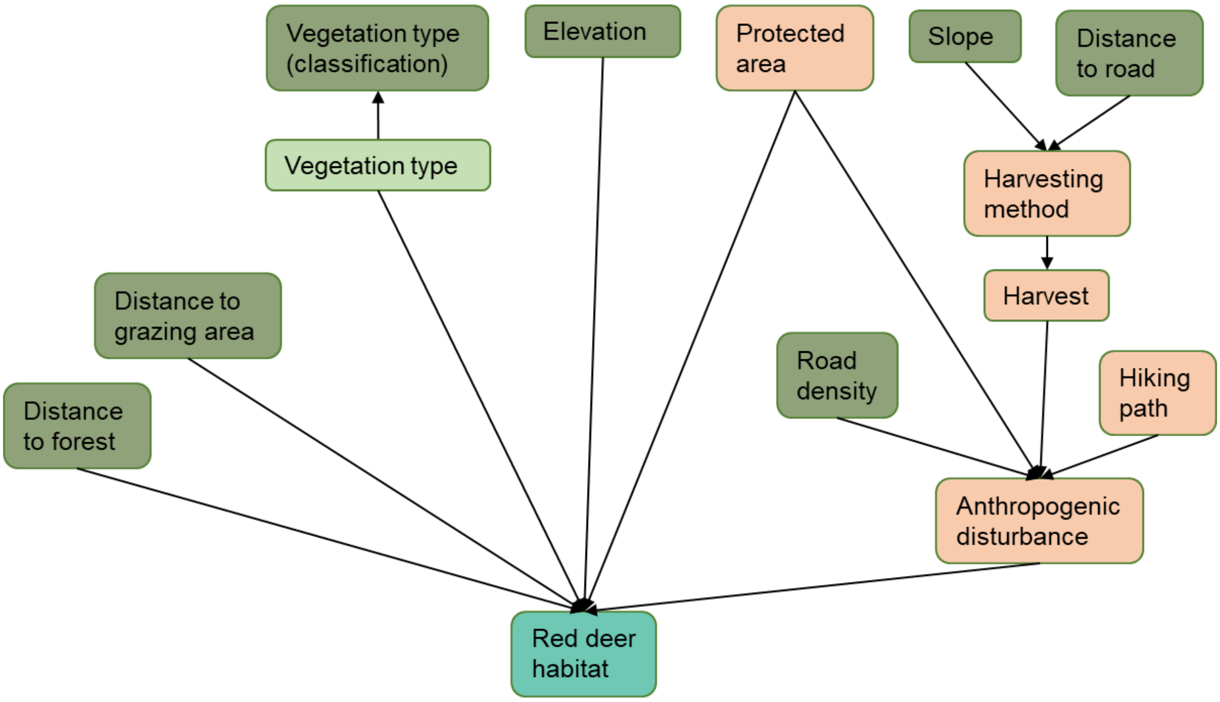

Figure D.4: Structure of the BN for red deer habitat.

D.1.3 Recreation

The recreation ES depends on recreation infrastructure (e.g. hiking paths) and accessibility, as well as the attractiveness of the landscape for recreationists. The most important factors determining the attractiveness for recreation were defined based on a workshop with experts from the SNP, the Biosfera Val Müstair, and tourism organizations from the surrounding communities (Crouzat et al., in review).

The spatial factors identified as most important for recreation potential were the topography of the landscape and view, places of cultural importance, and wildlife observation potential. As a proxy for topography and view, we calculated the number of mountain peaks visible from each pixel using viewshed analysis, while places of interest were extracted from Open Street Map (Crouzat et al., in review; OSM, 2020). This proxy was chosen because mountain peaks are the most common landscape feature occurring in Flickr photographs from both regions (Gosteli, 2019). The wildlife observation potential was determined based on the modelled habitats, with a higher weight given to red deer, since they are easier to observe and of high interest to visitors (Millhäusler et al., 2016). To assign a weight to each factor, the frequency of content categories in Flickr pictures from the study areas (Gosteli, 2019) was used as a proxy for what people value in these landscapes (Richards and Friess, 2015; Vaz et al., 2020). Since different frequencies were observed in pictures from inside the SNP compared to outside the park (e.g. a higher frequency of landscape and species photographs in the park and a higher frequency of cultural features outside the park), we used a different weighting for both areas.

To evaluate accessibility, we used data on roads, hiking paths, ski lifts and bus stops. Bus stops, parking lots, and ski lift stations were defined as “starting points” for recreationists. We calculated the distance along hiking paths from these starting points, as well as the distance to the starting points from the main towns of Davos, Zernez or Scuol. In the national park, where visitors are not allowed to leave the hiking trails, we assumed that all areas outside the paths are inaccessible, while areas without hiking paths outside the park have a low accessibility. The spatial pattern of recreation was validated using the locations of the Flickr pictures as a proxy for the actual use of recreation areas (Langemeyer et al., 2018; Wood et al., 2013).

