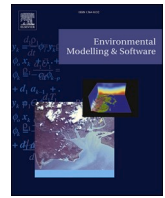




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## An online platform for spatial and iterative modelling with Bayesian Networks

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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.

### 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., 2013; 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 (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

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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., 2019). 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., 2019), 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., 2013; 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 it fails to take into account spatial interactions (Landuyt et al., 2015; Stritih et al., 2019) 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 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., 2013; 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.

## 2. Methods

### 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.  $X \rightarrow Y$ ). 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:  $P(Y = y) = \sum_x P(Y = y | X = x) * P(X = x)$ , in a process called marginalization (Kjaerulff and Madsen, 2013).

Fig. 1 shows an example of a BN, which predicts land-cover change in

**Table 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 <a href="https://www.norsys.com/WebHelp/NETICA/X_GeoNetica.htm">https://www.norsys.com/WebHelp/NETICA/X_GeoNetica.htm</a>	Mayfield et al. (2018)
PMAT (Probabilistic Map Algebra tool)	Yes	QGIS and Netica	Raster	No	No	No	Open <a href="https://github.com/DriesLanduyt/PMAT">https://github.com/DriesLanduyt/PMAT</a>	Landuyt et al. (2015)
Bnsatial R package	No	R	Raster	Potentially	No	Yes	Open <a href="http://github.com/darjomante/bnsatial">http://github.com/darjomante/bnsatial</a>	Masante (2019)
GeoBUGS	No	WinBUGS	Vector	Yes	Partially (spatial autocorrelation)	No	Open <a href="https://www.mrc-bsu.cam.ac.uk/software/bugs/the-bugs-project-winbugs/">https://www.mrc-bsu.cam.ac.uk/software/bugs/the-bugs-project-winbugs/</a>	Thomas et al. (2004)

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.

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.  $X \rightarrow Y \rightarrow Z$ ) according to the chain rule:  $P(X, Y, Z) = P(Z|Y) \cdot P(Y|X) \cdot P(X)$ , and from child nodes to parent nodes. For example, in the network in Fig. 1, knowledge about current land cover could be used to infer the past land cover.

### 2.2. Coupling BNs and spatial data with gBay

Here, we present gBay (**B**ayesian **N**etworks with **g**eo-data), an online tool to link a BN to spatial data and run a process over multiple time steps. Fig. 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).

The gBay platform consists of an online graphical user interface (Fig. 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”,

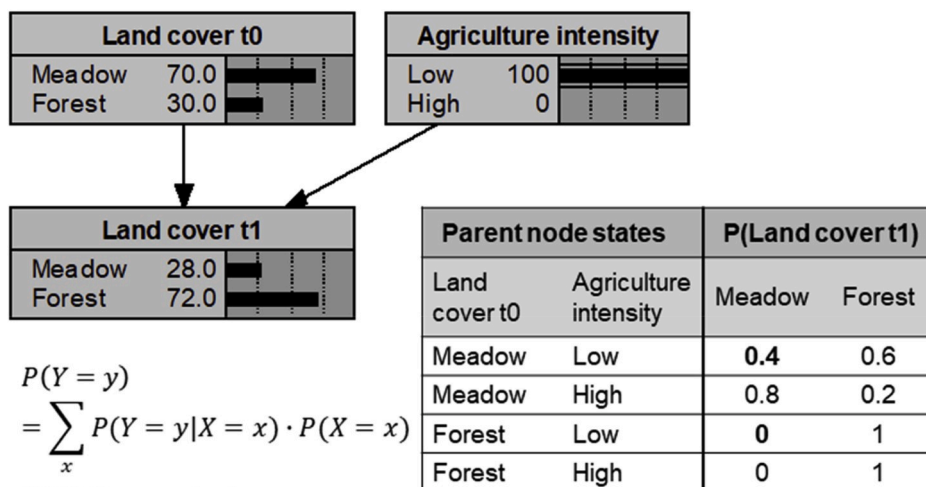


Fig. 1. Example of a simple Bayesian Network representing land cover change, where the future land cover (LC\_t1) is a child node of the current land cover (LC\_t0) and agriculture intensity (agr\_int), with the corresponding conditional probability table (CPT). In this network, hard evidence has been 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.

$$P(Y = y) = \sum_x P(Y = y|X = x) \cdot P(X = x)$$

$$P(LC_{t1} = meadow) = P(LC_{t1} = meadow | LC_{t0} = meadow, agr\_int = low) \cdot P(LC_{t0} = meadow) + P(LC_{t1} = meadow | LC_{t0} = forest, agr\_int = low) \cdot P(LC_{t0} = forest) = (0.4 \cdot 0.7) + (0 \cdot 0.3) = 0.28$$

