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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.

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., 2012). 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 measurement 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., 2013), 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-

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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., 2012; 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., 2015; 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., 2013). 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., 2013; 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.

2. Methods

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 $P(X) = P(X_1, \ldots, X_n) = \Pi^{n}_{i=1} P(X_i|Pa(X_i))$, 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: $P(X) = \Sigma_{Pa(X)} P(X|Pa(X)) * P(Pa(X))$. 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.

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 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 $P(X = c | Y = c')$ (e.g. the probability that a patch classified as forest is a forest in

Table 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

reality); or the forward probabilities P(Y = c' |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 |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 $Y = N(\beta_0, \sigma_{\beta 0}{}^2) + N(\beta_1, \sigma_{\beta 1}{}^2)*X_1 + \ldots + N(\beta_n, \sigma_{\beta n}{}^2)*X_n$, 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, 1992), 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 B). 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.

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.

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

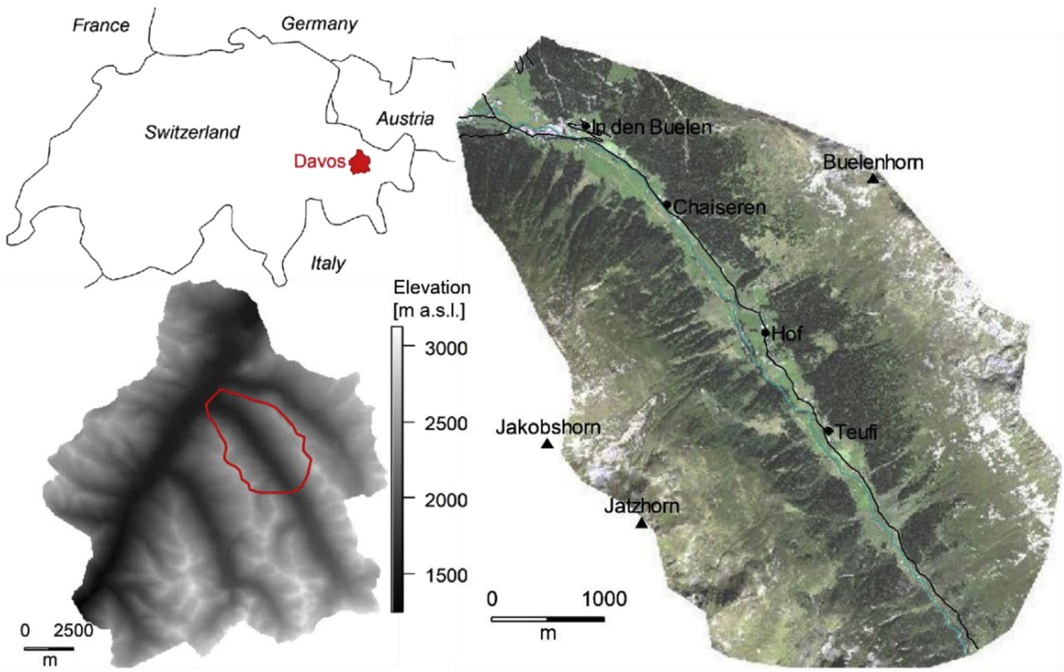

Fig. 1. Map showing the location of the study area on the DTM of Davos, Switzerland (swisstopo, 2015), with an orthophoto of the Dischma valley (swisstopo, 2013).

identify sources of uncertainty under different conditions.

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., 2013).

We based our avalanche protection model on previous models developed for this ES (Grêt-Regamey et al., 2013; 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 (Fig. 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 (Moeser et al., 2014), and terrain roughness (Sappington et al., 2007), 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, 2013), 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; Merz et al., 1995). 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 Fig. 1). Using an application based

