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A GIS plug-in for Bayesian belief networks: Towards a transparent software framework to assess and visualize uncertainties in ecosystem service mapping

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Abstract

The complexity and spatial heterogeneity of ecosystem processes driving ecosystem service delivery require spatially explicit models that take into account the different parameters affecting those processes. Current attempts to model ecosystem service delivery on a broad, regional scale often depend on indicator-based approaches that are generally not able to fully capture the complexity of ecosystem processes. Moreover, they do not allow quantification of uncertainty on their predictions. In this paper, we discuss a QGIS plug-in which promotes the use of Bayesian belief networks for regional modelling and mapping of ecosystem service delivery and associated uncertainties. Different types of specific Bayesian belief network output maps, delivered by the plug-in, are discussed and their decision support capacities are evaluated. This plug-in, used in combination with firmly developed Bayesian belief networks, has the potential to add value to current spatial ecosystem service accounting methods. The plug-in can also be used in other research domains dealing with spatial data and uncertainty.

Keywords

BBN, ES, spatial modelling, decision support, uncertainty maps, uncertainty analysis

Software availability

Name	Probabilistic Map Algebra Tool (PMAT)
Developer	Dries Landuyt
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Program language	Python
Software requirement	Quantum GIS 2.x (www.qgis.org)
	Netica (www.norsys.com/netica)
Source code	Available upon request

1. Introduction

The ecosystem services (ES) concept embraces all products and services delivered by natural and semi-natural ecosystems. The importance and value of these ES, publicly stressed by the Millennium Ecosystem Assessment (MEA, 2005), has been demonstrated in many studies (e.g. Costanza et al., 1997) and has resulted in emerging scientific and political attention to assess the delivery of these services, mainly through modelling (Seppelt et al., 2011) and mapping (Nemec and Raudsepp-Hearne, 2013). Absence of primary data on ES delivery currently impedes the use of complex spatial models for those assessments. Instead, proxy-based methods (e.g. Burkhard et al., 2012) generally based on only one simplified indicator are applied to map ES delivery. Land use, a frequently available spatial dataset, is often used as sole indicator. Using benefit transfer methods, an ES delivery value is assigned to each land use type. This eventually enables regional mapping of ES delivery. Although these methodologies are able to reveal spatial patterns of ES delivery, they are unable to fully capture the complexity of ES delivery processes (Van der Biest et al., 2015). As a result, proxy-based ES delivery maps often poorly fit primary data on ES delivery (Eigenbrod et al., 2010).

Recently, Bayesian belief networks (BBN), a semi-quantitative modelling approach that enables combining complex ecological models with expert knowledge, has been introduced in ES modelling and mapping (Van der Biest et al., 2014, Landuyt et al., 2013, Haines-Young, 2011). Compared to conventionally used indicator-based approaches for spatial assessment of ES delivery (e.g. Burkhard et al., 2012), BBNs offer several additional benefits. BBNs are able to deliver (semi-)quantitative results, can combine expert knowledge with empirical data and account for

uncertainties. Besides, in case less data or knowledge are available, indicator-based approaches can be used as well to develop parts of the network model. Although one third of the BBN modelling papers, reviewed by Landuyt et al. (2013), apply their models spatially (e.g. Smith et al., 2007; Haines-Young, 2011), the proposed methodologies are not standardized, nor easily applicable and consequently unable to serve as a robust, more advanced, alternative for proxy-based ES mapping approaches. Besides, communicating model uncertainties remains challenging (Spiegelhalter et al., 2011). While several studies have been conducted on visualising uncertainties on maps (MacEachren et al., 2005), mapping methodologies in BNN-based ES modelling research are currently restricted to mapping either the most probable state (e.g. Lehmkuhl et al., 2001, Haines-Young, 2011; Raphael et al., 2001) or the probability of one particular state (Smith et al., 2007; Rieman et al., 2001) of the network's output node.

In this paper, we propose a software framework which couples BBN software, to model ES delivery processes, and geographical information software, to map ES delivery and associated uncertainties. Netica (Norsys Software Corporation, 1998), a BBN software package frequently used in ES modelling research (Landuyt et al., 2013), was selected as model development platform due to its user-friendly interface. Quantum GIS (QGIS) (QGIS Development Team, 2012), freely available geographical information software, was chosen as interface to spatially apply the developed BBN models. The framework – a plug-in for QGIS – is developed in such a way that end-users with different backgrounds are able to carry out spatially explicit ES assessment in a relatively easy way. The main functionalities of the plug-in are illustrated by applying an existing ES assessment BBN model on spatial data of a land dune region, located in the northern part of Belgium. Several approaches to convey probabilistic uncertainties on maps are illustrated and their applicability in decision support is discussed.

2. Methods

2. 1. Bayesian belief networks

BBNs are graphical, multivariate, statistical models that comprise two structural components. The qualitative component consists of a causal network that captures all important system variables (biotic, abiotic and sociological ecosystem properties) and cause-effect flows among these variables (effects of ecosystem properties on ecological processes). The quantitative component consists of conditional probabilities that quantify the aforementioned cause-effect relations. The

causal network, often referred to as directed acyclic graph (DAG), consists of nodes, visually representing the system's variables, and arrows, representing causal relations among the system's variables. Each network node (X) consists of multiple states which can be defined both qualitatively (e.g. low, medium, high) or quantitatively (e.g. 0 – 100 tons.y^{-1}.ha^{-1}; 100-200 tons.y^{-1}.ha^{-1}; 200-300 tons.y^{-1}.ha^{-1}). The likelihood that a particular state of a node is realized is depicted by a probability (e.g. P(X = low) = 0.8). Conditional probabilities (P (X|parents(X))) are used to quantify the causal relations in the network. Through the rule of Bayes (eq.1), these probabilities are propagated through the network.

$$P(X) = \sum_{parents(X)} P\big(X \big| parents(X)\big) * P\big(parents(X)\big) \qquad (eq.1)$$

The use of probabilities enables BBNs to deal with uncertain input variables and uncertain relations among the system's variables. These uncertainties are propagated through the network and result in model predictions that explicitly account for uncertainties. Table 1 provides an overview of BBN terminology used throughout this paper. For a detailed description of BBNs, we refer to Jensen (2007). For model development guidelines, we refer to Chen and Pollino (2012) and Marcot et al. (2006).