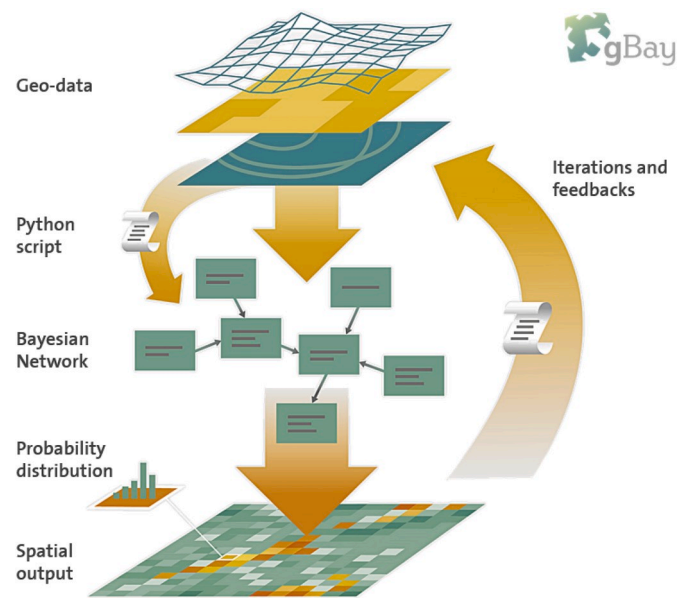
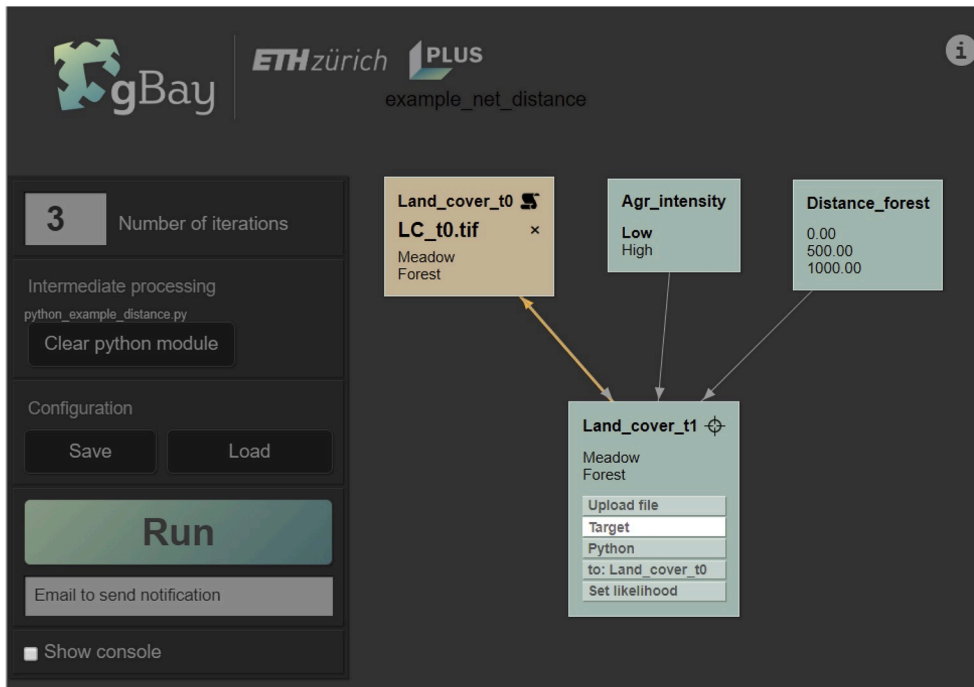


Fig. 2. Conceptual model of the gBay platform. Spatial inputs can be used as direct inputs to a BN, or processed using a Python script. The output of the BN is a spatial dataset with a probability distribution for each pixel or object. The output can be an input to the next time step in an iterative BN, to incorporate dynamics and feedbacks.

the 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 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.



**Fig. 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

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  $H = -\sum_{i=1}^N p_i \log_2 p_i$ ,  $H_{\max} = \log_2(N)$ , 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.

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.

### 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 (Kjaerulf 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<sub>t0</sub>). During one time step, land-cover change takes place, and through inference, we obtain the probability distribution of land cover after the first time step (LC<sub>t1</sub>, e.g. after 5 years). This LC<sub>t1</sub> 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<sub>t1</sub>) is selected as a “Link” node, an arrow appears that can be connected to the corresponding input node (LC<sub>t0</sub>). Multiple links can be used reflecting different variables that are connected over time.

### 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 Fig. 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 A). 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



**Table 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.

	Input format	Input values	Output
<b>Raster</b>	<b>.tif file per input node</b> (same resolution and extent)	<p><b>Hard evidence:</b> Single-band raster of the known value of a node (discrete or continuous)</p> <p><b>Soft evidence:</b> 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</p>	<p><b>target.tif:</b> 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</p> <p><b>target_stats.tif:</b> band 1: Evenness index For continuous nodes: band 2: mean band 3: median band 4: standard deviation</p>
<b>Vector</b>	one.shp file or geodatabase.gdb including one feature class (reads the attribute table)	<p><b>Hard evidence:</b> Attribute with the name of the input node, where the value corresponds to the known value of the node (discrete or continuous).</p> <p><b>Soft evidence:</b> 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</p>	<p>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</p>

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 A](#) 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.