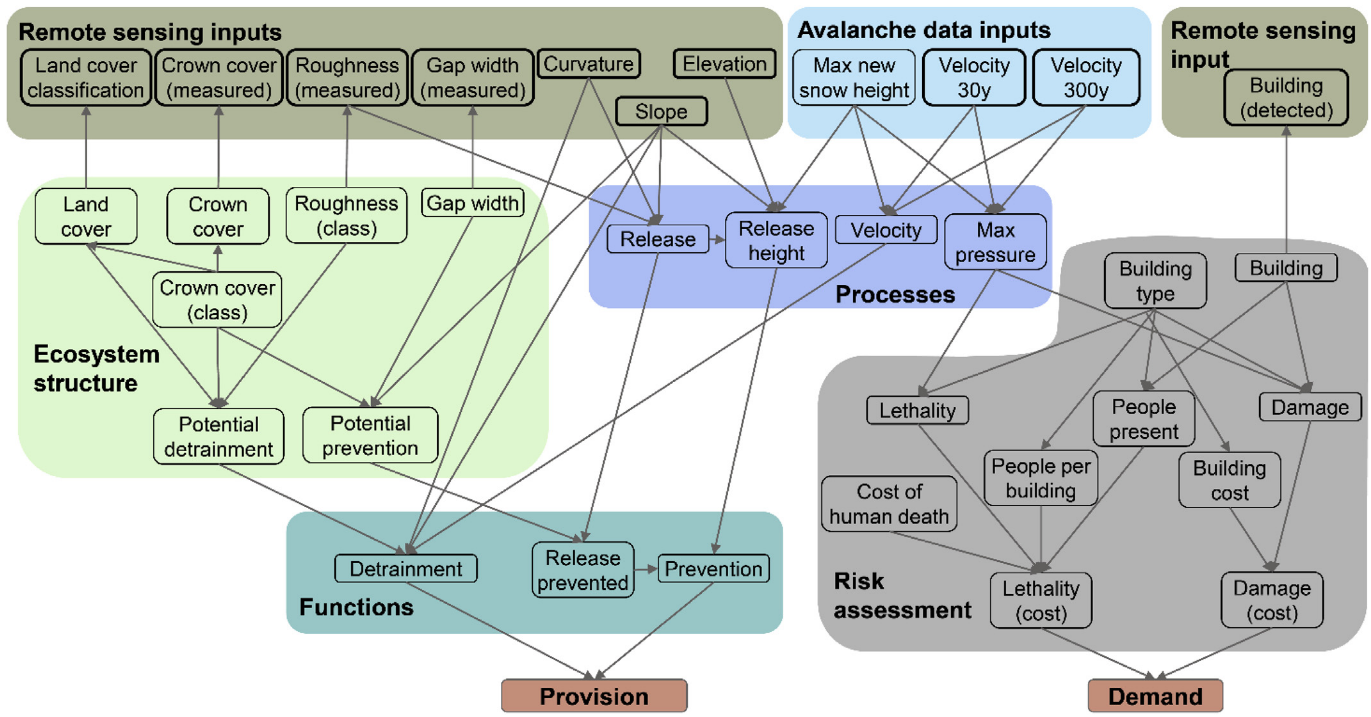

Fig. 2. Bayesian Network developed to model the ES of avalanche protection. The nodes are grouped and coloured based on the types of variables they represent. Spatial inputs (shown with a thick outline) are remote sensing and avalanche data, which are linked to variables describing ecosystem structure, 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.

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 D.

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 Fig. 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), as well as examples of posterior probability distributions (Appendix D) for ES provision and demand.

The spatially explicit model output of ES provision shows a high spatial heterogeneity (Fig. 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.

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 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

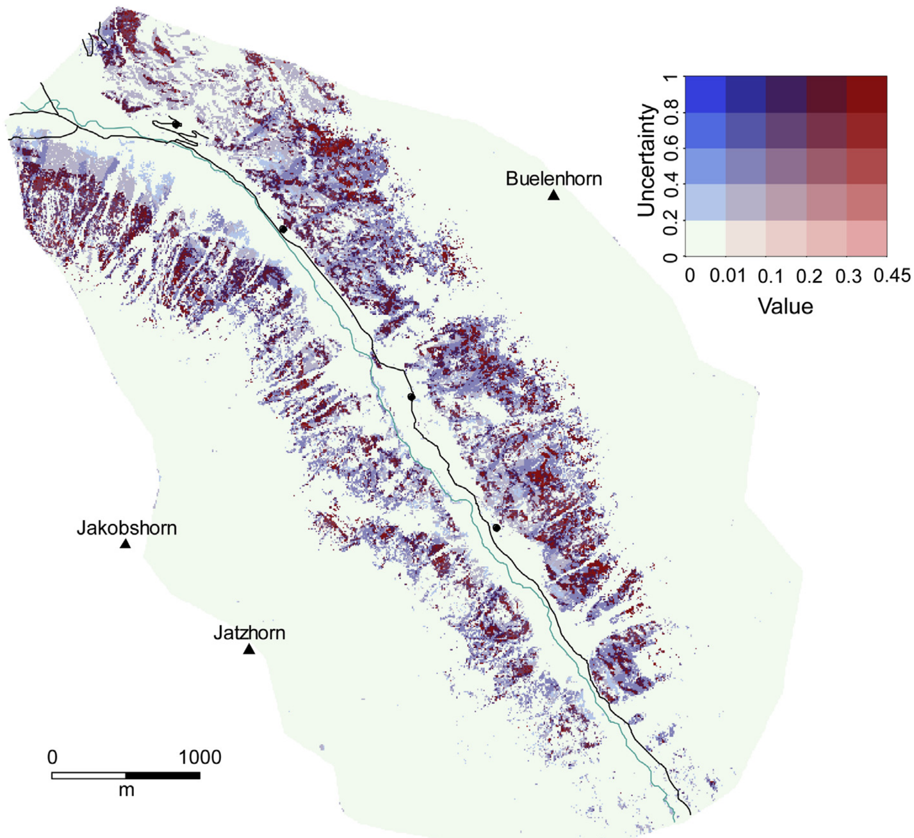

Fig. 3. Modelled provision of avalanche protection in the Dischma valley (5 m resolution). The value is expressed in m of snow, while the uncertainty is calculated as the evenness index of the posterior probability distribution. Most areas with a high value of the service also have a high uncertainty (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. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

these relationships in more detail, we performed a stepwise sensitivity analysis.

The results of the stepwise sensitivity analysis are visualized in a Sankey diagram (Fig. 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 C), 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 D for one pixel of ES provision and demand.

4. Discussion

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

Table 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			Sensitivity - Demand		
Group	Node	MI [%]	Group	Node	MI [%]
Function	Detrainment	77.2	Risk	Damage (cost)	96.1
	Prevention	19.7		Damage	88.4
	Release prevented	14.2		Building	60.8
Process	Velocity	38.1		People present	16.8
	Max pressure	37.7		Lethality (cost)	10.7
	Release height	13.2		Building cost	7.72
	Release	7.57		Lethality	5.16
Avalanche	Max new snow height	24.1		Building type	3.53
	Velocity 30y	5.46		People per building	3.33
	Velocity 300y	0.45	Remote sensing	Building (Lidar)	49.6
Ecosystem structure	Potential detrainment	5.73	Process	Max pressure	18.2
	Crown cover (class)	5.32		Flow velocity	18.1
	Land cover	4.98		Release height	0.50
	Crown cover	4.06	Avalanche	Max new snow height	12.4
	Potential prevention	2.49		Velocity 30y	2.79
	Gap width	1.3		Velocity 300y	0.23
	Roughness (class)	1.01	Function	Detrainment	10.3
Remote sensing	Crown cover (Lidar)	3.7		Prevention	0.17
	Roughness (measured)	2.49	Target	Provision	9.66
	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			

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.

4.2. 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., 2013). 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.

