A Bayesian Belief Network learning tool integrates multi-scale effects of riparian buffers on stream invertebrates

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HIGHLIGHTS

- Reach-scale riparian vegetation condition had the strongest improvements in ecological status.
- Bayesian belief network models were developed as a potential learning tool.
- Data collected from four European catchments were used to train the model.
- Model's strengths are fast simulation time and clarity, stimulating users' learning.

GRAPHICAL ABSTRACT
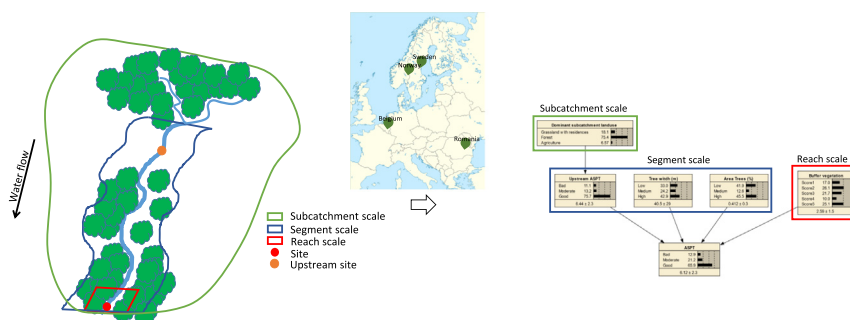
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ABSTRACT

Riparian forest buffers have multiple benefits for biodiversity and ecosystem services in both freshwater and terrestrial habitats but are rarely implemented in water ecosystem management, partly reflecting the lack of information on the effectiveness of this measure. In this context, social learning is valuable to inform stakeholders of the efficacy of riparian vegetation in mitigating stream degradation. We aim to develop a Bayesian belief network (BBN) model for application as a learning tool to simulate and assess the reach- and segment-scale effects of riparian vegetation properties and land use on instream invertebrates. We surveyed reach-scale riparian conditions, extracted segment-scale riparian and subcatchment land use information from geographic information system data, and collected macroinvertebrate samples from four catchments in Europe (Belgium, Norway, Romania, and Sweden). We modelled the ecological condition based on the Average Score Per Taxon (ASPT) index, a macroinvertebrate-based index widely used in European

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bioassessment, as a function of different riparian variables using the BBN modelling approach. The results of the model simulations provided insights into the usefulness of riparian vegetation attributes in enhancing the ecological condition, with reach-scale riparian vegetation quality associated with the strongest improvements in ecological status. Specifically, reach-scale buffer vegetation of score 3 (i.e. moderate quality) generally results in the highest probability of a good ASPT score (99–100%). In contrast, a site with a narrow width of riparian trees and a small area of trees with reach-scale buffer vegetation of score 1 (i.e. low quality) predicts a high probability of a bad ASPT score (74%). The strengths of the BBN model are the ease of interpretation, fast simulation, ability to explicitly indicate uncertainty in model outcomes, and interactivity. These merits point to the potential use of the BBN model in workshop activities to stimulate key learning processes that help inform the management of riparian zones.

1. Introduction

Worldwide, streams are degraded due to excess nutrients, pesticide contamination, wastewater discharge and habitat alterations (Casquin et al., 2020; Deknock et al., 2019; Forio and Goethals, 2020; Mercado-Garcia et al., 2018). Thus, various measures have been assessed and implemented to improve the ecological conditions of streams. For instance, the minimum environmental flows were applied in heavily regulated rivers which resulted in habitat improvements (Arthington et al., 2010; Carolli et al., 2021; Göthe et al., 2019); constructed wetlands were employed to partially remove nutrients from wastewater before discharging to streams (Donoso et al., 2015; Vymazal, 2007); and, natural retention measures such as wetlands, cover crops, riparian buffers were restored or installed to reduce impacts of agriculture (Di and Cameron, 2002; Feld et al., 2018; Taramelli et al., 2019; Zedler, 2003). In particular, the benefits of riparian forest buffers are well-documented. They have shown to improve the water quality of streams, stabilize streambank, enhance groundwater recharge and regulate the thermal regime of streams (Johnson and Almlöf, 2016; Newbold et al., 2010; Singh et al., 2021). Nevertheless, several studies have highlighted the importance of considering the different spatial scales of riparian buffers when assessing their benefits (Fitzpatrick et al., 2001; Forio et al., 2020a; Leps et al., 2015; Popescu et al., 2021). For instance, Xu et al. (2021) showed that landscape structures within a 300-m buffer zone had the greatest impact on water quality, while Forio et al. (2020a) found that macroinvertebrate diversity was strongly associated with the extent of trees in the riparian zone 100–300 m upstream of the study sites. Another study claims that upstream riparian conditions >2.5 km has a strong influence on the local ecological status (Lorenz and Feld, 2013). Thus, considering the multi-scale effects of riparian buffers is paramount when evaluating their benefits.