TABLE 1

2.2. Mapping Bayesian belief network predictions

In this paper, we focus on pixel-based spatial application of BBNs. Pixel characteristics are used as model input and will instantiate the input nodes of the network. After the inserted information is propagated through the network, the network returns a probabilistic estimate for its output variable which can be assigned to the pixel again. An important advantage of using BBNs in spatial analyses is the ability to deal with missing data. For some pixels in the study area one or more characteristics may be unknown, resulting in uninstantiated input nodes in the network. In this case, a BBN model is able to make a prediction for that pixel, albeit more uncertain, based on the input variables' prior distributions. These prior distributions can be estimated based on the characteristics of the entire study area.

Table 2 presents several indicators that can be used to map the probabilistic output of a BBN: the expected value, the most probable state (or mode), the standard deviation of the expected value and the probability of the most probable state. The two first indicators are used to produce maps that represent quantity (hereafter referred to as quantity maps) while the other two are used to produce maps that represent the uncertainty associated to that quantity (hereafter referred to as uncertainty maps). Both map types deliver important information to support decision making (see, for example, Ligmann-Zielinska and Jankowski, 2014). Additionally, we propose three more advanced output maps that combine information on uncertainty and quantity in a single layer: ignorance maps, sampled maps and cumulative probability maps. Ignorance maps represent for each pixel the most probable state only in case the probability of attaining that state is higher than a predefined threshold (Rocchini et al., 2011). Map samples represent for each pixel a sampled state, sampled out of the output node's probability distribution. Cumulative probability maps represent for each pixel the probability that the model's prediction is higher than a predefined threshold.

TABLE 2

2.3. QGIS plug-in architecture

The software framework is designed to enhance interaction between BBN models and spatial data. It integrates the graphical user interfaces for BBN model development (Netica) and spatial data visualization (QGIS) through a QGIS plug-in written in Python (van Rossum, 1995). After the user feeds in a BBN model and a set of spatial datasets for all input variables of the developed model, the plug-in will return several maps representing different types of BBN model output. The plug-in performs four main tasks. It preprocesses the spatial input data (1), merges the raster datasets into one joint input database (2), runs the model for each line of this database (3) and maps different types of BBN model output (4).

Figure 1 schematically represents the architecture of the framework. For each input node of the developed BBN, a raster layer should be available. As input raster data, the plug-in accepts GeoTIFF (.tif) files. As these files only support numerical data, each raster input file should be accompanied with a .csv file which assigns to each mapped, numerical code a name referring to a particular state of the corresponding input node. The pre-processing of the input rasters is automatically done by the plug-in and consists of excluding non-overlapping areas and eliminating raster offset.

After reshaping, all input rasters are merged into one joint map database (.csv format). The plug-in offers two possible ways to run the model. A fast run which requires considerable amounts of memory or a slow run with less memory usage. The slow run mode is based on a built-in function of Netica and runs the BBN model for each pixel (or row of the joint map database) independently. In the fast approach, only unique pixels are retrieved from the joint map database and the model is run on this substantially smaller set of pixels. The output of this model run is used to generate a look-up table that lists all unique pixels with their corresponding probabilistic model output. This table, implemented as a dictionary structure in Python, is then used to assign a model output to each pixel of the study area. As dictionary structures allocate considerable amounts of memory, large numbers of unique pixels may cause memory errors. Using the fast method in combination with networks that require a large set of input maps is therefore not recommended.

FIGURE 1

After running the model, raster output files are produced. The dialog screen of the plug-in (Figure 2) offers the possibility to select one or more output maps. The user can select among seven types of BBN output maps, previously discussed in section 2.2.

FIGURE 2

2.4. Case study application

To illustrate the functionalities of the developed plug-in, a BBN model for map-based assessment of ES delivery and biodiversity was developed for a small study area (160 km²), located in the Campine Region in the upstream part of the Grote Nete basin in Belgium (Figure 3). It consists of a series of inland dune relicts covered with monotonous pine plantations, mixed forests, heather and bare soil. The area is intersected by numerous brooks and meandering streams with adjacent valley wetlands. Although the area is located in the densely populated northern half of the country, it is known for its high quality nature and rural characteristic.

FIGURE 3

Four ES which are important for the area were selected: wood production, agricultural production, climate regulation through soil organic carbon sequestration and clean water provision through infiltration. Additionally, the biodiversity potential was modelled. Wood is mostly produced on the dry dune soils that are covered with monoculture pine forest stands. These highly permeable dune soils are also important for infiltration of precipitation and replenishment of groundwater reserves. Soil organic carbon sequestration is especially important along the river valleys covered with marsh grassland and brook forests. Agricultural production is mostly found on the ground between the very wet river valleys and the very dry inland dunes.

To model the four selected ES and biodiversity, a BBN model with five output nodes was developed (Figure 4). Input nodes of the network are all related to land cover, land management, soil type and hydrology and are structured in a set of ten input nodes for which spatial data were available for the entire study region. Knowledge to develop the model was elicited from experts and extracted from literature. A detailed description of the modelled processes and services can be found in Supporting Information.