For the disturbance scenario, we included a small negative effect of dead wood on the landscape attractiveness (Rewitzer et al., 2017). However, this effect was not included in the SNP, where the education of visitors about the ecological importance of dead wood has been found to affect their perception of dead wood in the park, and it is now perceived as neutral or even positive (Backhaus et al., 2013).

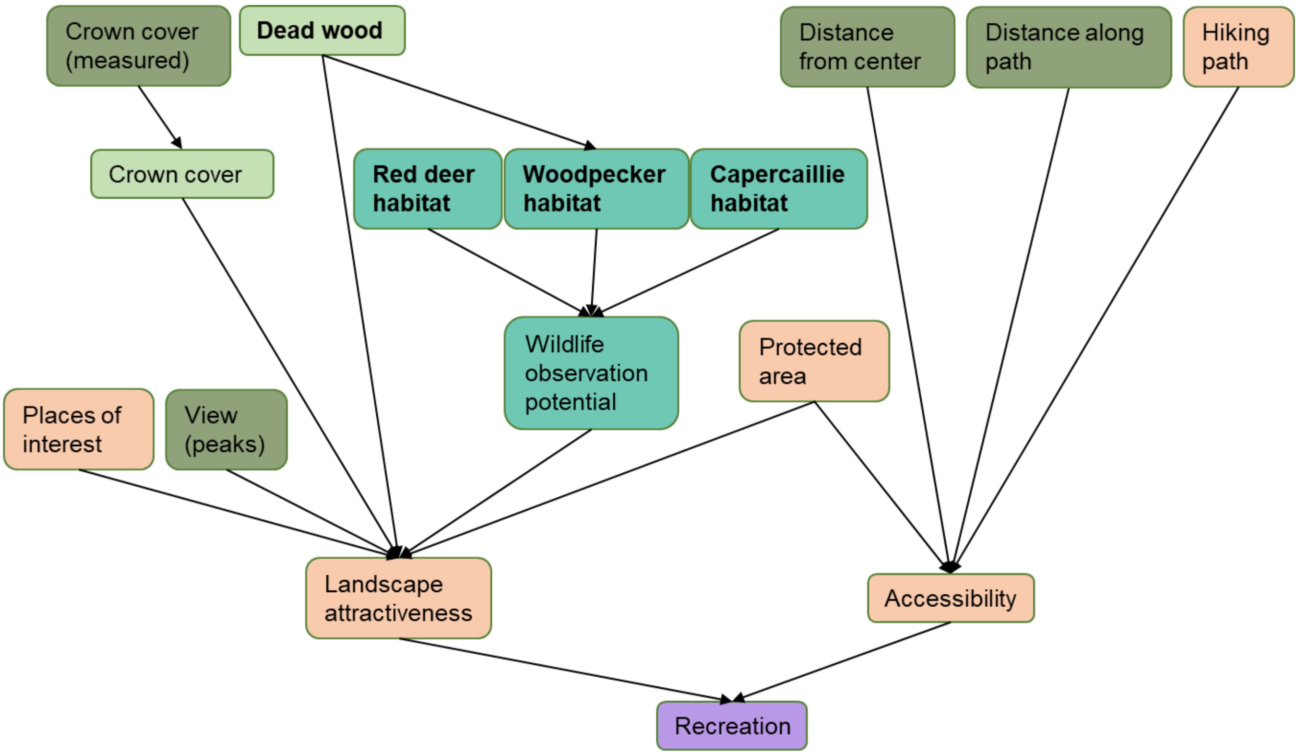

Figure D.5: Structure of the BN for recreation. Nodes in bold are influenced by the disturbance BN and the habitat BNs.

D.1.4 Avalanche protection

The model for avalanche protection was based on the BN described in Stritih et al. (2019), where forests play a role in preventing avalanche releases and also have a braking effect on avalanche flows. The model includes both the provisioning side, where the avalanche protection function depends on topography and forest structure, and the demand side, which depends on the infrastructure and people at risk. Since the demand and provision of avalanche protection do not occur at the same location, the total value of demand for avalanche protection (modelled using BN in Figure D.7) under different scenarios was summed up for each avalanche track (modelled in the simulation software RAMMS (Christen et al., 2010)) and then assigned to all the pixels in the avalanche track.

The model from (Stritih et al., 2019a) was adapted to include the effects of natural disturbances. A disturbance affects the forest protection capacity by reducing the canopy cover in case of mortality and creating gaps, which can increase the probability of an avalanche release. However, in the absence of salvage logging, snags, downed logs and root plates remaining in the stand can maintain the protection effect of the forest (Teich et al., 2019) by increasing terrain roughness and preventing avalanche releases (Wohlgemuth et al., 2017).