The efficacy of riparian buffers was assessed in various ways. Studies have evaluated their effectiveness in reducing nutrient loads or losses using nutrient concentrations as an indicator (e.g. Lee et al. (2020), Zhang et al. (2017), Schilling and Jacobson (2014)), and in retaining sediments using carbon stable isotopes ($\delta^{13}C$) and sediments loads in streams as indicators (e.g. Sirabahenda et al. (2020), Cordeiro et al. (2020)). Moreover, riparian buffers showed to have a positive effect for enhancing the ecological conditions using biological metrics based on invertebrate, amphibian and fish communities (e.g. Lorion and Kennedy (2009), Teels et al. (2006), Kupilas et al. (2021), Forio et al. (2020a), Muenz et al. (2006)). Particularly, biological metrics assess the cumulative impacts of chemical pollutants over time, and thus integrate the current and past environmental conditions (Holt and Miller, 2010). Biological metrics also indicate indirect biotic effects of pollutants, reflect habitat quality which is not detected by traditional physical and chemical water quality assessments, and denote the state of ecosystem functioning (De Pauw et al., 2006; Holt and Miller, 2010; USEPA, 1997). In this context, biological metrics provide a holistic indication of ecosystem health.

Despite the usefulness of the riparian forest buffers, their implementation in water management has often been limited, which is partly due to the disinterest or distrust of stakeholders or the limited transfer of scientific knowledge to practice (Durham et al., 2014; Megdal et al., 2017; Thoradeniya and Maheshwari, 2017). The involvement of stakeholders is key to effectively implement riparian buffers as measures to maintain or improve the ecological quality of streams. In this context, social learning is valuable in informing stakeholders and facilitating the successful implementation of particular measures in environmental management (Cundill and Rodela, 2012). Social

learning is a process wherein stakeholders come together and share their experiences, perspectives and ideas, with participation and engagement as key elements driving meaningful outcomes (Muro and Jeffrey, 2008; Rodela, 2011); furthermore, it often leads to awareness of human-environment concerns, improved problem-solving capacity and decision-making, changes in perceptions, values and norms and come up with collective action on a particular environmental concern (Armitage et al., 2008; Cundill and Rodela, 2012; Daniels and Walker, 1996). It also develops and sustains the capacity of different authorities, experts, interest groups and the public to manage their water resources effectively (Pahl-Wostl, 2007). Tools used during the learning activities play a significant role in achieving the learning goals (Pahl-Wostl, 2007). Among these tools are participatory GIS platforms and visual aids such as photos to visualize spatial data and display the local landscape, respectively (Toderi et al., 2007). To our knowledge, the output or the interactive model is rarely applied as a learning tool. A key strength of these tools is the provision of evidence-based predictions on the outcomes of certain management actions such as particular conservation management (Newton et al., 2007) and water resource management (Phan et al., 2019) strategies and are promising social learning tools.

Mathematical models are commonly used to simulate environmental processes. The outputs of some models are easy to interpret and use such as those of decision trees, fuzzy logic, generalized linear regression and Bayesian Belief Network (BBN) models (Van Echelpoel et al., 2015); therefore, they can be potentially used as a learning tool during a stakeholder engagement. Among the enumerated models, the BBN models are interactive, explicitly account for uncertainties, are able to complement empirical data with expert knowledge, and straightforwardly propagate uncertainties associated with model inputs (Boets et al., 2015; Forio et al., 2020b; Landuyt et al., 2015; Nel et al., 2021). These advantages clearly indicate the great potential of BBNs as social learning tools (Kelly et al., 2013; Smith et al., 2018); however, hitherto BBN models are scarcely used in social learning activities.

In our study, we constructed BBN models as the basis for a potential learning tool for riparian-stream management. In particular, we developed a BBN model to simulate and assess the reach- and segment-scale effects of riparian vegetation and the upstream catchment land use on stream macroinvertebrates, specifically on the Average Score Per Taxon index, indicating ecological quality (Fig. 1) as a proof of principle. We selected an index based on macroinvertebrate communities because macroinvertebrates (i) are generally ubiquitous and abundant in an aquatic ecosystem, (ii) integrate environmental conditions over time, (iii) show the impacts of habitat loss and (iv) are relatively easy to sample and identify (Dahm et al., 2013; De Pauw et al., 2006; Forio and Goethals, 2020); furthermore, these organisms (v) respond to the widest array of stressors and (vi) play an essential role in the ecosystem functioning and food web (Dahm et al., 2013; Hering et al., 2013; Hering et al., 2006). Data were collected in four catchments across Europe (Belgium, Norway, Romania and Sweden) and were used to train the model. We elaborated on the benefits and weaknesses of BBN model for application as a potential learning tool.