FIGURE 4

3. Results and discussion

3.1. Uncertainty maps

Conventional BBN output maps

The first four output maps, produced by the plug-in, spatially visualize the expected ES delivery (quantity maps) and the uncertainties associated to these predictions (uncertainty maps) on separate maps. While maps representing the most probable state and the probability of that state are more intuitive and thus probably preferred by laymen, scientists are generally more confident with the expected value and standard deviation approach. An important drawback of the latter approach is its incompatibility with models that contain output nodes whose states are only qualitatively defined. Besides, standard deviation maps are less informative in case the predicted distributions are skewed. People usually tend to assume an un skewed distribution while interpreting standard deviation values. This may result in unintended map interpretation. For example, in case the standard deviation is higher than the expected value, map readers may assume that negative values are probable as well, which may not be the case for a skewed

distribution (see Table 2). A major disadvantage of the other approach is that the probability of the most probable state can only be interpreted relatively, taking into account the number of states of the output variable. A large number of states in the output node of the network will increase the chance for low probabilities in the uncertainty layer. The standard deviation as a measure for uncertainty, on the other hand, is not sensitive to changes in the number of states of the output node. Standard deviation and expected value maps are thus preferably chosen for quantitative output variables (preferably with an un skewed distribution), while maps representing the most probable state and associated probability are preferred to visualize qualitative output variables. A major weakness of these conventional BBN output maps is that information related to quantity and uncertainty are visualized on separate maps which makes map interpretation cognitively more demanding (Kubíček and Šašinka, 2011).

FIGURE 5

Sampled maps

Using map samples is a first approach to visualize both quantity and uncertainty on a single map. These map samples represent one, according to the model, possible truth. In these maps, uncertainty of the model output will be visualized on the scale of land parcels, which we define as parts of the land that consist of a set of pixels with a common land cover and use. As pixels within one land parcel have almost the same characteristics, the model will predict a similar probability distribution for all these pixels. In case the model predictions are relatively uncertain for a particular land parcel, this parcel will be characterized with a high degree of speckle noise in the sampled maps. Thus, quantity is visualized through pixel colors, while uncertainty is represented by speckle noise (Figure 7). In addition to the advantage of representing both quantity and uncertainty on a single layer, these maps are also able to visualize skewness of probability distributions. In figure 6, for example, the sampled map is considerably darker compared to the map that represents the most probable state for each pixel. This suggests skewness of the probability distributions, for most pixels the chance for a value that is higher than the most probable state is higher than the chance for a value that is lower.

As mentioned by Uusitalo et al. (2015), decision makers generally prefer information on the entire study area rather than information on individual pixels. An advantage of sampled maps is that we can use them to infer the probability distribution of total ES delivery in the study area. The sum of all pixels of one map sample will constitute one sample of the probability distribution of total ES

delivery in the study area. By sampling multiple maps and, thus, generating multiple samples of the study area's total ES delivery, the probability distribution of total ES delivery can be approximated. This distribution can be used to derive the expected value and standard deviation of the study area's total ES delivery. An important limitation of the proposed approach is the assumption that spatial autocorrelation among the study area's pixels is absent. However, within one land parcel pixel values are generally similar which violates this assumption. As shown by Canters (1997), wrongly assuming absence of spatial autocorrelation within land parcels may affect the obtained probability distribution for the entire study area. Wrongly assuming absence of spatial autocorrelation will not affect the expected value of the study area's total ES delivery but will result in an underestimation of the uncertainty associated to the study area's total ES delivery.

FIGURE 6

FIGURE 7

Ignorance maps

Figure 8 shows the most probable state map of the ES climate regulation without (left) and with an ignorance mask (right) that hides areas where the probability of the model's predicted most probable state is lower than 60%. As can be seen in Figure 8, most of the areas where the model predicts high climate regulation potential are masked denoting that these predictions are relatively uncertain. Ignorance maps can be used to focus the attention of map readers on those areas where model predictions are relatively sure. An important drawback of this method is that information is lost for those areas where uncertainty is high. As previously discussed, the probability of the most probable state highly depends on the number of states. This has to be accounted for while defining the threshold.

FIGURE 8

Cumulative probability maps

As discussed by MacEachren et al. (2005), laymen tend to simplify information related to uncertainty to simple heuristics that can support their decision making. Similarly, probability distributions can be translated into cumulative probabilities denoting the probability of exceeding a certain threshold ES delivery. The legibility of such cumulative probabilities is known to be higher than that of probability density values (Ibbrek and Morgan, 1987). For an illustration of this approach to guide decision making in integrated pond management, we refer to Landuyt et al.

(2014). In a cumulative probability map, a pixel's value is calculated as the sum of the probabilities of all the states above a certain threshold state. The cumulative probability maps (Fig. 9) represent for each pixel the probability of exceeding the predefined ES delivery threshold. An important feature of this type of uncertainty mapping is the strong effect of the selected threshold on the output map. Probability values depend on the selected threshold and become more extreme as thresholds are more extreme (Figure 9). The possibility to set a threshold on the other hand allows users to focus on areas of particular interest with a certain degree of service delivery. Cumulative probabilities can also be linked to risk-averse and risk-taking behavior. Risk-averse decision makers, which tend to minimize the probability of low values, will be interested in cumulative probability maps produced with a lower threshold value than risk-taking decision makers, which tend to maximize the probability of very high values (Makinson et al., 2012).

FIGURE 9

Comparison of maps

The decision on which type of uncertainty map to use depends on different factors such as type of ES, type of output data (qualitative, quantitative, monetary), targeted audience, degree of uncertainty and research objectives. Table 3 gives an overview of the main technical advantages and disadvantages of the different uncertainty maps, allowing users to make a more informed decision on which type(s) of uncertainty visualization to use.