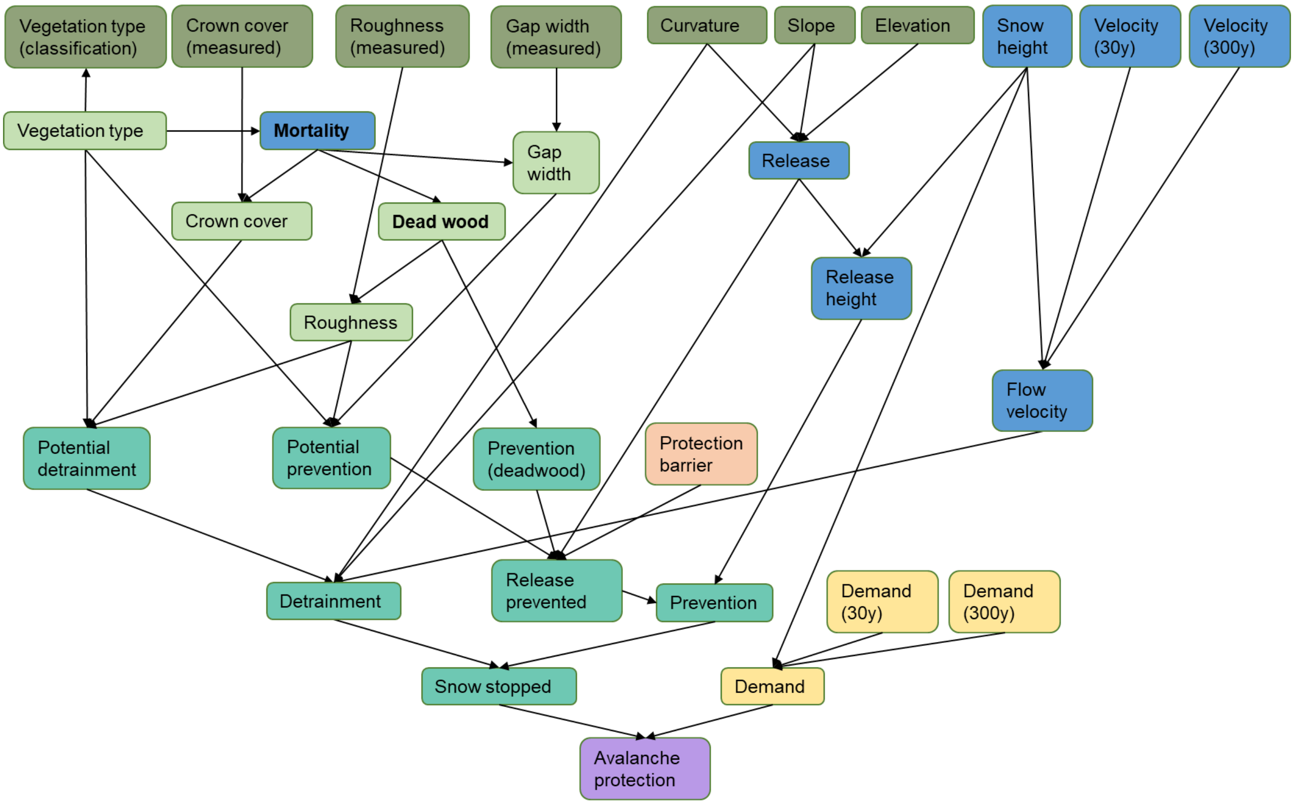

Figure D.6: Structure of the BN for avalanche protection. Nodes in bold are influenced by the disturbance BN, while nodes "Demand (30y)" and "Demand (300y)" represent the outputs of the network for demand (Figure D.7), summed up over each avalanche track.