## 2.5. Case studies

### 2.5.1. Avalanche protection in Davos: accounting for neighbourhood effects

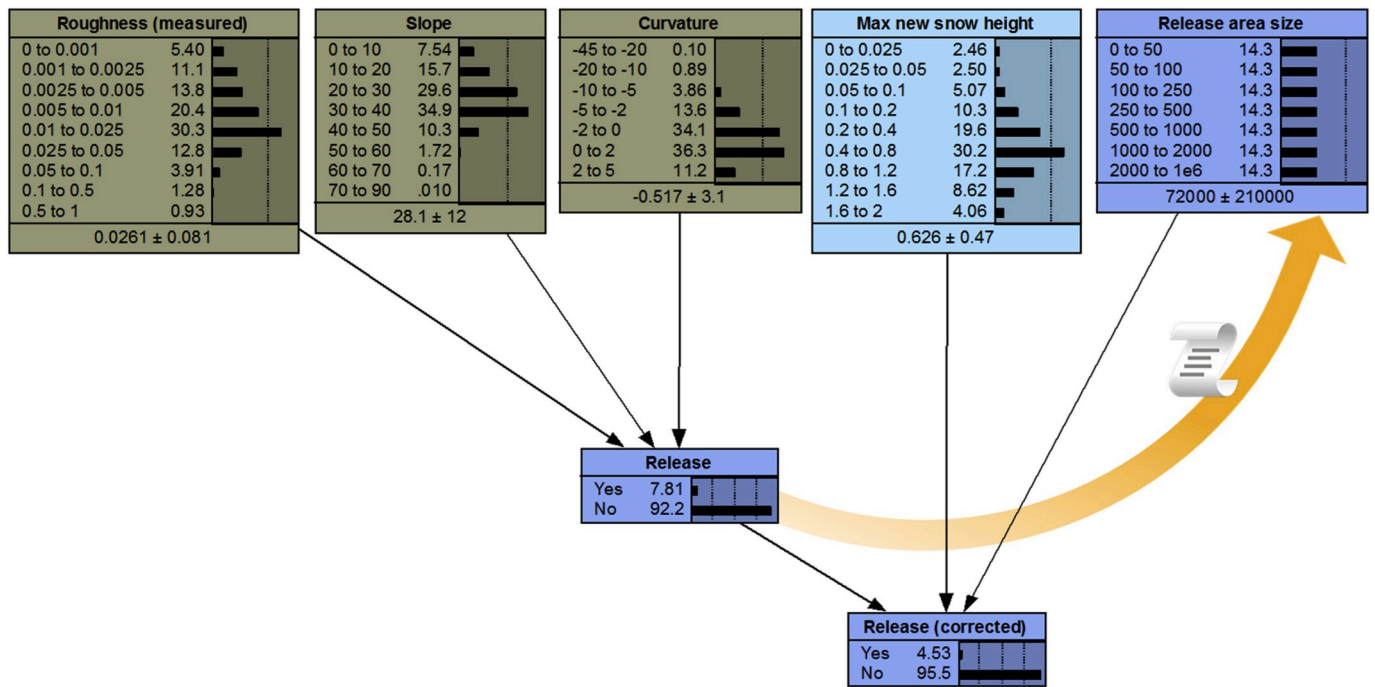
Protection from snow avalanches is one of the most important ecosystem services provided by forests in the Swiss Alps ([Grêt-Regamey et al., 2008](#)). An avalanche release is less likely inside a forest ([Bebi et al., 2009](#)), and forests also reduce the mass and velocity of avalanches that flow through 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., 2019](#)). 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°, but the release probability is highest between 35 and 45°. 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, 2017](#))) 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 [Fig. 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  $\alpha$  (between 0 and 1). For each threshold, all pixels with  $P(\text{release}) > \alpha$  were considered to be release pixels, and adjoining release pixels form a release area. A release area size was calculated for each  $\alpha$ , and based on the different sizes for different threshold probabilities, we could estimate a probability distribution of release area size (see [Appendix B](#) 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



**Fig. 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.

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.1. 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.

### 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 and 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 Fig. 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 C.