TABLE 3

3.2. Software framework

The plug-in, discussed in this paper, has the potential to facilitate BBN model development and application in the ES modelling research domain. First of all, it can be used during expert-based adaptive model development. BBNs are frequently mentioned as a suitable tool to be included in an adaptive model development framework (e.g. Lynam et al., 2010, Howes et al., 2010). Aside from new data that become available, expert knowledge can be used for sequential model updating. The possibility to generate maps supports this iterative process. In this iterative process maps can be useful to identify flaws in model performance under specific biophysical conditions. Map-based model validation is a second potential application of the plug-in. As mentioned in Landuyt et al. (2013), model validation by experts in ES modelling research is crucial as data for

quantitative model validation are usually not available. Face validity tests, as proposed by Pitchforth and Mengersen (2013), are an example of qualitative model validation. These tests, where experts evaluate the plausibility of model outputs, can be carried out on mapped model results as well (Van der Biest et al., 2014). By using maps, experts can evaluate the behavior of the model for multiple land uses and biophysical conditions at once.

Another important advantage of the use of BBN models in a mapping context is its high flexibility related to input data. BBN models can be easily transferred and applied in other case studies where differing spatial input data are available. A land use map, for example, usually building on a specific classification system, frequently differs among study areas. As a consequence, the original model's land use node will not be able to deal with the land use map of the new study area. Adding a new input node to the model that includes all possible classes of the new land use map can easily solve this problem. Subsequently, the causal link between this new node and the original input node can be quantified through expert knowledge. A similar model adaption enables the use of primary data, such as satellite images, as model input. In this case, BBNs offer an additional advantage as classification uncertainty, associated to the translation of primary data to the states of the model's original input node, can be explicitly taken into account while defining the CPT of the added causal link (Hou et al., 2013).

Although several alternative software packages exist to apply BBNs on spatial data (e.g. QuickScan (Verweij et al., 2014), Geo-Netica (www.norsys.com)), none of them focuses on meaningful ways to cartographically represent the uncertainties associated to BBN output. The inclusion of this tool as a plug-in within an existing GIS package offers some additional advantages over currently available stand-alone packages. As our tool requires spatial data, familiarity with a GIS package is a prerequisite to be able to use the tool. As QGIS is currently one of the most-used open source packages, for most users the threshold to apply this plug-in will be low as no additional software packages need to be purchased, installed and understood. Moreover, QGIS includes numerous map processing tools that enable all necessary manipulations of input and output maps, avoiding the need to transfer spatial data across multiple software packages. Another advantage of open-source plug-ins is the potential of continual improvement resulting from interactions between end-users and software developers. In the context of this plug-in, this process may, for example, lead to end-users suggesting alternative approaches or indicators to map uncertainty. This will in the end improve the decision support capacity of the plug-in and the maps it produces.

An important limitations of the proposed software framework is its inability to account for spatial interactions. As denoted by Hein et al. (2006), spatial interactions and scales frequently play an important role in ES assessments (Hein et al., 2006). Pollination, flood retention and recreational use are classic examples of ES whose delivery processes are spatially explicit. Although the software framework does not support interactions among pixels, BBNs can, to a limited extent, deal with spatial interactions by including input nodes that describe particular characteristics of the pixel's neighborhood. Landscape metrics, frequently used in landscape ecology, can, for example, do the trick (Syrbe and Walz, 2012). However, including extra input variables will increase model complexity and, hence, will increase both the plug-in's calculation time and memory usage.

Although this paper focuses on the use of BBNs in ES assessment studies, the ability of BBNs to transparently deal with uncertainties, a universal challenge across a broad range of research domains (Uusitalo et al., 2015), promotes its use in a wide range of applications, ranging from medical diagnosis (Kahn et al., 1997), machine learning (Ordóñez Galán et al., 2009), classification problems (Aguilera et al., 2010), to environmental modelling and management studies (Aguilera et al., 2011). A subset of these research domains also deal with spatial data. Aside from ES assessments, popular spatial BBN applications include habitat suitability mapping (Smith et al., 2007), image classification in remote sensing (Park and Stenstrom, 2006), spatial multi-criteria analysis (Stassopoulou et al., 1998) and risk assessment (Grêt-Regamey and Straub, 2006). The QGIS plug-in, discussed in this paper, may complement current spatial BBN studies by bridging the gap between science and decision support by spatially representing the output of these studies in a meaningful way. Moreover, the plug-in may promote the use of BBNs as an alternative approach to analyze uncertainties in spatial analyses far beyond the ES research domain (e.g. Ligmann-Zielinski and Janowski, 2014).

4. Conclusions

The developed QGIS plug-in promotes the use of BBNs to model and map ES delivery. BBN models can add value to current ES mapping research as they enable the integration of uncertainties and expert knowledge in spatial ES accounting studies. However, interpretation of mapped uncertainties remains a challenging task. In this paper, we discussed several mapping approaches, tailored to probabilistic BBN output, to facilitate interpretation of mapped uncertainties and to support decision making based on mapped uncertainties. Clearly, no one-fits-all visualization approach exists. Depending on whether the output variable is qualitatively or quantitatively

defined, the cognitive capacity of the map reader and the questions that need to be answered, different visualization approaches are needed.

Meanwhile, we acknowledge the limitations of BBN models. Knowledge-based models can be subjective and are generally hard to validate and are less robust compared to validated data-driven or process-based models. However, in management domains that predominantly rely on expert opinion for decision making (as no other information is available), this tool may be extremely useful as it offers a structured and standardized approach to include expert knowledge into spatial analysis and decision support.