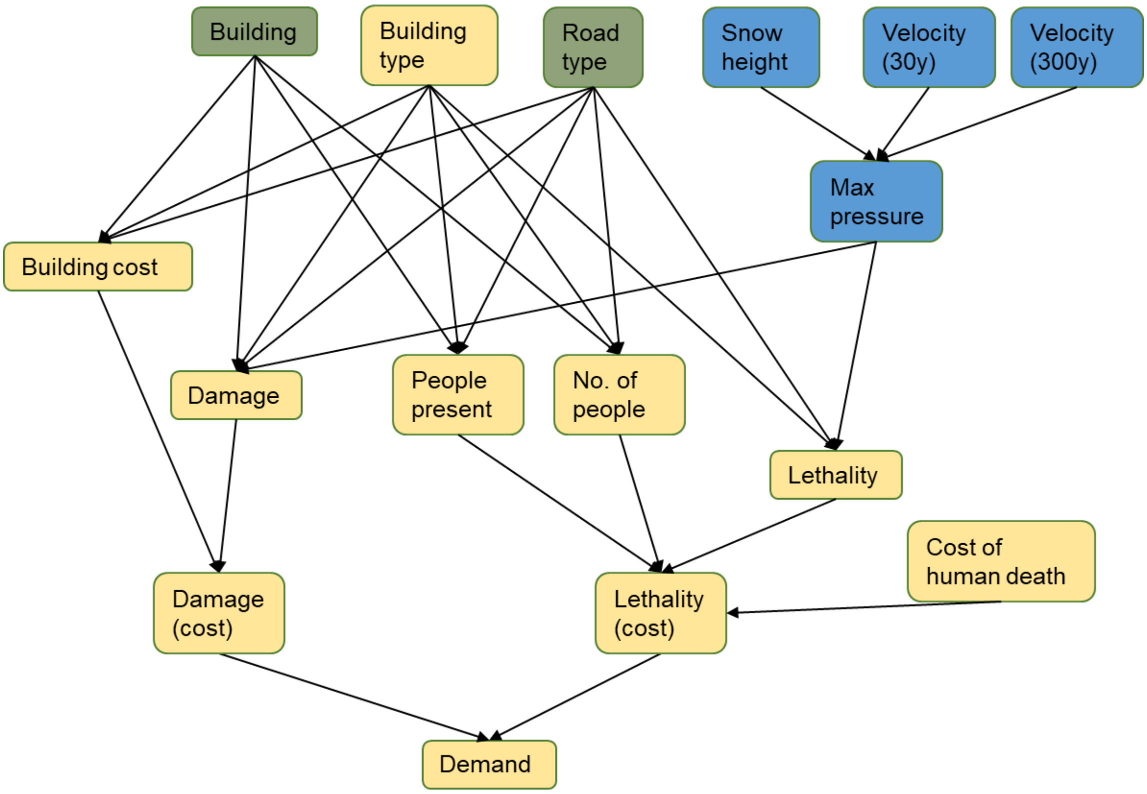

Figure D.7: Structure of the BN for demand for avalanche protection.

D.1.5 Natural disturbance module

The prior probability of a natural disturbance was estimated based on the overall natural disturbance rate in the region Canton of Graubünden (Stritih et al., 2021), while the probability of a specific pixel being affected by a disturbance also depends on the stand's susceptibility. The susceptibility to disturbances was modelled based on a study of natural disturbances in the region, where susceptibility was related to stand and site characteristics, land-use history and recent management (Stritih et al., 2021). The mortality in case of a disturbance was estimated based on local forest management records (AWN, unpublished) and literature (Leverkus et al., 2018; Schmid-Haas and Bachofen, 1991). Depending on the rate of salvage logging (also estimated based on forest management records), tree mortality can lead to an increase in the amount of dead wood in the stand.

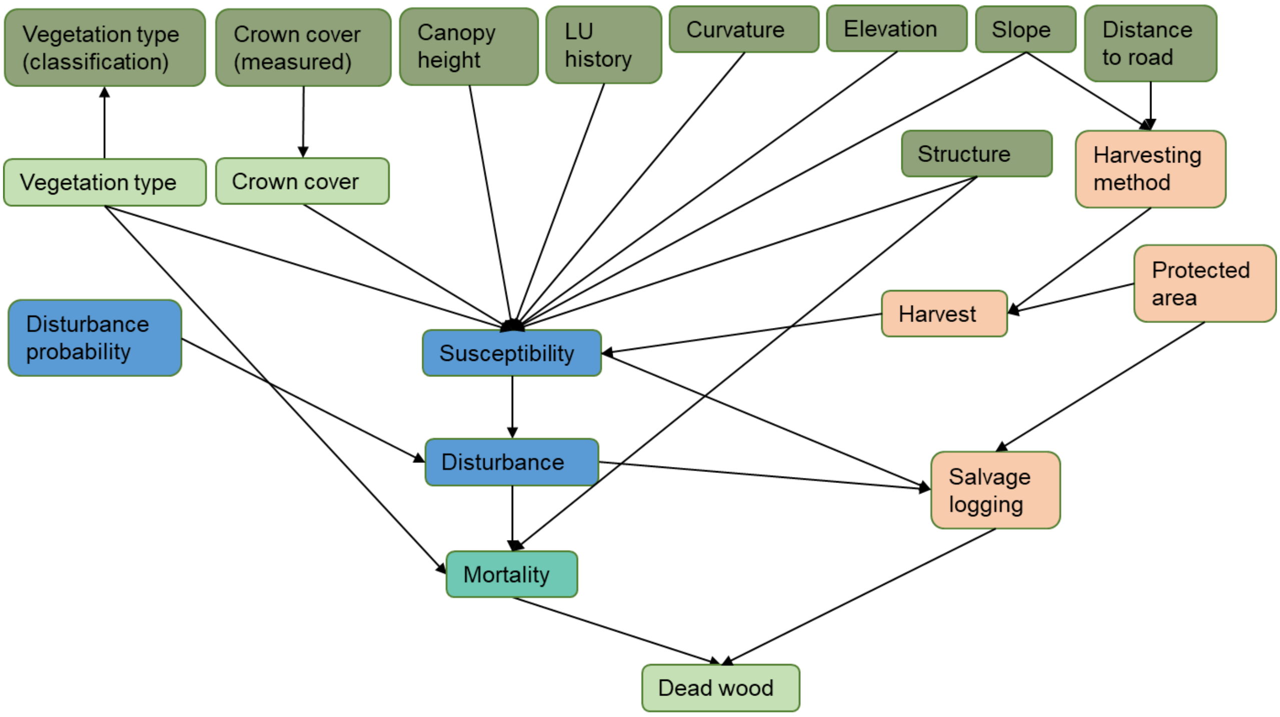

Figure D.8: Structure of the BN describing the susceptibility of a forest to natural disturbances.