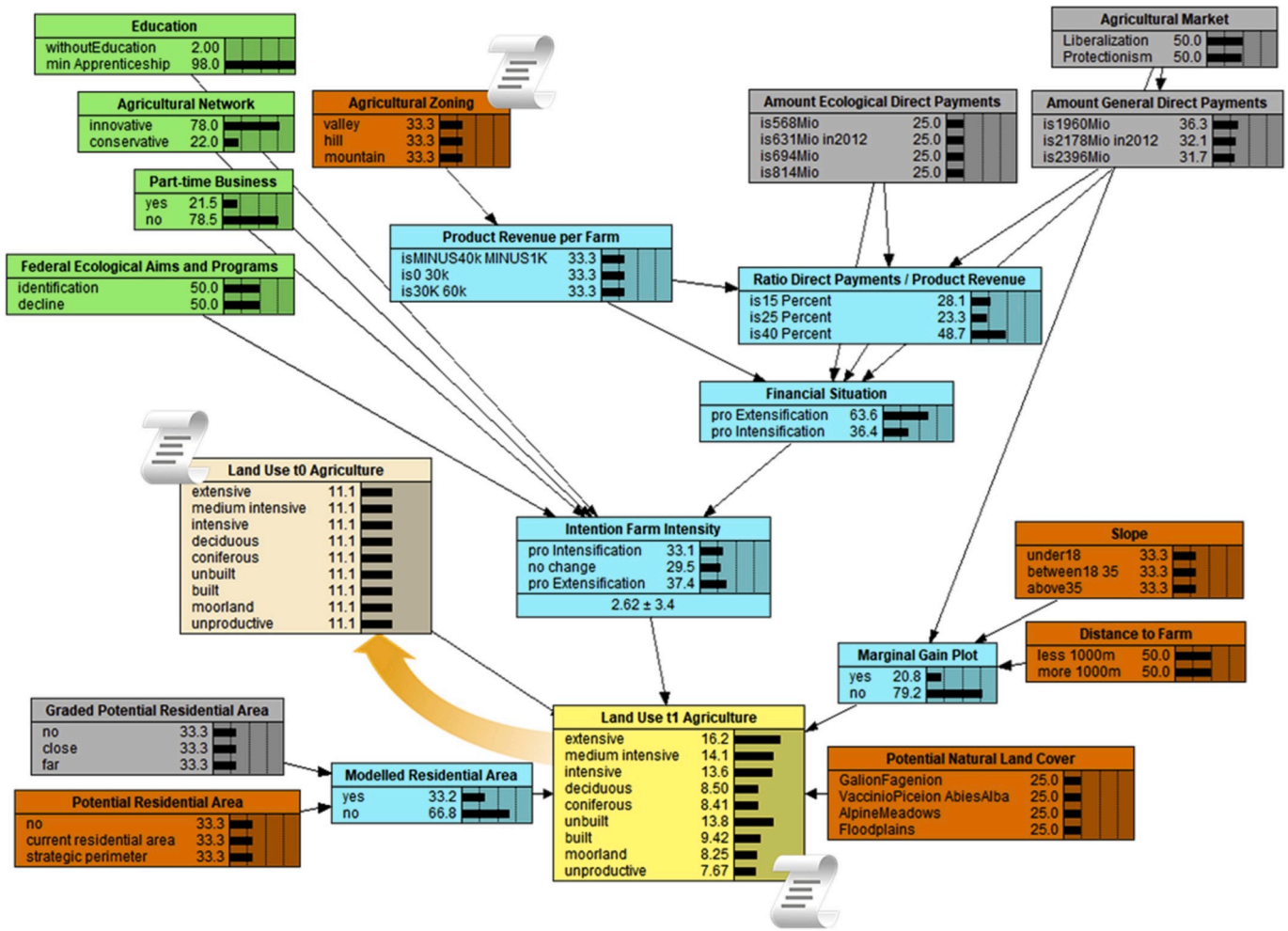


Fig. 5. BN for agricultural land-use decisions in the Entlebuch, where land-use change is driven by spatial factors (orange, mainly biophysical factors), agricultural policy (grey), farmer characteristics (green). The target node is depicted in yellow. Intermediate nodes are shown in blue, and nodes used in the Python script to implement boundary conditions are indicated with a script icon (Source of the BN: Celio and Grêt-Regamey, 2016). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

### 3. Case study results

#### 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 (Strith et al., 2019). 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. Fig. 6a and 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).

Fig. 6c and 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 (Fig. 6d), as smaller areas are less likely to reach a sufficient volume of snow for an

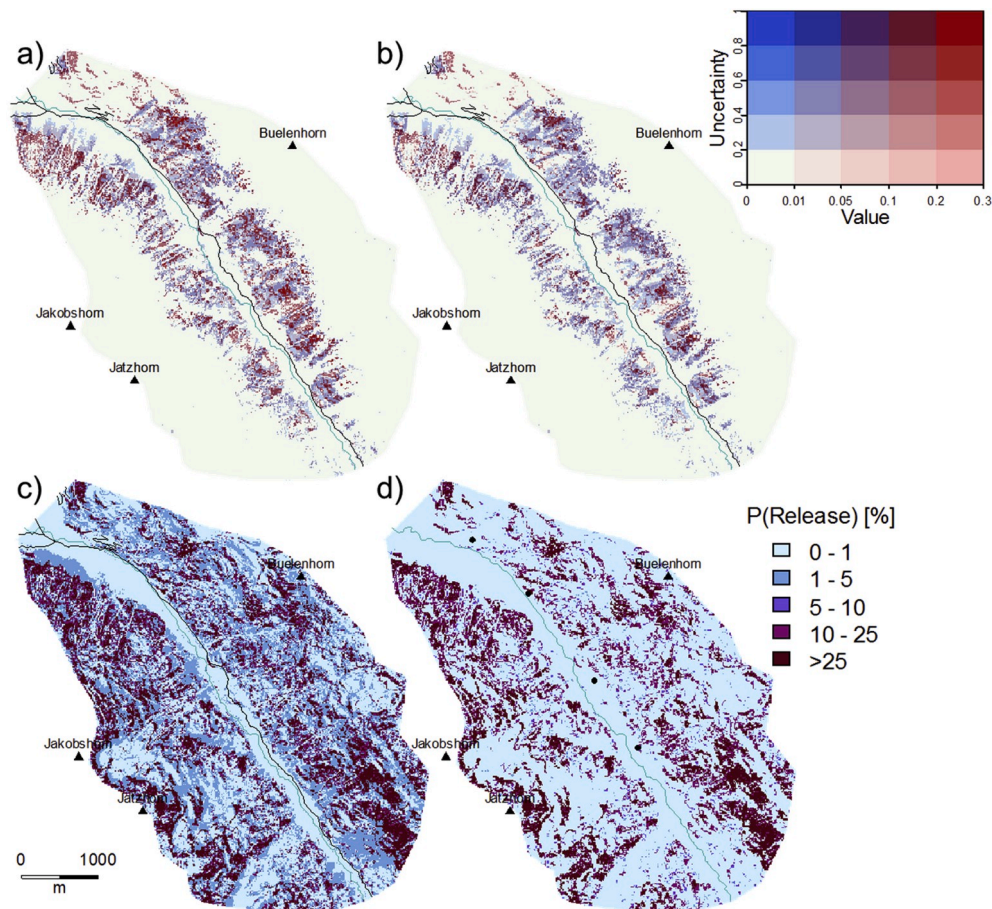
avalanche release. In addition, in areas that are originally assigned a low release probability, the probability is additionally reduced as they are unlikely to form part of a large release area. Thus, a clearer spatial pattern of potential release areas emerges, with the mean entropy (uncertainty) of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

#### 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 (Fig. 7). In both scenarios, the boundary conditions had an effect on the final 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





**Fig. 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).

more likely to maintain their intensive agriculture. However, the medium-intensive plots are converted to extensive use if the minimum limits are not implemented.