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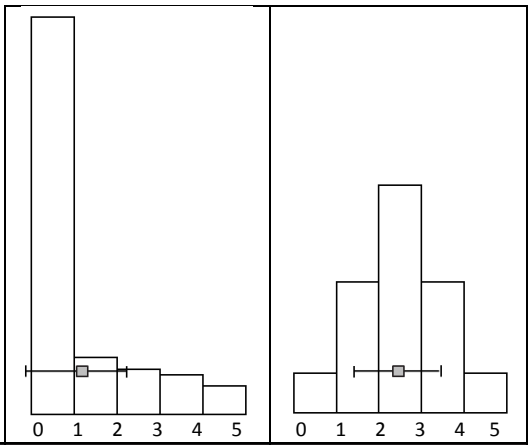
Tables

Table 1. Frequently used Bayesian belief network terminology

Terminology	Description
Nodes	Graphical representation of the system's variables in a Bayesian belief network model.
State	A value, discrete class or qualitative level a variable can be assigned to. Each variable in a Bayesian belief network model has a set of states it can manifest.
Probability distribution	The set of probabilities assigned to the states of a variable that express the probability that the variable is in one of its states. This set of probabilities always sums up to 1.
Arrows	Graphical representation of the causal relations among the system's variables. Each arrow flows from a parent node to a child node. Together with the nodes, they define a directed acyclic graph or DAG.
Conditional probability	The probabilities that quantify the model's causal relations and express the probability distribution of a child node given the status of its parent nodes.
Conditional probability table	A table that contains a child node's conditional probabilities for all possible combinations of the parent nodes' states. Abbreviated as CPT.
To instantiate	Assigning a 100% probability to one of the states of a variable. This can be done, for example, in case the exact value of that variable is known.

Table 2. An overview of indicators that can be derived from the probability distribution of a Bayesian belief network's output node. Real value examples for a highly skewed and an un skewed discrete probability distribution are provided. S represents the output variable's set of states**.**



Terminology	Equation	Skewed distribution	Un skewed distribution
Most probable state	$MPS[X] = \underset{x \in S}{arg\,max}\ P(x)$	0.5	2.5

Probability of the most probable state	$PMPS[X] = \max_{x \in S} P(x)$	70%	40%
Expected value	$E[X] = \sum_{x \in S} P(x) . x$	1.17	2.5
Standard deviation	$SD[X] = \sqrt[2]{\sum_{x \in S} (E[X] - x)^2 . P(x)}$	1.18	1.01
Cumulative probability	$P(X > T) = \sum_{x > T} P(x)$	20% (for T = 2)	70% (for T = 2)

Table 3. Advantages and disadvantages of the different types of uncertainty map

Map type	Advantages	Disadvantages
Standard deviation map	-Independent of the number of states of the output node	-Only for quantitatively defined output nodes -No integration of quantity and uncertainty in one map -Less informative in case distributions are skewed
Probability map	-Straightforward interpretation -Integrates information on quantity and uncertainty in case the model's output node has two states	-Dependent on the number of states of the output node -No integration of quantity and uncertainty in one map
Sampled map	-Integrates information on quantity and uncertainty -Visualizes distribution skewness	-Represented quantities potentially deviate more from expected value
Ignorance map	-Integrates information on quantity and uncertainty -High flexibility in mapping output by setting threshold value -Straightforward interpretation -Focus on most confident model predictions	-No quantitative information when the probability is below the threshold -Strong dependency on user-defined threshold
Cumulative probability map	-Integrates information on quantity and uncertainty -High flexibility in mapping output by setting threshold value -Straightforward interpretation -Close to mental heuristic for decision making	-No absolute values for ES delivery -Strong dependency on user-defined threshold