D.1.6 Overview of all network nodes

Table D.1: Description of all network nodes, with the node name, description, states (for continuous nodes, breaks between states are shown), description of how the conditional probability table was defined, and data source. The column "ES" indicates in which ecosystem service model this node is used (A: avalanche protection, C: carbon sequestration, W: wood production, H: habitats, R: recreation).

ES	Node	Description	States	Input probabilities / CPT	Source
Nodes representing remote sensing and other inputs					
A C W H R	Vegetation type (classification)	Classification	Dwarf shrubs, Grassland, Bare rock/ Sealed, Larch forest, Spruce forest, Pine forest, Shrubs	Soft evidence based on classification output	Random forest classification based on Sentinel-2 images from May, June, and Oct 2016, trained using groundtruth observations (n = 122) in Davos and habitat mapping in the SNP (Hauenstein and Haller, 2013), accuracy 86.1 %

A C W H R	Canopy height	Canopy height model	9 states: 0,3,5,10,15,20, 25,30,35,48	Hard evidence	Derived from digital surface model from stereo-image matching (Ginzler and Hobi, 2015)
A C W H R	Crown cover (measured)	Cover of vegetation above 3 m, derived from CHM	4 states: 10,40,70,100	Hard evidence	
A	Roughness (measured)	Measured terrain roughness	9 states: 0,0.001,0.0025, 0.005,0.01,0.025,0 .05,0.1,0.5	Hard evidence	Calculated based on DTM (Sappington et al., 2007)
A	Gap width (measured)	Width (along contour lines) of non-forested area [m]	9 states: 0,1,5,15,30,60, 100,200,500, 500000	Hard evidence	Derived from CHM
A C W H R	Curvature	Slope curvature	7 states: -45,-20,-10,-5, -2, 0,2,5	Hard evidence	Calculated based on DTM
A C W H R	Slope	Slope angle [°]	8 states: 0,15,25,35,45,55,6 5,70,90	Hard evidence	Calculated based on DTM
A C W H R	Elevation	Elevation [m a.s.l.]	7 states: 900,1200,1400, 1800, 2200, 2800, 3500	Hard evidence	DTM (swisstopo)
A C W H R	Land use history	Class determined based on forest cover in historic maps	Pre-1880: present before 1872-1908 Post-1880: established after 1872-1908 and before 1917-1944 Post-1920: established after 1917-1944	Hard evidence	Siegfried maps (1872-1908 and 1917-1944), (Loran et al., 2016)
A C W H R	Structure	Vertical forest structure	Even Uneven	Hard evidence	Forest stand map (AWN, 2019)
A C W H R	Dead wood t0	Current volume of dead wood	8 states: 0,1,15,50,150, 300,600,900,1500	Spatially explicit hard evidence available in the SNP, prior distribution based on inventory data elsewhere	Habitalp project (Hauenstein and Haller, 2013)
C W	Distance to road	Distance from roads that are suitable for harvesting	4 states: 0,300,1000,1500, 30000	Hard evidence	Calculated based on road data from TLM3D

H	Road density	Density of roads [km/km2]; influences habitat suitability for three-toed woodpecker	2 states: 0,2.5,10	Hard evidence	Calculated based on road data from TLM3D (swisstopo, 2020); threshold based on (Bütler et al., 2004a)
H	Neighbourhood cover	Forest cover in 250ha window; influences habitat suitability for capercaillie [%]	3 states: 0,40,70,100	Calculated based on forest cover	
H	Distance to forest	Distance to forest (cover for red deer) [m]	3 states: 0, 200, 1000, 10000	Calculated based on vegetation type	
H	Distance to grazing	Distance to grazing area for red deer (grassland or dwarf shrubs) [m]	3 states: 0, 200, 1000, 10000	Calculated based on vegetation type	
R	Distance along path	Length along hiking path from starting point (bus stop or parking lot) [m]	3 states: 0,5000,15000, 50000	Calculated based on road and hiking path network	swissTLM3D (swisstopo, 2020)
R	Distance from center	Distance from center (main town, Davos, Zernez or Scuol) to bus stop or parking lot [m]	3 states: 0,2500,5000, 25000	Calculated based on road and hiking path network	swissTLM3D (swisstopo, 2020)
R	View (peaks)	No. of peaks visible as a proxy for topography-dependent view	None, Few (0-5), Many	Calculated based on viewsheds of peaks	swissTLM3D (swisstopo, 2020)
Nodes representing ecosystem structure					
A C W H R	Crown cover t0	Cover of vegetation above 3 m	4 states: 10,40,70,100	Normal distribution around measured value	Distribution width estimated based on (Moeser et al., 2014)
A	Crown cover	Crown cover taking into account potential disturbance effect	Dense, scattered, open, non-forest	Calculated as Crown cover t0 reduced by mortality [%]	
A	Roughness	Terrain roughness, taking into account dead wood	Rough, knobby, smooth	Fuzzy definition of categories based on ground truth. In case of high amount of dead wood, the roughness is assumed to be "rough"	