4.3. 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)

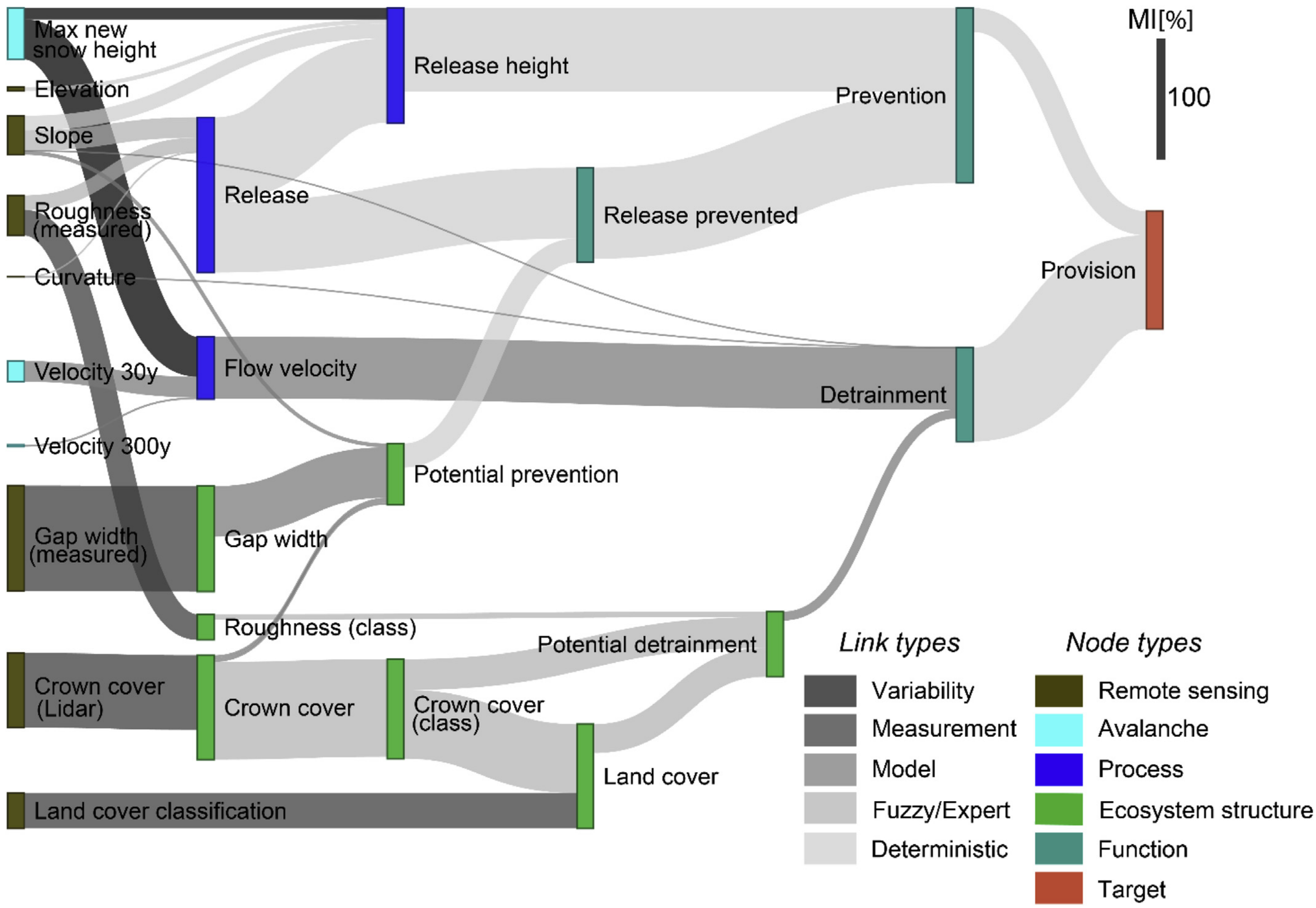

Fig. 4. Stepwise sensitivity analysis of the BN, where the width of a link between two nodes corresponds to the relative mutual information (MI %), i.e. the percentage of the entropy on a node that can be reduced by a finding on a preceding node. The nodes are labelled and coloured by the type of variable represented (see Fig. 2), while the link colours represent the types of uncertainty taken into account while quantifying the link in the BN. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

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. 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., 2013), 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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2018.09.005.

References

Aguilera, P.A., Fernández, A., Fernández, R., Rumí, R., Salmerón, A., 2011. Bayesian networks in environmental modelling. Environ. Model. Software 26, 1376–1388. https://doi.org/10.1016/j.envsoft.2011.06.004.

Albert, C., Aronson, J., Fürst, C., Opdam, P., 2014. Integrating ecosystem services in landscape planning: requirements, approaches, and impacts. Landsc. Ecol. 29, 1277–1285. https://doi.org/10.1007/s10980-014-0085-0.

Ames, D.P., Neilson, B.T., Stevens, D.K., Lall, U., 2005. Using Bayesian networks to model watershed management decisions : an East Canyon Creek case study. J. Hydroinf. 7, 267–282. https://doi.org/10.1073/pnas.0703993104.

Andrew, M.E., Wulder, M.A., Nelson, T.A., 2014. Potential contributions of remote sensing to ecosystem service assessments. Prog. Phys. Geogr. 38, 328–353. https://doi.org/10.1177/0309133314528942.

Andrew, M.E., Wulder, M.A., Nelson, T.A., Coops, N.C., 2015. Spatial data, analysis approaches, and information needs for spatial ecosystem service assessments: a review. GIScience Remote Sens. 52, 344–373. https://doi.org/10.1080/15481603.2015.1033809.

Arnot, C., Fisher, P.F., Wadsworth, R., Wellens, J., 2004. Landscape metrics with ecotones: pattern under uncertainty. Landsc. Ecol. 19, 181–195. https://doi.org/10.1023/B:LAND.0000021723.24247. ee.

Ascough, J.C., Maier, H.R., Ravalico, J.K., Strudley, M.W., 2008. Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. Ecol. Model. 219, 383–399. https://doi.org/10.1016/j.ecolmodel.2008.07.015.