Figures

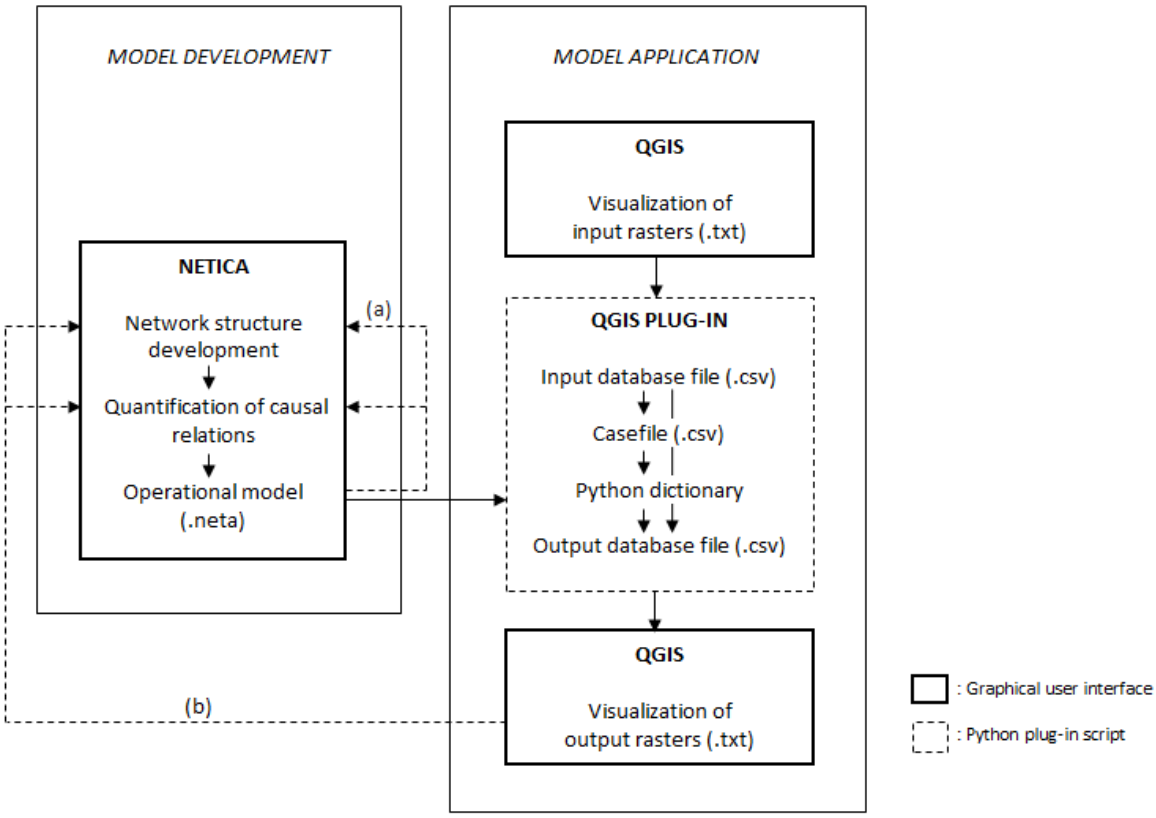


Figure 1. Schematic visualization of the plug-in architecture, embedded in an adaptive model development framework. Full arrows represent conventional plug-in usage: a Bayesian belief network model is developed in Netica (left) and subsequently applied on spatial raster data by using the plug-in (right). Feedback loops (a) and (b) represent potential adaptive model development pathways, using respectively non-spatial and spatial model output to revise the previously developed model.

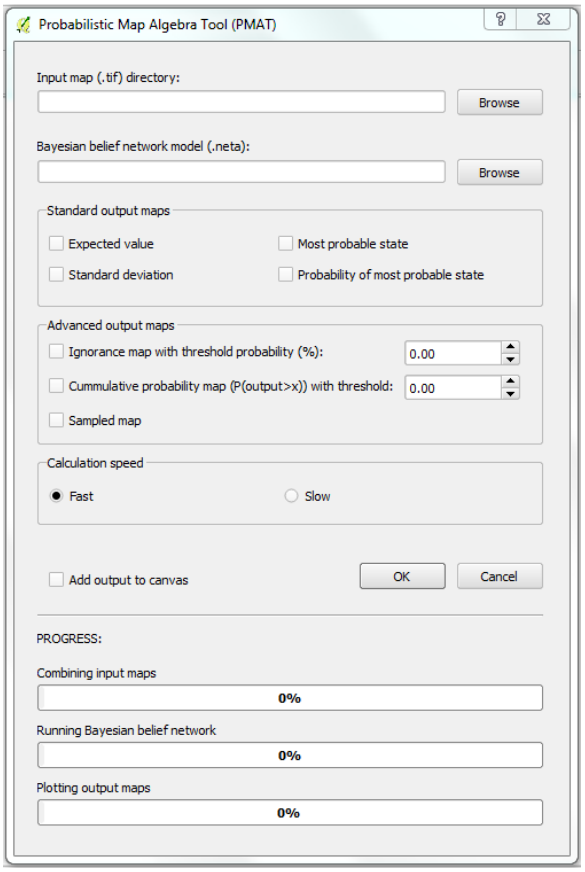


Figure 2. Dialog screen of the QGIS plug-in to apply Bayesian belief networks on spatial input data.

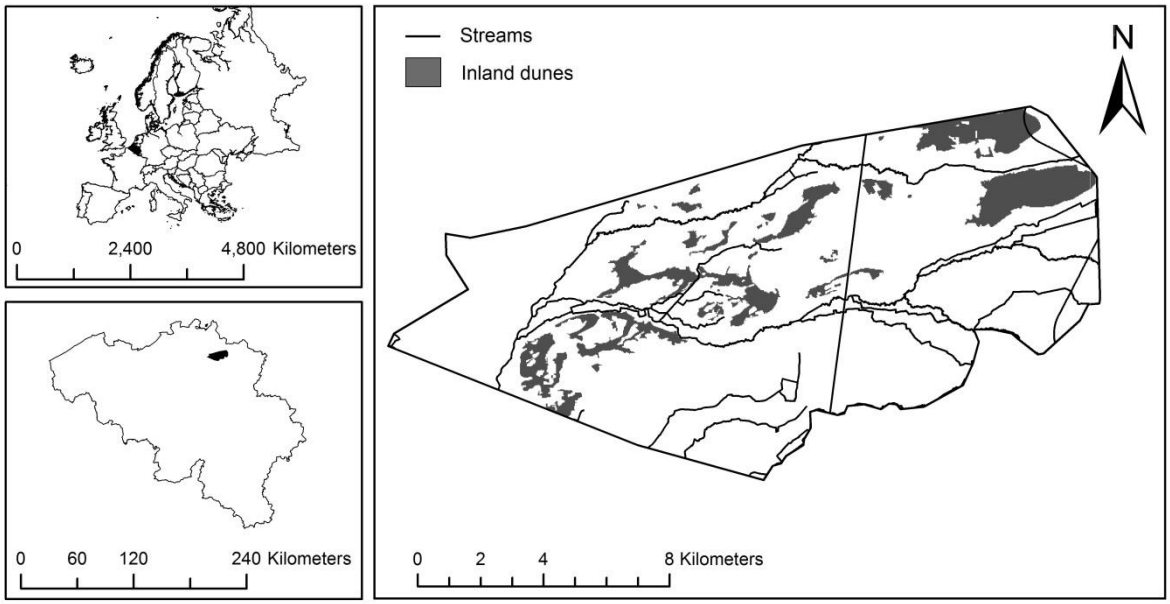


Figure 3. Location of Belgium within Europe (top left), location of the study area within Belgium (bottom left) and a map of the Belgian Land dune region (right) depicting the inland dunes and the major streams in the area.