#### 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.

##### 4.1. Integrating information across scales

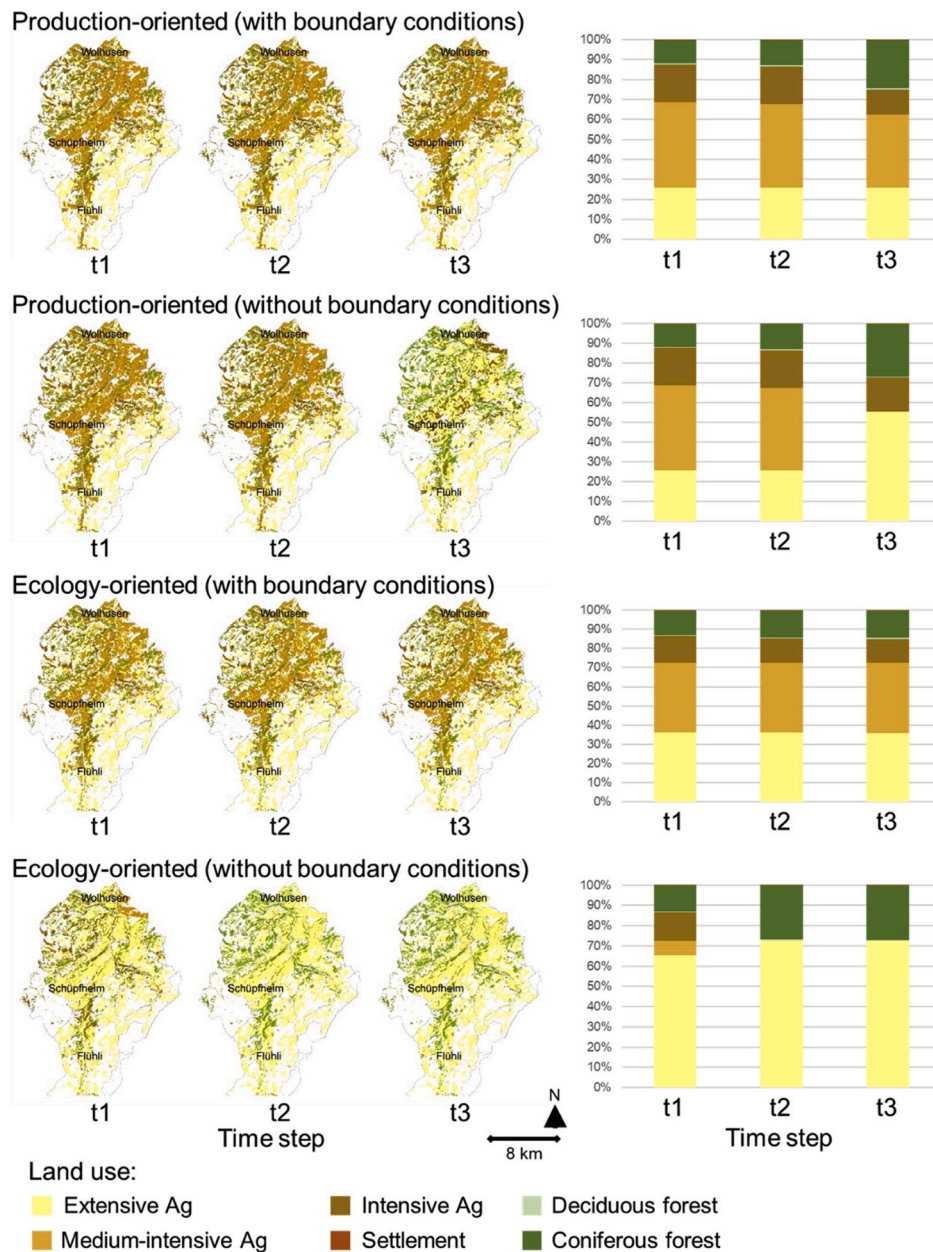
Data on socio-ecological systems is becoming increasingly available through sources such as Earth Observation and social media, and information is also available in the form of local actors' or expert knowledge. BNs are well suited to integrating these different types of information, as is illustrated in the avalanche protection case study, where remote sensing inputs were combined with process-based, empirical models and expert knowledge (Strith et al., 2019).

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 organizational 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., 2013; 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





**Fig. 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.

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.

#### 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 (Strith et al., 2019;

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 Fig. 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 (Fig. 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.

#### 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., 2013). 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.

#### 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., 2014). 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.

### 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](https://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, backend 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](https://wiki.gbay.ethz.ch).

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Acknowledgements

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## APPENDIX A

### 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 processed (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:
  - o name: <str>name of the node
  - o type: <int> type of the node (PY\_DISCRETE/PY\_CONTINUOUS (PY\_DISCRETE if omitted)
  - o 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 from 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.