Ayanu, Y.Z., Conrad, C., Nauss, T., Wegmann, M., Koellner, T., 2012. Quantifying and mapping ecosystem services supplies and demands: a review of remote sensing applications. Environ. Sci. Technol. 46, 8529–8541. https://doi.org/10.1021/es300157u.

Bacon, P.J., Cain, J.D., Howard, D.C., 2002. Belief network models of land manager decisions and land use change. J. Environ. Manag. 65, 1–23. https://doi.org/10.1006/jema.2001.0507.

Bagstad, K.J., Johnson, G.W., Voigt, B., Villa, F., 2013. Spatial dynamics of ecosystem service flows: a comprehensive approach to quantifying actual services. Ecosyst. Serv. 4, 117–125. https://doi.org/10.1016/j.ecoser.2012.07.012.

Barredo, J.I., Bastrup-Birk, A., Anne Teller, M.O., Manuel, B.F. de, Madariaga, I., Rodríguez-Loinaz, G., Pinho, P., Nunes, A., Ramos, A., Batista, M., Mimo, S., Cordovil, C., Branquinho, C., Grêt-Regamey, A., Bebi, P., Brunner, S.H., Weibel, B., Kopperoinen, L., Itkonen, P., Viinikka, A., Chirici, G., Bottalico, F., Pesola, L., Vizzarri, M., Garfì, V., Antonello, L., Barbati, A., Corona, P., Cullotta, S., Giannico, V., Lafortezza, R., Lombardi, F., Marchetti, M., Nocentini, S., Riccioli, F., Travaglini, D., Sallustio, L., Rosário, I., von, Essen, M., Nicholas, K.A., Máguas, C., Rebelo, R., Santos-Reis, M., Santos-Martín, F., Zorrilla-Miras, P., Montes, C., Benayas, J., Martín-López, B., Snäll, T., Berglund, H., Bengtsson, J., Moen, J., Busetto, L., San-Miguel-Ayanz, J., Thurner, M., Beer, C., Santoro, M., Carvalhais, N., Wutzler, T., Schepaschenko, D., Shvidenko, A., Kompter, E., Ahrens, B., Levick, S.R., Schmullius, C., 2008. Mapping and Assessment of Ecosystems and Their Services. Ecosystems & Environment, Agriculture. https://doi.org/10.2779/12398.

Barton, D.N., Kuikka, S., Varis, O., Uusitalo, L., Henriksen, H.J., Borsuk, M., La, Hera, A.D., Farmani, R., Johnson, S., Linnell, J.D.C., 2012. Bayesian networks in environmental and resource management. Integrated Environ. Assess. Manag. 8, 418–429. https://doi.org/10.1002/ieam.1327.

Bebi, P., Kienast, F., Schönenberger, W., 2001. Assessing structures in mountain forests as a basis for investigating the forests' dynamics and protective function. For. Ecol. Manage. 145, 3–14. https://doi.org/10.1016/S0378-1127(00)00570-3.

Bebi, P., Kulakowski, D., Rixen, C., 2009. Snow avalanche disturbances in forest ecosystems-State of research and implications for management. For. Ecol. Manage. 257, 1883–1892. https://doi.org/10.1016/j.foreco.2009.01.050.

Benjamin-Fink, N., Reilly, B.K., 2017. A road map for developing and applying object-oriented bayesian networks to "WICKED" problems. Ecol. Model. 360, 27–44. https://doi.org/10.1016/j.ecolmodel.2017.06.028.

Borsuk, M.E., Stow, C.A., Reckhow, K.H., 2004. A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecol. Model. 173, 219–239. https://doi.org/10.1016/j.ecolmodel.2003.08.020.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. https://doi.org/10.1023/A:1010933404324.

Bromley, J., 2005. Guidelines for the Use of Bayesian Networks as a Participatory Tool for Water Resource Management, Management of the Environment and Resources Using Integrated Techniques. Centre for Ecology and Hydrology, Wallingford.

Brunner, S.H., Huber, R., Grêt-Regamey, A., 2017. Mapping uncertainties in the future provision of ecosystem services in a mountain region in Switzerland. Reg. Environ. Change. https://doi.org/10.1007/s10113-017-1118-4.

Brunner, S.H., Huber, R., Grêt-Regamey, A., 2015. A backcasting approach for matching regional ecosystem services supply and demand. Environ. Model. Software 75. https://doi.org/10.1016/j.envsoft.2015.10.018.

Bühler, Y., Hueni, A., Christen, M., Meister, R., Kellenberger, T., Buehler, Y., Hueni, A., Christen, M., Meister, R., Kellenberger, T., 2009. Automated detection and mapping of avalanche deposits using airborne optical remote sensing data RID B-9859-2011. Cold Reg. Sci. Technol. 57, 99–106. https://doi.org/10.1016/j.coldregions.2009.02.007.

Bühler, Y., Kumar, S., Veitinger, J., Christen, M., Stoffel, A., Snehmani, 2013. Automated identification of potential snow avalanche release areas based on digital elevation models. Nat. Hazards Earth Syst. Sci. 13, 1321–1335. https://doi.org/10.5194/nhess-13-1321-2013.

Bundesamt für Umwelt (BAFU), 2015. EconoMe 4.0: Wirksamkeit und Wirtschaftlichkeit von Schutzmassnahmen gegen Naturgefahren.

Cain, J., 2001. Planning Improvements in Natural Resources Management: Guidelines for Using Bayesian Networks to Support the Planning and Management of Development Programmes in the Water Sector and beyond. Centre for Ecology and Hydrology, Wallingford.

Carpenter, S.R., Mooney, H.A., Agard, J., Capistrano, D., Defries, R.S., Díaz, S., Dietz, T., Duraiappah, A.K., Oteng-Yeboah, A., Pereira, H.M., Perrings, C., Reid, W.V., Sarukhan, J., Scholes, R.J., Whyte, A., 2009. Science for managing ecosystem services: beyond the millennium ecosystem assessment. Proc. Natl. Acad. Sci. U.S.A. 106, 1305–1312. https://doi.org/10.1073/pnas.0808772106.