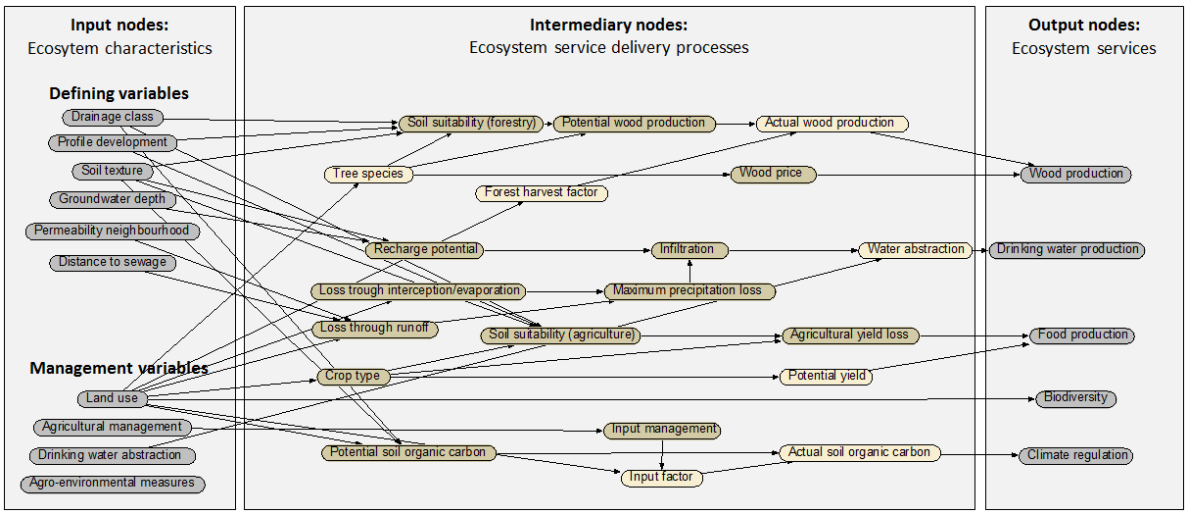


Figure 4. Graphical representation of the BBN model, developed to model pixel-based delivery of four ecosystem services and biodiversity.

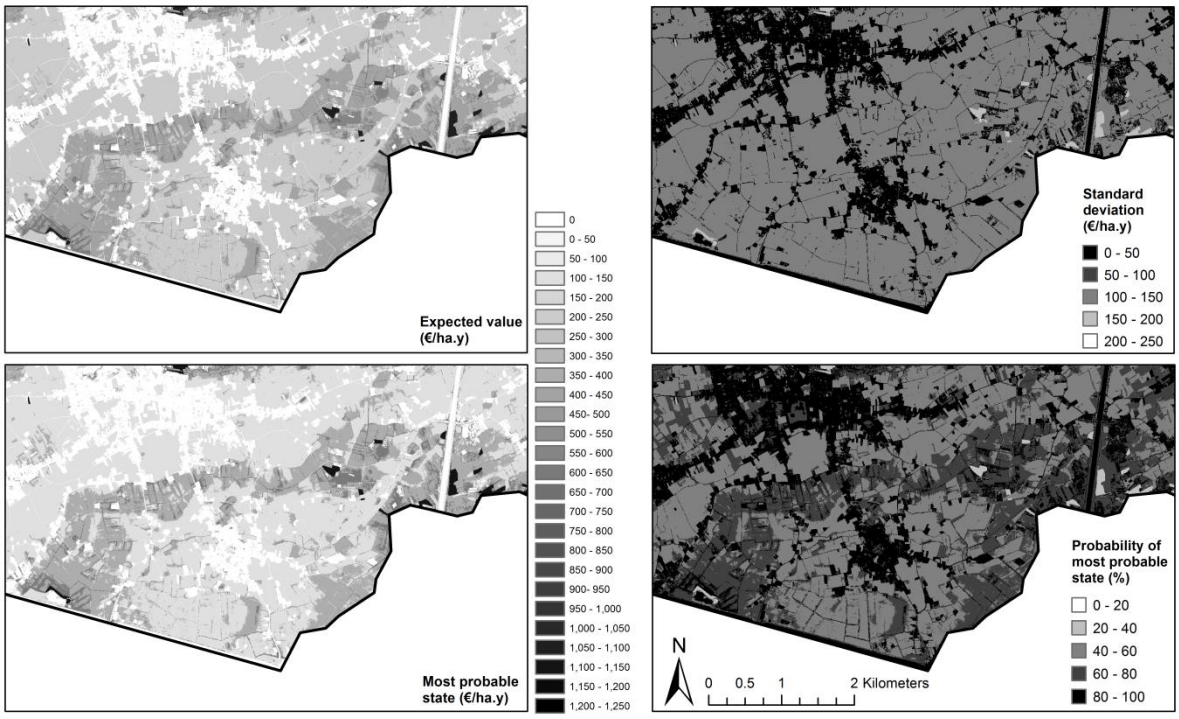


Figure 5. Left: Maps representing the monetary value of climate regulation predicted by the model as expected value (top) and most probable state (bottom). Right: maps representing the uncertainty associated to the model predictions as standard deviation (top) and probability of the most probable state (bottom). Zoom in on the southern part of the study area.

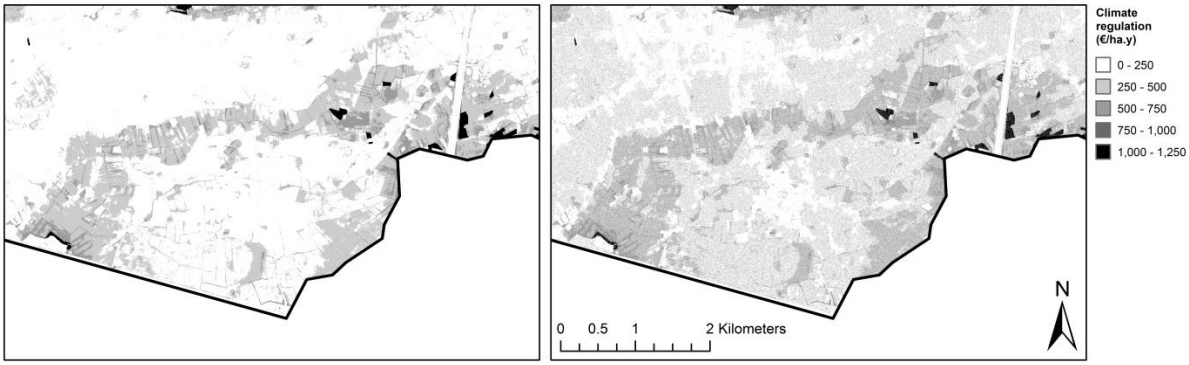


Figure 6. Left: a most probable state map, depicting for each pixel the predicted most probable state of the ecosystem service climate regulation. Right: a sampled map wherein each pixel represents a state that is sampled from the model's predicted probability distribution for that pixel. Zoom in on the southern part of the study area.