### Example

Besides the factors affecting future land cover described in Fig. 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 an 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: ")

```

. (continued).

## APPENDIX B

### 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).





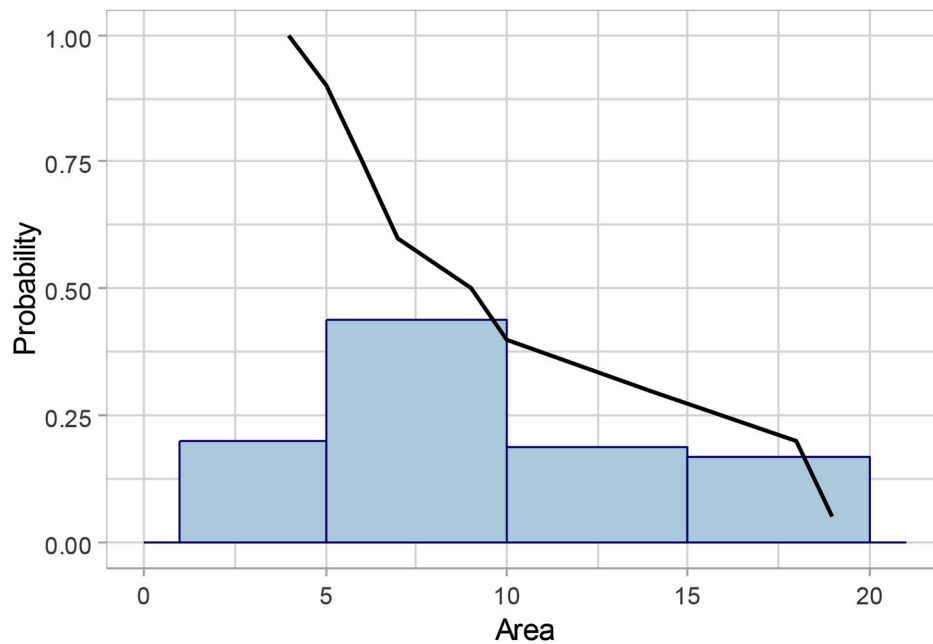


Fig. B.3. Resulting cumulative probability distribution of area (black line) and the probability distribution of area in classes (1–5, 5–10, 10–15, 15–20 pixels).

**Table B.1**  
Area calculation for different  $\alpha$ -values.

Threshold probability ( $\alpha$ )	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

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).

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

## APPENDIX C

### 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 C.1.

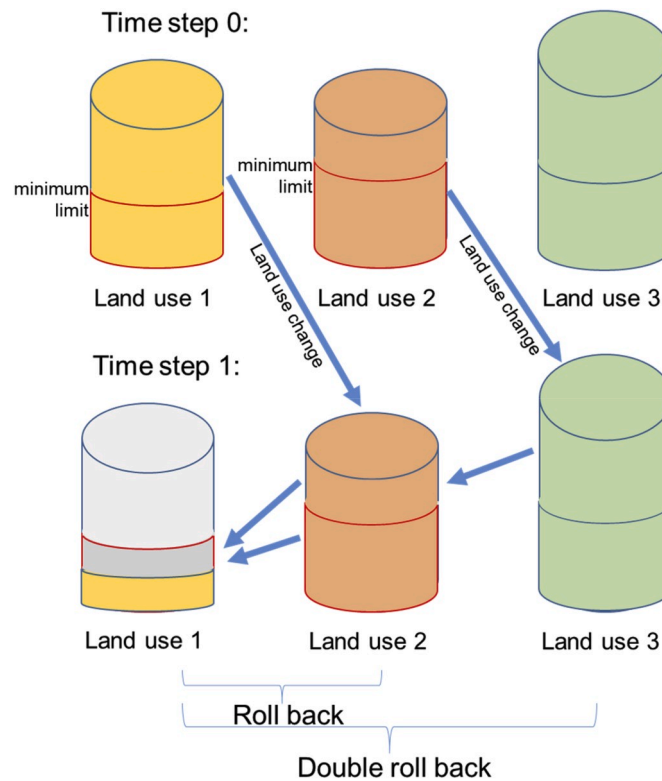


Fig. C.1. Representation of the roll-back mechanism to ensure that the minimum frequencies of Land use 1 and 2 are maintained. During the first iteration of the land-use change BN, LU1 is converted to LU2 and LU2 changes to LU3. However, if the frequency of LU1 and LU2 drops below the minimum limit,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

The conversion matrix (Table C.1) 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 C.1

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

<u>ITERATION 2</u>						
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					
Region: Mountain		extensive	med-intensive	intensive	other	SUM
target land-use category	extensive				9	9
	med-intensive					0
	intensive					0
	other					
<u>ITERATION 3</u>						
Region: Hill		extensive	med-intensive	intensive	other	SUM
target land-use category	extensive				54	54
	med-intensive			112	1400	1512
	intensive				(112)	0
	other					
Region: Mountain		extensive	med-intensive	intensive	other	SUM
target land-use category	extensive					0
	med-intensive	69544		5558		75102
	intensive					0
	other					

## References

- Arnot, C., Fisher, P.F., Wadsworth, R., Wellens, J., 2004. Landscape metrics with ecotones: pattern under uncertainty. *Landscape Ecol.* 19, 181–195. <https://doi.org/10.1023/B:LAND.0000021723.24247.ee>.
- 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., 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>.
- 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>.
- 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>.
- BayesFusion, 2017. *GeNie Modeler*.
- 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>.
- 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>.
- 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.
- 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>.
- Bühler, Y., Von Rickenbach, D., Stoffel, A., Margreth, S., Stoffel, L., Christen, M., 2018. Automated snow avalanche release area delineation - validation of existing algorithms and proposition of a new object-based approach for large-scale hazard indication mapping. *Nat. Hazards Earth Syst. Sci.* 18, 3235–3251. <https://doi.org/10.5194/nhess-18-3235-2018>.
- Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A., Mace, G.M., Tilman, D., Wardle, D.A., Kinzig, A.P., Daily, G.C., Loreau, M., Grace, J.B., Larigauderie, A., Srivastava, D.S., Naeem, S., 2012. Biodiversity loss and its impact on humanity. *Nature* 486, 59–67. <https://doi.org/10.1038/nature11148>.
- Carpenter, S.R., Mooney, H.A., Agard, J., Capistrano, D., Defries, R.S., Díaz, S., Dietz, T., Duraipapp, 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>.
- Carpenter, S.R., Booth, E.G., Gillon, S., Kucharik, C.J., Loheide, S., Mase, A.S., Motew, M., Qiu, J., Rissman, A.R., Seifert, J., Soyly, E., Turner, M., Wardropper, C. B., 2015. Plausible futures of a social-ecological system: Yahara watershed, Wisconsin, USA. *Ecol. Soc.* 20 <https://doi.org/10.5751/ES-07433-200210>.
- Celio, E., Grêt-Regamey, A., 2016. Understanding farmers' influence on land-use change using a participatory Bayesian network approach in a pre-Alpine region in Switzerland. *J. Environ. Plann. Manag.* 59, 2079–2101. <https://doi.org/10.1080/09640568.2015.1120713>.
- Celio, E., Brunner, S.H., Grêt-Regamey, A., 2012. Participatory land use modeling with Bayesian networks: a focus on subjective validation. *Int. Environ. Model. Softw. Soc. (iEMSS)*. In: 2012 Int. Congr. Environ. Model. Software. Manag. Resour. a Ltd. Planet. Sixth Bienn. Meet.
- 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>.
- Chee, Y.E., Wilkinson, L., Nicholson, A.E., Quintana-Ascencio, P.F., Fauth, J.E., Hall, D., Ponzio, K.J., Rumpff, L., 2016. Modelling spatial and temporal changes with GIS and spatial and dynamic Bayesian networks. *Environ. Model. Software* 82, 108–120. <https://doi.org/10.1016/j.envsoft.2016.04.012>.
- Das, B., 2004. Generating Conditional Probabilities for Bayesian Networks: Easing the Knowledge Acquisition Problem. *CoRR* 1–24. DSTO-TR-0918. <https://arxiv.org/abs/cs/0411034>.
- Dlamini, W.M., 2010. A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. *Environ. Model. Software* 25, 199–208. <https://doi.org/10.1016/j.envsoft.2009.08.002>.