Celio, E., Koellner, T., Grêt-Regamey, A., 2014. Modeling land use decisions with Bayesian networks: spatially explicit analysis of driving forces on land use change. Environ. Model. Software 52, 222–233. https://doi.org/10.1016/j.envsoft.2013.10.014.

Cha, Y.K., Stow, C.A., 2014. A Bayesian network incorporating observation error to predict phosphorus and chlorophyll a in Saginaw Bay. Environ. Model. Software 57, 90–100. https://doi.org/10.1016/j.envsoft.2014.02.010.

Christen, M., Kowalski, J., Bartelt, P., 2010. RAMMS: numerical simulation of dense snow avalanches in three-dimensional terrain. Cold Reg. Sci. Technol. 63, 1–14. https://doi.org/10.1016/j.coldregions.2010.04.005.

Convention on Biological Diversity, 2010. The Strategic Plan for Biodiversity 2011-2020 and the Aichi Biodiversity Targets. https://doi.org/10.1111/cobi.12383.

Cord, A.F., Brauman, K.A., Chaplin-Kramer, R., Huth, A., Ziv, G., Seppelt, R., 2017. Priorities to advance monitoring of ecosystem services using Earth observation. Trends Ecol. Evol. 32, 416–428. https://doi.org/10.1016/j.tree.2017.03.003.

Costanza, R., D'Agre, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R., Paruelo, J., Raskin, R., Sutton, P., van den Belt, M., 1997. The value of the world's ecosystem services and natural capital. Nature 387, 253–260. https://doi.org/10.1007/s13398-014-0173-7.2.

Cripps, E., O Hagan, A., Quaife, T., Anderson, C., 2009. Modelling Uncertainty in Satellite-derived Land Cover maps., Research Report No. 573/08. Department of Probability and Statistics, University of Sheffield.

Daily, G.C., Polasky, S., Goldstein, J., Kareiva, P.M., Mooney, H.A., Pejchar, L., Ricketts, T.H., Salzman, J., Shallenberger, R., 2009. Ecosystem services in decision making: time to deliver. Front. Ecol. Environ. 7, 21–28. https://doi.org/10.1890/080025.

de Groot, R.S., Alkemade, R., Braat, L., Hein, L., Willemen, L., 2010. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. Ecol. Complex. 7, 260–272. https://doi.org/10.1016/j.ecocom.2009.10.006.

Dempster, A.P., Laird, N.M., Rubin, D.B., 1977. Maximum likelihood from incomplete data via the EM algorithm. J. R. Stat. Soc. Ser. B Methodol. 39, 1–38. https://doi.org/10.2307/2984875.

Eigenbrod, F., Armsworth, P.R., Anderson, B.J., Heinemeyer, A., Gillings, S., Roy, D.B., Thomas, C.D., Gaston, K.J., 2010. The impact of proxy-based methods on mapping the distribution of ecosystem services. J. Appl. Ecol. 47, 377–385. https://doi.org/10.1111/j.1365-2664.2010.01777.x.

European Commission, 2011. Our Life Insurance, Our Natural Capital: an EU Biodiversity Strategy to 2020. Brussels.

European Space Agency, 2016. Sentinel-2A.

Fassnacht, F.E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L.T., Straub, C., Ghosh, A., 2016. Review of studies on tree species classification from remotely sensed data. Remote Sens. Environ. 186, 64–87. https://doi.org/10.1017/CBO9781107415324.004.

Feistl, T., Bebi, P., Teich, M., Bühler, Y., Christen, M., Thuro, K., Bartelt, P., 2014. Observations and modeling of the braking effect of forests on small and medium avalanches. J. Glaciol. 60, 124–138. https://doi.org/10.3189/2014JoG13J055.

Feng, X., Fu, B., Yang, X., Lü, Y., 2010. Remote sensing of ecosystem services: an opportunity for spatially explicit assessment. Chin. Geogr. Sci. 20, 522–535. https://doi.org/10.1007/s11769-010-0428-y.

Garmendia, E., Gamboa, G., 2012. Weighting social preferences in participatory multi-criteria evaluations: a case study on sustainable natural resource management. Ecol. Econ. 84, 110–120. https://doi.org/10.1016/j.ecolecon.2012.09.004.

Gonzalez-Redin, J., Luque, S., Poggio, L., Smith, R., Gimona, A., 2016. Spatial Bayesian belief networks as a planning decision tool for mapping ecosystem services trade-offs