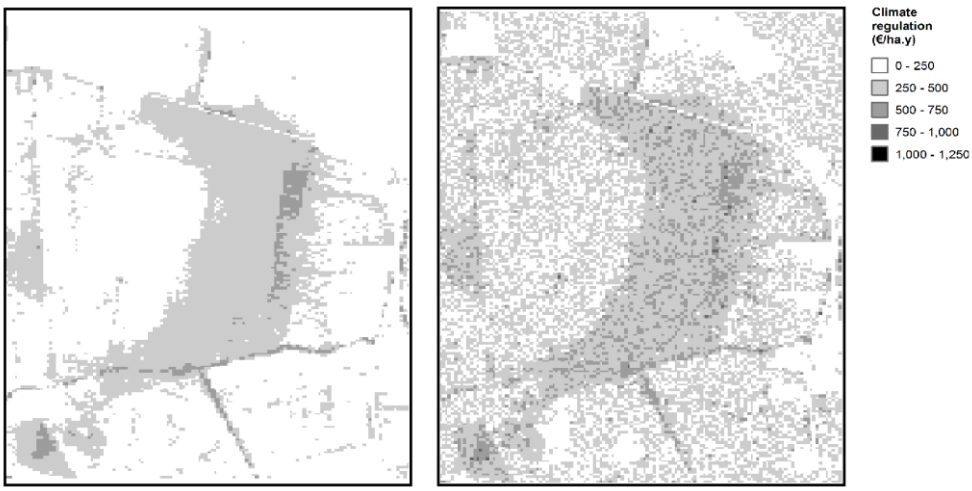


Figure 7. Speckle noise in a sampled map (right pane) as an indicator of uncertainty associated to the model predictions, represented as the most probable state (left pane). Zoom in of the maps shown in Figure 6.

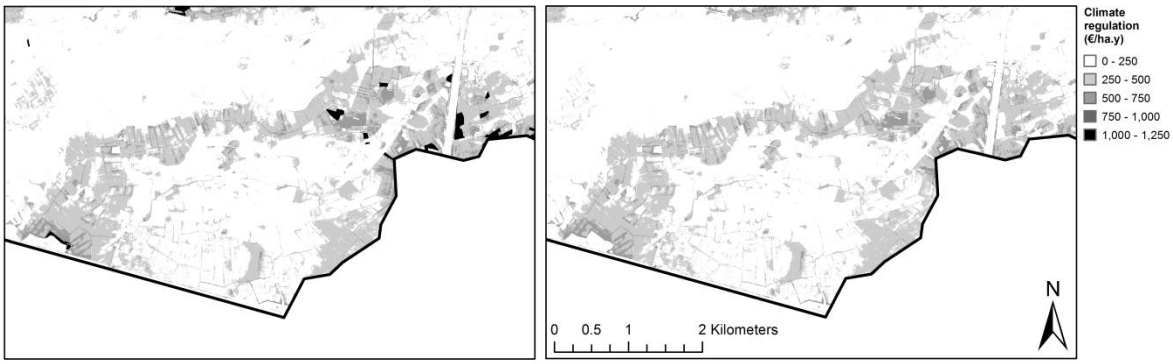


Figure 8. Maps depicting for each pixel the predicted most probable state of the ecosystem service climate regulation without (left) and with (right) ignorance mask. The ignorance mask hides model predictions in case the probability of the predicted most probable state is lower than 60 %. Zoom in on the southern part of the study area.

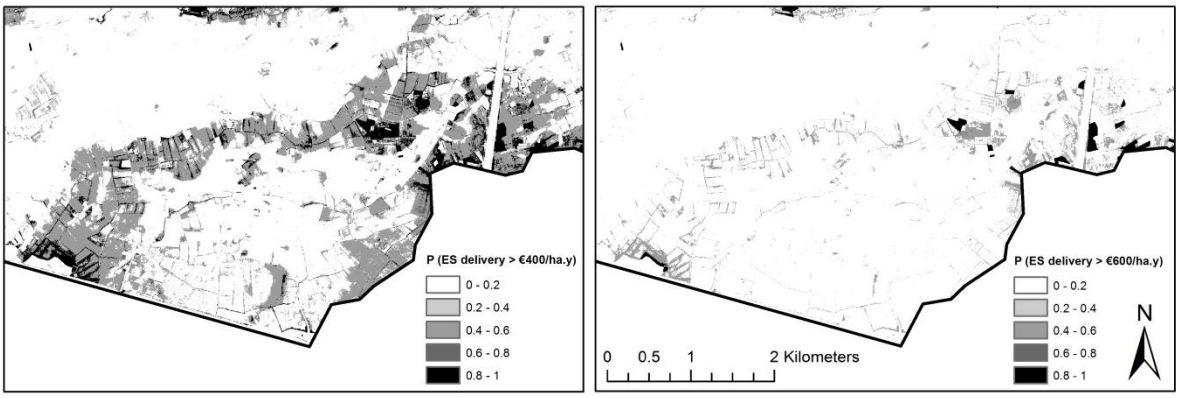


Figure 9. Maps depicting for each pixel the probability of attaining a climate regulation capacity value above €400/ha.y (left) and €600/ha.y (right). Zoom in on the southern part of the study area.