- Federal Office for the Environment, 2013. *Nutzungsintensität der landwirtschaftlichen Fläche. Basisdaten aus dem Biodiversitäts-Monitoring Schweiz BDM*. Stand 2013.
- 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/10.3189/2014JG13J055>.
- Foley, J.A., Defries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E. a, Kucharik, C.J., Monfreda, C., Patz, J. a, Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. *Science* 309, 570–574. <https://doi.org/10.1126/science.1111772>.
- Fonte, C.C., Lodwick, W.A., 2004. Areas of fuzzy geographical entities. *Int. J. Geogr. Inf. Sci.* 18, 127–150. <https://doi.org/10.1080/13658810310001620933>.
- 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., 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>.
- Grêt-Regamey, A., Bebi, P., Bishop, I.D., Schmid, W.A., 2008. Linking GIS-based models to value ecosystem services in an Alpine region. *J. Environ. Manag.* 89, 197–208. <https://doi.org/10.1016/j.jenvman.2007.05.019>.
- 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. *Landscape Ecol.* 29, 201–212. <https://doi.org/10.1007/s10980-013-9957-y>.
- Hamilton, S.H., ElSawah, S., Guillaume, J.H.A., Jakeman, A.J., Pierce, S.A., 2015a. Integrated assessment and modelling: Overview and synthesis of salient dimensions. *Environ. Model. Software* 64, 215–229. <https://doi.org/10.1016/j.envsoft.2014.12.005>.
- Hamilton, S.H., Pollino, C.A., Jakeman, A.J., 2015b. Habitat suitability modelling of rare species using Bayesian networks: model evaluation under limited data. *Ecol. Model.* 299, 64–78. <https://doi.org/10.1016/j.ecolmodel.2014.12.004>.
- Henriksen, H.J., Zorrilla-Miras, P., La Hera, A.D., Brugnach, M., 2012. Use of Bayesian belief networks for dealing with ambiguity in integrated groundwater management. *Integrated Environ. Assess. Manag.* 8, 430–444. <https://doi.org/10.1002/ieam.195>.
- Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and evaluation of environmental models. *Environ. Model. Software* 21, 602–614. <https://doi.org/10.1016/j.envsoft.2006.01.004>.
- Jensen, F.V., 2001. *Bayesian Networks and Decision Graphs*. Springer.
- Johnson, G.W., Snapp, R., Villa, F., Bagstad, K., 2012. Modelling ecosystem services flows under uncertainty with stochastic SPAN. In: *International Environmental Modelling & Software Society (iEMSS) 2012 International Congress on Environmental Modelling and Software Managing Resources of a Limited Planet, Sixth Biennial Meeting, Leipzig, Germany*.
- Kelly (Letcher), R.A., Jakeman, A.J., Barretero, 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>.
- Kjaerulf, U., Madsen, A., 2013. *Bayesian Networks and Influence Diagrams*. Springer.
- Kleemann, J., Celio, E., Nyarko, B.K., Jimenez-Martinez, M., Fürst, C., 2017. Assessing the risk of seasonal food insecurity with an expert-based Bayesian Belief Network approach in northern Ghana, West Africa. *Ecol. Complex.* 32, 53–73. <https://doi.org/10.1016/j.ecocom.2017.09.002>.
- 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>.
- 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., Broeckx, 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., Broeckx, 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>.
- Lauf, S., Haase, D., Hostert, P., Lakes, T., Kleinschmit, B., 2012. Uncovering land-use dynamics driven by human decision-making - a combined model approach using cellular automata and system dynamics. *Environ. Model. Software* 27 (28), 71–82. <https://doi.org/10.1016/j.envsoft.2011.09.005>.
- MacEachren, A.M., Robinson, A., Hopper, S., Gardner, S., Murray, R., Gahegan, M., Hertzler, 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>.
- 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.
- Maier, H.R., Guillaume, J.H.A., van Delden, H., Riddell, G.A., Haasnoot, M., Kwakkel, J. H., 2016. An uncertain future, deep uncertainty, scenarios, robustness and adaptation: how do they fit together? *Environ. Model. Software* 81, 154–164. <https://doi.org/10.1016/j.envsoft.2016.03.014>.
- 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>.
- Marcot, B.G., Penman, T.D., 2019. Environmental modelling & software advances in Bayesian network modelling: integration of modelling technologies. *Environ. Model. Software* 111, 386–393. <https://doi.org/10.1016/j.envsoft.2018.09.016>.
- Masante, D., 2019. *Package "Bnsptial": Spatial Implementation of Bayesian Networks and Mapping*.
- Mayfield, H.J., Smith, C.S., Lowry, J.H., Watson, C.H., Baker, M.G., Kama, M., Nilles, E. J., Lau, C.L., 2018. Predictive risk mapping of an environmentally-driven infectious



- disease using spatial Bayesian networks: a case study of leptospirosis in Fiji. *PLoS Neglected Trop. Dis.* 12, e0006857 <https://doi.org/10.1371/journal.pntd.0006857>.
- McDonald, K.S., Tighe, M., Ryder, D.S., 2016. An ecological risk assessment for managing and predicting trophic shifts in estuarine ecosystems using a Bayesian network. *Environ. Model. Software* 85, 202–216. <https://doi.org/10.1016/j.envsoft.2016.08.014>.
- 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>.