A	Vegetation type (classification)	Actual vegetation type	Dwarf shrubs Grassland Bare rock/Sealed Larch forest Spruce forest Pine forest Shrubs	Confusion matrix of the classification	
A C W H R	Dead wood	Volume of dead wood (m3/ha) after disturbance	8 states: 0,1,15,50,150, 300,600,900, 1500	Calculated based on current volume, mortality, and salvage logging	
C	C content	Carbon content in biomass		Based on literature	(Tappeiner et al., 2008)
A	Gap width	Width (along contour lines) of non-forested area [m]	9 states: 0,1,5,15,30,60, 100,200,500,5000 00	Normal distribution around measured value; increase in case of disturbance	Distribution width estimated based variability of estimates using different thresholds; increase due to disturbance based on median disturbance area in the region (Stritih et al., 2021)
Nodes representing natural disturbances and hazards					
A C W H R	Disturbance probability	Prior probability of a natural disturbance	Boolean	Prior estimated based on overall average natural disturbance rate in the region. Hard evidence set for disturbance and non-disturbance scenarios	(Stritih et al., 2021)
A C W H R	Susceptibility	Likelihood that a stand is affected by a natural disturbance, determined based on site and stand characteristics	Boolean	Predicted based on a random forest model of natural disturbance susceptibility in the Canton of Graubünden	(Stritih et al., 2021)
A C W H R	Disturbance	Combination of overall disturbance probability	Boolean	AND-function of distrubance probability and susceptibility	
A	Max new snow height	Annual maximum new snow height, which determines the avalanche release scenario [m]	7 states: 0,0.01,0.05,0.1, 0.5,1,1.5,2	Gumbel distribution of maximum new snow height, Davos, Fluelastrasse	(Salm et al., 1990; SLF, 2017b)

A	Velocity 300	Maximum velocity under the 300 year scenario [m/s]	8 states: 0, 1e-6, 5, 10, 15, 20, 30, 40, 70	Hard evidence	RAMMS (Christen et al., 2010) model output
A	Velocity 30	Maximum velocity under the 30 year scenario [m/s]	8 states: 0, 1e-6, 5, 10, 15, 20, 30, 40, 70	Hard evidence	RAMMS (Christen et al., 2010) model output
A	Release	Probability of an avalanche release	Boolean	Fuzzy logic	(Veitinger et al., 2016)
A	Release height	Height of snow released in the event of an avalanche [m]	6 states: 0,0.01,0.05,0.1, 0.5,1.5,3	Logical combination of "Release" and "Max new snow height", corrected for "Slope"	(Salm et al., 1990)
A	Velocity	Maximum avalanche flow velocity [m/s]	8 states: 0, 1e-06, 5, 10, 15, 20,30,40,70	Defined by scenarios, with uncertainty estimated based on simulations with varying input parameters	RAMMS
A	Max pressure	Maximum avalanche pressure	4 states: = 0 - 300 [kPa]	Derived from velocity, with uncertainty estimated based on simulations with varying input parameters	RAMMS
Nodes representing ecosystem functions and processes					
A C W H R	Mortality	Mortality rate of trees (in % of volume), higher in stands with homogeneous structure and spruce-dominated stands	5 states: 0,2,20,40, 80, 100	Estimated based on forest management data and literature	AWN (unpublished); (Leverkus et al., 2018; Schmid-Haas and Bachofen, 1991)
C W	Growth	Increment of stem volume, depending on stand and site characeristics [m3/ha]	7 states: 0,1,5,15,50,100, 150,300	Learned from GR inventory data	
C	Decay rate	Decay rate of dead woody debris	5 states: 0,0.05,0.1,0.2, 0.4,0.6	Estimated based on literature	(Kahl et al., 2017)
C	Decomposition	Volume of decomposed dead woody debris [m3/ha]	5 states: 0,1,15,50,150, 300,1500	Calculated from volume of dead wood and decay rate	
H R	Red deer habitat	Habitat suitability for red deer	None, Low, Medium, High	Defined based on literature	(Haller et al., 2002; Herfindal et al., 2019; Patrick, 2017)
H R	Capercaillie habitat	Habitat suitability for capercaillie	None, Low, Medium, High	Defined based on literature	(Graf et al., 2009, 2005; Storch, 1993)