on forested landscapes. Environ. Res. 144, 15–26. https://doi.org/10.1016/j.envres.2015.11.009.
Grêt-Regamey, A., Brunner, S.H., Altwegg, J., Bebi, P., 2013. Facing uncertainty in ecosystem services-based resource management. J. Environ. Manag. 127, 145–154. https://doi.org/10.1016/j.jenvman.2012.07.028.
Grêt-Regamey, A., Rabe, S.-E., Crespo, R., Lautenbach, S., Ryffel, A., Schlup, B., 2014. On the importance of non-linear relationships between landscape patterns and the sustainable provision of ecosystem services. Landsc. Ecol. 29, 201–212. https://doi.org/10.1007/s10980-013-9957-y.
Grêt-Regamey, A., Straub, D., 2006. Spatially explicit avalanche risk assessment linking Bayesian networks to a GIS. Nat. Hazards Earth Syst. Sci. 6, 911–926. https://doi.org/10.5194/nhess-6-911-2006.
Haines-Young, R.H., Potschin, M.B., 2009. The links between biodiversity, ecosystem services and human well-being. In: Raffaelli, D., Frid, C. (Eds.), Ecosystems Ecology: a New Synthesis. BES Ecological Reviews Series. CUP, Cambridge, pp. 31. https://doi.org/10.1017/CBO9780511750458.
Hill, M.O., 1973. Diversity and evenness: a unifying notation and its consequences. Ecology 54, 427–432. https://doi.org/10.2307/1934352.
Hou, Y., Burkhard, B., Müller, F., 2013. Uncertainties in landscape analysis and ecosystem service assessment. J. Environ. Manag. 127, S117–S131. https://doi.org/10.1016/j.jenvman.2012.12.002.
Isenburg, M., 2016. LAStools - Efficient LiDAR Processing Software.
Johnson, D., 1997. The triangular distribution as a proxy for the beta distribution in risk analysis. Stat 46, 387–398. https://doi.org/10.1111/1467-9884.00091.
Johnson, G., Snapp, R., Villa, F., Bagstad, K., 2012. Modelling Ecosystem Services Flows under Uncertainty with Stochastic SPAN. Ger, Leipzig.
Kelly (Letcher), R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., van Delden, H., Voinov, A.A., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Software 47, 159–181. https://doi.org/10.1016/j.envsoft.2013.05.005.
Kienast, F., Bolliger, J., Potschin, M., de Groot, R.S., Verburg, P.H., Heller, I., Wascher, D., Haines-Young, R., 2009. Assessing landscape functions with broad-scale environmental data: insights gained from a prototype development for Europe. Environ. Manag. 44, 1099–1120. https://doi.org/10.1007/s00267-009-9384-7.
Kjaerulff, U., Madsen, A., 2013. Bayesian Networks and Influence Diagrams. Springer.
Koetse, M., Brouwer, R., van Beukering, P.J., 2015. Economic valuation methods for ecosystem services. In: Ecosystem Services: from Concept to Practice, pp. 108–130.
Kuhnert, P.M., Martin, T.G., Griffiths, S.P., 2010. A guide to eliciting and using expert knowledge in Bayesian ecological models. Ecol. Lett. 13, 900–914. https://doi.org/10.1111/j.1461-0248.2010.01477.x.
Kuikka, S., Hildén, M., Gislason, H., Hansson, S., Sparholt, H., Varis, O., 1999. Modeling environmentally driven uncertainties in Baltic cod (Gadus morhua) management by Bayesian influence diagrams. Can. J. Fish. Aquat. Sci. 56, 629–641. https://doi.org/10.1139/cjfas-56-4-629.
Kulakowski, D., Bebi, P., Rixen, C., 2011. The interacting effects of land use change, climate change and suppression of natural disturbances on landscape forest structure in the Swiss Alps. Oikos 120, 216–225. https://doi.org/10.1111/j.1600-0706.2010.18726.x.
Kunz, M., Grêt-Regamey, A., Hurni, L., 2011. Visualization of uncertainty in natural hazards assessments using an interactive cartographic information system. Nat. Hazards 59, 1735–1751. https://doi.org/10.1007/s11069-011-9864-y.
Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., Goethals, P.L.M., 2013. A review of Bayesian belief networks in ecosystem service modelling. Environ. Model. Software 46, 1–11. https://doi.org/10.1016/j.envsoft.2013.03.011.
Landuyt, D., Van der Biest, K., Broekx, S., Staes, J., Meire, P., Goethals, P.L.M., 2015. A GIS plug-in for Bayesian belief networks: towards a transparent software framework to assess and visualise uncertainties in ecosystem service mapping. Environ. Model. Software 71, 30–38. https://doi.org/10.1016/j.envsoft.2015.05.002.
Lauritzen, S.L., 1995. The EM algorithm for graphical association models with missing data. Comput. Stat. Data Anal. 19, 191–201. https://doi.org/10.1016/0167-9473(93)E0056-A.
Lauritzen, S.L., Spiegelhalter, D.J., 1988. Local computations with probabilities on graphical structures and their application to expert systems. J. R. Stat. Soc. Ser. B 50, 157–224.
Lautenbach, S., Volk, M., Strauch, M., Whittaker, G., Seppelt, R., 2013. Optimization-based trade-off analysis of biodiesel crop production for managing an agricultural catchment. Environ. Model. Software 48, 98–112. https://doi.org/10.1016/j.envsoft.2013.06.006.
Lavorel, S., Bayer, A., Bondeau, A., Lautenbach, S., Ruiz-Frau, A., Schulp, N., Seppelt, R., Verburg, P., Teeffelen, A., van Vannier, C., Arneth, A., Cramer, W., Marba, N., 2017. Pathways to bridge the biophysical realism gap in ecosystem services mapping approaches. Ecol. Indicat. 74, 241–260. https://doi.org/10.1016/j.ecolind.2016.11.015.
Lavorel, S., Grigulis, K., Lamarque, P., Colace, M.P., Garden, D., Girel, J., Pellet, G., Douzet, R., 2011. Using plant functional traits to understand the landscape distribution of multiple ecosystem services. J. Ecol. 99, 135–147. https://doi.org/10.1111/j.1365-2745.2010.01753.x.
MacEachren, A.M., Robinson, A., Hopper, S., Gardner, S., Murray, R., Gahegan, M., Hetzler, E., 2005. Visualizing geospatial information uncertainty: what we know and what we need to know. Cartogr. Geogr. Inf. Sci. 32, 139–160. https://doi.org/10.1559/1523040054738936.
Maes, J., Egoh, B., Willemen, L., Liquete, C., Vihervaara, P., Schägner, J.P., Grizzetti, B., Drakou, E.G., Notte, A. La Zulian, G., Bouraoui, F., Luisa Paracchini, M., Braat, L., Bidoglio, G., 2012. Mapping ecosystem services for policy support and decision making in the European Union. Ecosyst. Serv. 1, 31–39. https://doi.org/10.1016/j.ecoser.2012.06.004.