- Norsys, 2010. *Netica API. Programmer's Library*.
- Pearl, J., 1988. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Morgan Kaufmann Publishers.
- Pérez-Miñana, E., 2016. Improving ecosystem services modelling: insights from a Bayesian network tools review. *Environ. Model. Software* 85, 184–201. <https://doi.org/10.1016/j.envsoft.2016.07.007>.
- Peters, D.P.C., Bestelmeyer, B.T., Turner, M.G., 2007. Cross-scale interactions and changing pattern-process relationships: consequences for system dynamics. *Ecosystems* 10, 790–796.
- 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>.
- Pollino, C.A., Woodberry, O., Nicholson, A., Korb, K., Hart, B.T., 2007. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. *Environ. Model. Software* 22, 1140–1152. <https://doi.org/10.1016/j.envsoft.2006.03.006>.
- Raudsepp-Hearne, C., Peterson, G.D., Bennett, E.M., 2010. Ecosystem service bundles for analyzing tradeoffs in diverse landscapes. *Proc. Natl. Acad. Sci.* 107, 5242–5247. <https://doi.org/10.1073/pnas.0907284107>.
- 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. [https://doi.org/10.1890/1051-0761\(2002\)012\[0618:ATATOU\]2.0.CO;2](https://doi.org/10.1890/1051-0761(2002)012[0618:ATATOU]2.0.CO;2).
- 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>.
- Rounsevell, M.D.A., Metzger, M.J., 2010. Developing qualitative scenario storylines for environmental change assessment. *Wiley Interdiscip. Rev. Clim. Chang.* 1, 606–619. <https://doi.org/10.1002/wcc.63>.
- Ruckelshaus, M., McKenzie, E., Tallis, H., Guerry, A., Daily, G., Kareiva, P., Polasky, S., Ricketts, T., Bhagabati, N., Wood, S.A., Bernhardt, J., 2013. Notes from the field: lessons learned from using ecosystem service approaches to inform real-world decisions. *Ecol. Econ.* 115, 11–21. <https://doi.org/10.1016/j.ecolecon.2013.07.009>.
- Salliou, N., Barnaud, C., Vialatte, A., Monteil, C., 2017. A participatory Bayesian Belief Network approach to explore ambiguity among stakeholders about socio-ecological systems. *Environ. Model. Software* 96, 199–209. <https://doi.org/10.1016/j.envsoft.2017.06.050>.
- Schreinemachers, P., Berger, T., 2011. An agent-based simulation model of human-environment interactions in agricultural systems. *Environ. Model. Software* 26, 845–859. <https://doi.org/10.1016/j.envsoft.2011.02.004>.
- Schulp, C.J.E., Burkhard, B., Maes, J., Van Vliet, J., Verburg, P.H., 2014. Uncertainties in ecosystem service maps: a comparison on the European scale. *PLoS One* 9. <https://doi.org/10.1371/journal.pone.0109643>.
- SLF, 2017. *Weissfluhjoch, 2540 m. Gumbel-Statistik*.
- SLF, 2018. *Avalanche sizes [WWW Document]*. URL. <https://www.slf.ch/en/avalanche-bulletin-and-snow-situation/about-the-avalanche-bulletin/avalanche-sizes.html>. accessed 4.5.19.
- 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>.
- Stelzenmüller, V., Lee, J., Garnacho, E., Rogers, S.I., 2010. Assessment of a Bayesian Belief Network-GIS framework as a practical tool to support marine planning. *Mar. Pollut. Bull.* 60, 1743–1754. <https://doi.org/10.1016/j.marpolbul.2010.06.024>.
- Stritih, A., Bebi, P., Grêt-Regamey, A., 2019. Quantifying uncertainties in earth observation-based ecosystem service assessments. *Environ. Model. Software* 111, 300–310. <https://doi.org/10.1016/j.envsoft.2018.09.005>.
- 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>.
- Syrbe, R.U., Walz, U., 2012. Spatial indicators for the assessment of ecosystem services: providing, benefiting and connecting areas and landscape metrics. *Ecol. Indic.* 21, 80–88. <https://doi.org/10.1016/j.ecolind.2012.02.013>.
- 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>.
- Thomas, A., Best, N., Lunn, D., Arnold, R., Spiegelhalter, D., 2004. *GeoBUGS User Manual*.
- Tomlin, C.D., 1994. Map algebra: one perspective. *Landscape Urban Plann.* 30, 3–12. [https://doi.org/10.1016/0169-2046\(94\)90063-9](https://doi.org/10.1016/0169-2046(94)90063-9).
- 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>.
- 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>.
- Verburg, P.H., Schot, P.P., Dijst, M.J., Veldkamp, A., 2004. *Land use change modelling: current practice and research*. *Geojournal* 61, 309–324.
- Verkerk, P.J., Lindner, M., Pérez-Soba, M., Paterson, J.S., Helming, J., Verburg, P.H., Kuemmerle, T., Lotze-Campen, H., Moiseyev, A., Müller, D., Popp, A., Schulp, C.J.E., Stürck, J., Tabeau, A., Wolfslehner, B., van der Zanden, E.H., 2018. Identifying pathways to visions of future land use in Europe. *Reg. Environ. Change* 18, 817–830. <https://doi.org/10.1007/s10113-016-1055-7>.
- Villa, F., Bagstad, K.J., Voigt, B., Johnson, G.W., Portela, R., Honzak, 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., Bousquet, F., 2010. Modelling with stakeholders. *Environ. Model. Software* 25, 1268–1281. <https://doi.org/10.1016/j.envsoft.2010.03.007>.
- 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>.
- Wu, J., 2013. Landscape sustainability science: ecosystem services and human well-being in changing landscapes. *Landscape Ecol.* 28, 999–1023. <https://doi.org/10.1007/s10980-013-9894-9>.