H R	Three-toed woodpecker habitat	Habitat suitability for the three-toed woodpecker	None, Low, Medium,High	Defined based on literature	(Bütler et al., 2004a, 2004b)
A	Potential release prevention	Potential of forest to prevent an avalanche release	Boolean	Logistic model	(Bebi et al., 2001)
A	Release prevention (deadwood)	Dead wood increases terrain roughness and can prevent an avalanche release on moderate slopes	Boolean	Expert knowledge	
A	Potential detrainment	Capacity of forest to remove snow from avalanche flow (K factor, [Pa])	6 states: 0,0.0001,10,20, 40,80,120	Expert knowledge	(Feistl et al., 2014; Teich et al., 2014)
A	Release prevented	Probability a release would be prevented by the forest	Boolean	True in case Release is true and Potential release prevention, Release prevention (deadwood) OR Protection barriers are true	
A	Prevention	Height of snow in prevented avalanche release [m]	6 states: 0,0.01,0.05,0.1, 0.5,1.5,3	Equals Release height if Release prevention is true	
A	Detrainment	Height of snow detrained in forest during avalanche [m]	7 states: 0,1e-06,0.01,0.05,0.1,0.5,1.5	Learning from simulations with varying input parameters	RAMMS
A	Snow stopped	Combination of prevented release and detrained snow height [m]	None: 0 Low: 0.01 Medium: 0.01-0.1 High: >0.1	Sum of "Prevention" and "Detrainment"; states defined based on quantiles in the region of Davos	
Management and co-production nodes					
A C W H R	Protected area	Presence of a PA (SNP)	Boolean	Hard evidence	
A C W H R	Harvesting method	Type of harvesting method that can be used (depending on terrain)	Ground-based, Cable system, Helicopter	Defined based on literature	(Bont et al., 2018)
A C W H R	Harvest	Binary node indicating whether harvesting takes place	Boolean	Prior estimated based on overall harvest rate in the region	(Stritih et al., 2021)
A C W H R	Salvage logging	% of dead wood that is salvaged after a disturbance	3 states: 0,0.1,90,100	Estimated based on forest management data	

C W	Harvestable amount	Amount of wood available for sustainable harvest, depending on growth rate (stem volume increment) [m3/ha]	7 states: 0,1,5,15,50,100, 150,300	Calculated based on growth rate	(Grêt-Regamey et al., 2013a)
C W	Salvage amount	Amount of wood salvaged after disturbance [m3/ha]	8 states: 0,0.1,5,50,150, 300,600,900,1500	Calculated based on dead wood volume and Salvage logging %	
W	Harvest amount	Total amount of wood harvested [m3]	None: 0 Low: 0-15 Medium: 15-50 High: >50	Combination of salvage logging (in case of disturbance) and harvestable amount	
W	Wood products	Type of wood products	Stem wood, Energy wood	Estimated based on forest management plans	(AWN, 2018a)
C	HWP oxidation	CO_2 released from harvested wood products	7 states: 0,1,50,150,300,600,900,2500	Calculated according to the methodology of the GHG inventory	(IPCC, 2006)
R	Places of interest	Locations of cultural interest and amenities	Boolean	Points from Openstreetmap	
R	Landscape attractiveness	Attractiveness of the landscape for recreation, based on view, wildlife observation probability, and places of interest	Low, Medium, High	NoisyMax of view, wildlife observation probability, amd places of interest (weights based on frequency of Flickr content), small decrease in case of dead wood >100 m3/ha	(Rewitzer et al., 2017)
H R	Hiking path	Presence of a hiking path	Boolean	Hard evidence	swissTLM3D (swisstopo, 2020)
R	Accessibility	Ease of access, depending on length of hike from starting point and distance from center	None, Low, Medium, High	Expert knowledge	
H	Anthropogenic habitat disturbance	Habitat disturbance from management, roads and hiking paths	Boolean	OR-function of road density, management, or hiking path (lower weight of hiking paths in the SNP, since there is no hiking in winter)	
A	Protection barrier	Presence of avalanche protection barriers	Boolean	Hard evidence	swissTLM3D (swisstopo, 2020)

Nodes representing the demand for ES					
W	Wood price	Market price of wood [CHF]	6 states: 0,30,60,80,120, 200,300	Distribution estimated based on wood price statistics in the region	(FOEN, 2019b)
W	Harvesting cost	Cost of harvesting [CHF]	5 states: 30,60,80,100, 120, 200	Based on literature	(Bont et al., 2018)
W	Wood return	Difference between wood price and harvesting costs [CHF]	Low: -200 to -30 Medium: -30 to 30 High: >30	Calculated from Wood price and Harvesting cost	
A	Demand for avalanche protection (30 y) [CHF]	Sum of demand per avalanche track under a 30-year scenario	6 states: 0, 500, 5*10^6, 1.5*10^7, 5*10^7, 10^10	Modelled using the BN for avalanche protection demand, summed up by avalanche track modelled in RAMMS	(Christen et al., 2010; Stritih et al., 2019a)
A	Demand for avalanche protection (300 y) [CHF]	Sum of demand per avalanche track under a 300-year scenario	6 states: 0, 500, 5*10^6, 1.5*10^7, 5*10^7, 10^10	Modelled using the BN for avalanche protection demand, summed up by avalanche track modelled in RAMMS	(Christen et al., 2010; Stritih et al., 2019a)
A	Demand for avalanche protection	Combined demand per avalanche track	4 states: 0,200,10^6, 10^7, 10^9	Defined by scenarios, with uncertainty estimated based on simulations with varying input parameters	
A	Building	Presence of a building	Boolean	Hard evidence	swissTLM3D (swisstopo, 2020)
A	Building type	Type of building	One-family house, farm building, guesthouse, multi-family house, industrial, infrastructure	Distribution of types from local data	Communal cadaster (Davos, unpublished)
A	Road type	Type of road	Class 2, class 3, class 4, no road	Hard evidence	swissTLM3D (swisstopo, 2020)
A	Lethality	Avalanche pressure is lethal	Boolean	Fuzzy logic based on values from literature	Swiss National Platform for Natural Hazards (BAFU, 2015; Planat, 2008)
A	People per building	Average no. of people per building	6 states: 0,0.5,1.5,2.5,5, 10,50,400	Fuzzy logic based on values from literature	Swiss National Platform for Natural Hazards