Maier, H.R., Ascough, J.C., Wattenbach, M., Renschler, C.S., Labiosa, W.B., 2008. Uncertainty in Environmental Decision Making: Issues, Challenges and Future Directions. Publ. from USDA-ARS/UNL Fac.
Marcot, B.G., 2012. Metrics for evaluating performance and uncertainty of Bayesian network models. Ecol. Model. 230, 50–62. https://doi.org/10.1016/j.ecolmodel.2012.01.013.
Merz, H.A., Schneider, T., Bohnenblust, H., 1995. Bewertung von technischen Risiken: Beiträge zur Strukturierung und zum Stand der Kenntnisse: Modelle zur Bewertung von Todesfallrisiken. ETH, Zürich.
Metcalf, S.J., Wallace, K.J., 2013. Ranking biodiversity risk factors using expert groups - treating linguistic uncertainty and documenting epistemic uncertainty. Biol. Conserv. 162, 1–8. https://doi.org/10.1016/j.biocon.2013.03.005.
Moeser, D., Roubinek, J., Schleppi, P., Morsdorf, F., Jonas, T., 2014. Canopy closure , LAI and radiation transfer from airborne LiDAR synthetic images. Agric. For. Meteorol. 197, 158–168. https://doi.org/10.1016/j.agrformet.2014.06.008.
Myllymäki, P., Silander, T., Tirri, H., Uronen, P., 2002. B-course: a web-based tool for Bayesian and causal data analysis. Int. J. Artif. Intell. Tools 11, 369–387. https://doi.org/10.1142/S0218213002000940.
Nelson, E., Mendoza, G., Regetz, J., Polasky, S., Tallis, H., Cameron, D.R., Chan, K.M.A., Daily, G.C., Goldstein, J., Kareiva, P.M., Lonsdorf, E., Naidoo, R., Ricketts, T.H., Shaw, M.R., 2009. Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. Front. Ecol. Environ. 7, 4–11. https://doi.org/10.1890/080023.
Neuendorf, F., von Haaren, C., Albert, C., 2018. Assessing and coping with uncertainties in landscape planning: an overview. Landsc. Ecol. 33, 1–18. https://doi.org/10.1007/s10980-018-0643-y.
Norsys, 2010. Netica API. Programmer's Library.
O'Hagan, A., 2012. Probabilistic uncertainty specification: overview, elaboration techniques and their application to a mechanistic model of carbon flux. Environ. Model. Software 36, 35–48. https://doi.org/10.1016/j.envsoft.2011.03.003.
O'Neill, S.J., Osborn, T.J., Hulme, M., Lorenzoni, I., Watkinson, A.R., 2008. Using expert knowledge to assess uncertainties in future polar bear populations under climate change. J. Appl. Ecol. 45, 1649–1659. https://doi.org/10.1111/j.1365-2664.2008.01552.x.
Petrou, Z.I., Kosmidou, V., Manakos, I., Stathaki, T., Adamo, M., Tarantino, C., Tomaselli, V., Blonda, P., Petrou, M., 2013. A rule-based classification methodology to handle uncertainty in habitat mapping employing evidential reasoning and fuzzy logic. Pattern Recogn. Lett. 48, 24–33. https://doi.org/10.1016/j.patrec.2013.11.002.
Petrou, Z.I., Manakos, I., Stathaki, T., 2015. Remote sensing for biodiversity monitoring: a review of methods for biodiversity indicator extraction and assessment of progress towards international targets. Biodivers. Conserv. 24, 2333–2363. https://doi.org/10.1007/s10531-015-0947-z.
Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., R Core Team, 2017. Nlme: Linear and Nonlinear Mixed Effects Models.
Planat, 2008. Risikomanagement in der Praxis - Beispiele zum Umgang mit Naturgefahren, Strategie Naturgefahren Schweiz.
Plummer, M.L., 2009. Assessing benefit transfer for the valuation of ecosystem services. Front. Ecol. Environ. 7, 38–45. https://doi.org/10.1890/080091.
Plummer, S.E., 2000. Perspectives on combining ecological process models and remotely sensed data. Ecol. Model. 129, 169–186. https://doi.org/10.1016/S0304-3800(00)00233-7.
Polasky, S., Carpenter, S.R., Folke, C., Keeler, B., 2011. Decision-making under great uncertainty: environmental management in an era of global change. Trends Ecol. Evol. 26, 398–404. https://doi.org/10.1016/j.tree.2011.04.007.
Qian, S.S., Miltner, R.J., 2015. A continuous variable Bayesian networks model for water quality modeling: a case study of setting nitrogen criterion for small rivers and streams in Ohio, USA. Environ. Model. Software 69, 14–22. https://doi.org/10.1016/j.envsoft.2015.03.001.
R Core Team, 2013. R: a Language and Environment for Statistical Computing.
Regan, H.M., Colyvan, M., Burgman, M.A., 2002. A taxonomy and treatment of uncertainty for ecology and conservation Biology. Ecol. Appl. 12, 618–628. doi:10.1890/1051-0761(2002)012[0618:ATATOU]2.0.CO;2.
Rocchini, D., Balkenhol, N., Carter, G.A., Foody, G.M., Gillespie, T.W., He, K.S., Kark, S., Levin, N., Lucas, K., Luoto, M., Nagendra, H., Oldeland, J., Ricotta, C., Southworth, J., Neteler, M., 2010. Remotely sensed spectral heterogeneity as a proxy of species diversity: recent advances and open challenges. Ecol. Inf. 5, 318–329. https://doi.org/10.1016/j.ecoinf.2010.06.001.
Ropero, R.F., Rumí, R., Aguilera, P.A., 2013. Modelling uncertainty in social-natural interactions. Environ. Model. Software 75, 362–372. https://doi.org/10.1016/j.envsoft.2014.07.008.
Salm, B., Burkhard, A., Gubler, H.U., 1990. Berechnung von Fließlawinen: eine Anleitung für Praktiker mit Beispielen. Mitteilungen des Eidgenössischen Institutes für Schnee und Lawinenforsch. SLF 47, 5.
Sappington, J.M., Longshore, K.M., Thompson, D.B., 2007. Quantifying landscape ruggedness for animal habitat analysis: a case study using bighorn sheep in the mojave desert. J. Wildl. Manag. 71, 1419–1426. https://doi.org/10.2193/2005-723.
Schägner, J.P., Brander, L., Maes, J., Hartje, V., 2013. Mapping ecosystem services' values: current practice and future prospects. Ecosyst. Serv. 4, 33–46. https://doi.org/10.1016/j.ecoser.2013.02.003.
Schirpke, U., Leitinger, G., Tasser, E., Schermer, M., Steinbacher, M., Tappeiner, U., 2013. Multiple ecosystem services of a changing Alpine landscape: past, present and future. Int. J. Biodivers. Sci. Ecosyst. Serv. Manag. 9, 123–135. https://doi.org/10.1080/21513732.2012.751936.
Schröter, M., Albert, C., Marques, A., Tobon, W., Lavorel, S., Maes, J., Brown, C., Klotz, S., Bonn, A., 2016. National ecosystem assessments in europe: a review. Bioscience 66,

813–828. https://doi.org/10.1093/biosci/biw101.
Schulp, C.J.E., Burkhard, B., Maes, J., Van Vliet, J., Verburg, P.H., 2014a. Uncertainties in ecosystem service maps: a comparison on the European scale. PLoS One 9. https://doi.org/10.1371/journal.pone.0109643.
Schulp, C.J.E., Thuiller, W., Verburg, P.H., 2014b. Wild food in Europe: a synthesis of knowledge and data of terrestrial wild food as an ecosystem service. Ecol. Econ. 105, 292–305. https://doi.org/10.1016/j.ecolecon.2014.06.018.
Schweizer, J., 2008. Snow avalanche formation and dynamics. Cold Reg. Sci. Technol. 54, 153–154. https://doi.org/10.1016/j.coldregions.2008.08.005.
Seppelt, R., Dormann, C.F., Eppink, F.V., Lautenbach, S., Schmidt, S., 2011. A quantitative review of ecosystem service studies: approaches, shortcomings and the road ahead. J. Appl. Ecol. 48, 630–636. https://doi.org/10.1111/j.1365-2664.2010.01952.x.
Shannon, C.E., 1948. A mathematical theory of communication. Bell Syst. Tech. J. 27, 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.
SLF, 2017. Davos Fluelastr, 1560 m. Gumbel-Statistik.
Speirs-Bridge, A., Fidler, F., McBride, M., Flander, L., Cumming, G., Burgman, M., 2010. Reducing overconfidence in the interval judgments of experts. Risk Anal. 30, 512–523. https://doi.org/10.1111/j.1539-6924.2009.01337.x.
Straub, D., Grêt-Regamey, A., 2006. A Bayesian probabilistic framework for avalanche modelling based on observations. Cold Reg. Sci. Technol. 46, 192–203. https://doi.org/10.1016/j.coldregions.2006.08.024.
Sun, Z., Müller, D., 2013. A framework for modeling payments for ecosystem services with agent-based models, Bayesian belief networks and opinion dynamics models. Environ. Model. Software 45, 15–28. https://doi.org/10.1016/j.envsoft.2012.06.007.
swisstopo, 2015. swissALTI3D© (5704000000).
swisstopo, 2013. swissimage© (5704000000).
Teich, M., Bebi, P., 2009. Evaluating the benefit of avalanche protection forest with GIS-based risk analyses—a case study in Switzerland. For. Ecol. Manage. 257, 1910–1919. https://doi.org/10.1016/j.foreco.2009.01.046.
Teich, M., Fischer, J.T., Feistl, T., Bebi, P., Christen, M., Grêt-Regamey, A., 2014. Computational snow avalanche simulation in forested terrain. Nat. Hazards Earth Syst. Sci. 14, 2233–2248. https://doi.org/10.5194/nhess-14-2233-2014.
Troy, A., Wilson, M.A., 2006. Mapping ecosystem services: practical challenges and opportunities in linking GIS and value transfer. Ecol. Econ. 60, 435–449. https://doi.org/10.1016/j.ecolecon.2006.04.007.
Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. Model. 203, 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033.
Uusitalo, L., Lehikoinen, A., Helle, I., Myrberg, K., 2015. An overview of methods to evaluate uncertainty of deterministic models in decision support. Environ. Model. Software 63, 24–31. https://doi.org/10.1016/j.envsoft.2014.09.017.
Veitinger, J., Stuart Purves, R., Sovilla, B., 2016. Potential slab avalanche release area identification from estimated winter terrain: a multi-scale, fuzzy logic approach. Nat. Hazards Earth Syst. Sci. 16, 2211–2225. https://doi.org/10.5194/nhess-16-2211-2016.
Villa, F., Bagstad, K.J., Voigt, B., Johnson, G.W., Portela, R., Honz, k.M., Batker, D., 2014. A methodology for adaptable and robust ecosystem services assessment. PLoS One 9. https://doi.org/10.1371/journal.pone.0091001.
Voinov, A., Kolagani, N., McCall, M.K., Glynn, P.D., Kragt, M.E., Ostermann, F.O., Pierce, S.A., Ramu, P., 2016. Modelling with stakeholders – next generation. Environ. Model. Software 77, 196–220. https://doi.org/10.1016/j.envsoft.2015.11.016.
Vorstius, A.C., Spray, C.J., 2015. A comparison of ecosystem services mapping tools for their potential to support planning and decision-making on a local scale. Ecosyst. Serv. 15, 75–83. https://doi.org/10.1016/j.ecoser.2015.07.007.
Wolff, S., Schulp, C.J.E., Verburg, P.H., 2015. Mapping ecosystem services demand: a review of current research and future perspectives. Ecol. Indicat. 55, 159–171. https://doi.org/10.1016/j.ecolind.2015.03.016.
Zadeh, L. a., 1965. Fuzzy sets. Inf. Control 8, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X.
Zimmerman, H.J., 1992. Fuzzy Set Theory - and its Applications. https://doi.org/10.1007/978-94-010-0646-0.