A	People present	People are present in a building	Boolean	Fuzzy logic based on values from literature	Swiss National Platform for Natural Hazards
A	Damage	Building is destroyed by avalanche	Boolean	Fuzzy logic based on values from literature	Swiss National Platform for Natural Hazards
A	Building cost	Cost of destroyed building [CHF]	5 states: 0,1, 10^4, 10^5, 10^6, 10^8	Distribution per type from local data	Communal cadaster (Davos, unpublished)
A	Damage (cost)	Cost due to damaged building [CHF]	6 states: 0, 1, 10^4, 10^5, 10^6, 10^7, 10^8	Logical combination of "Damage" and "Building cost"	
A	Cost of human death	[CHF]	Constant: 5*10^6	Constant value from literature	Life Quality Index approach (Merz et al., 1995)
A	Lethality (cost)	[CHF]	6 states: 0, 1, 5*10^6, 10^7, 10^8, 10^9, 10^10	Logical combination of "Lethality" and "Cost of human death"	
Output nodes - ecosystem services					
C	Carbon sequestration	Total carbon sequestration [tC/10 years]	Negative: -1200 to -1 Low: -1 to 1 Medium: 1-15 High: >15	Calculated based on growth, BEF, C content and wood density (literature), minus oxidized harvested products and decomposition	(Thürig and Schmid, 2008)
W	Wood production	Amount and value of wood production	None, Low, Medium, High	MIN-function of harvest amount and harvest return (defined by the lower value; High only if the amount and return are high)	
R	Recreation	Combination of potential (landscape attractiveness) and accessibility	None, Low, Medium, High	MIN-function of landscape attractiveness and accessibility	
H	Habitats		None, Low, Medium, High	MAX-function of capercaillie, red deer, and three-toed woodpecker habitats (high if highly suitable for any of the species)	
A	Avalanche protection	Combination of demand and provision (Snow stopped)	None, Low, Medium, High	MIN-function of provision and demand	

D.2: Correlations between services

Table D.2: Correlations between different metrics for each modelled ecosystem service (most likely state, uncertainty, expected value, and risk - difference between non-disturbed and disturbed scenario).

carbon				
	state	uncertainty	exp. value	risk
state	1	0.51	0.89	-0.85
uncertainty	0.51	1	0.75	-0.62
exp. value	0.89	0.75	1	-0.9
risk	-0.85	-0.62	-0.9	1
avalanche				
	state	uncertainty	exp. value	risk
state	1	0.70	0.90	-0.82
uncertainty	0.70	1	0.89	-0.86
exp. value	0.90	0.89	1	-0.93
risk	-0.82	-0.86	-0.93	1
recreation				
	state	uncertainty	exp. value	risk
state	1	0.74	0.93	-0.26
uncertainty	0.74	1	0.82	-0.34
exp. value	0.93	0.82	1	-0.29
risk	-0.26	-0.34	-0.29	1
habitat				
	state	uncertainty	exp. value	risk
state	1	-0.3	0.73	0.01
uncertainty	-0.3	1	-0.74	0.08
exp. value	0.73	-0.74	1	0.05
difference	0.01	0.08	0.05	1
wood				
	state	uncertainty	exp. value	risk
state	1	0.91	0.93	-0.72
uncertainty	0.91	1	0.99	-0.76
exp. value	0.93	0.99	1	-0.77
risk	-0.72	-0.76	-0.77	1

Table D.3: Correlations of the different distribution metrics (most likely state, uncertainty, expected value, and risk - difference between non-disturbed and disturbed scenario) between different services.

Expected value					
	recreation	carbon	wood	habitat	avalanche
recreation	1	-0.06	0.18	-0.16	0.1
carbon	-0.06	1	0.79	0.44	0.51
wood	0.18	0.79	1	0.26	0.52
habitat	-0.16	0.44	0.26	1	0.17
avalanche	0.09	0.51	0.52	0.17	1
Uncertainties					
	recreation	carbon	wood	habitat	avalanche
recreation	1	-0.09	0.11	0.26	0.13
carbon	-0.09	1	0.48	-0.39	0.38
wood	0.11	0.48	1	-0.23	0.64
habitat	0.26	-0.39	-0.23	1	-0.15
avalanche	0.13	0.38	0.64	-0.15	1
Risk					
	recreation	carbon	wood	habitat	avalanche
recreation	1	0.19	0.19	-0.03	0.14
carbon	0.19	1	0.67	-0.36	0.55
wood	0.19	0.67	1	-0.13	0.48
habitat	-0.03	-0.36	-0.13	1	-0.17
avalanche	0.14	0.55	0.48	-0.17	1