2. Methods

2.1. Sampling scheme

Four catchments in Europe were investigated in this study: Arges (44.2099306, 26.1831623 decimal degrees (DD); Romania), Fyrisån
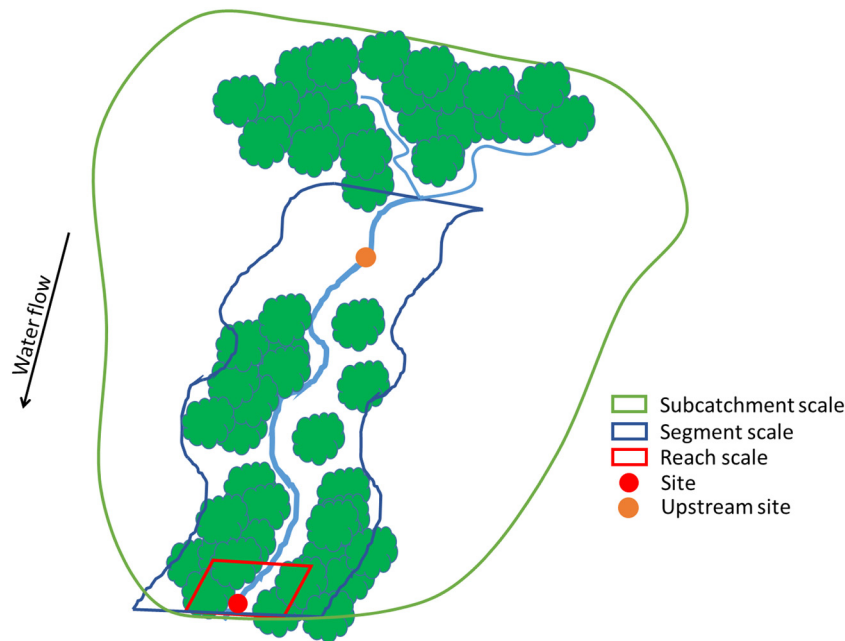
Fig. 1. Graphical representation of the different spatial scales assessed in this study. Macroinvertebrates were sampled in the two sites with riparian vegetation (red dot) and without (orange dot). Segment scale refers to a stream length of about >100 m but <1000 m, while reach scale refers to a stream length of about >10 m but <100 m (Frissell et al., 1986). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(59.786667, 17.655556 DD; Sweden), Oslo Fjord (59.3499986, 10.583331 DD; Norway), and Zwalm (50.88880, 3.66789 DD; Belgium) (Fig. S1). Arges has a catchment area of 12,590 km^2 and is dominated by forest in the upstream areas with some agricultural activities in the midstream (pasture and orchards) and downstream of the catchment. Fyrisån is 1982 km^2 in size and consists of a mixture of forest and agriculture, with urban areas downstream from our study sites. The Oslo Fjord subcatchments considered in our study have a total area of 423 km^2 and are dominated by upstream forest areas with increasing urban land use further downstream; and, Zwalm drains 117 km^2 and is mainly dominated by agriculture-pasture land use with about 10% urban and residences interlaced within the catchment. Although the Arges catchment is the largest of all catchments, the total area of the subcatchments that were sampled covered only 1135 km^2. These subcatchments are located in the central and northern parts of the catchment and are mainly dominated by forest with some agricultural activities. Further descriptions of each case study catchment are provided by Forio et al. (2020a), Ramberg et al. (2020), Mutinova et al. (2020), Kupilas et al. (2021), Sargac et al. (2021) and Popescu et al. (2021).

This study was conducted as part of the European BiodivERsA project CROSSLINK, which used the tiered study design described in Burdon et al. (2020). The CROSSLINK project applied a "paired approach" to investigate aspects of lateral and longitudinal connectivity. In each case-study catchment, we selected 10–12 streams, each with two paired sites: an upstream site with no riparian buffer (i.e. "unbuffered"), and a downstream "buffered" site with a woody riparian buffer (i.e. leading to 20–24 sites per catchment in total). The paired sites were relatively close together with a distance of between 50 and 1000 m to ensure a similar stream size in terms of discharge. We further selected 10–12 additional sites in each catchment, located upstream and downstream of the site pairs, which consisted of pristine or least impacted headwater sites and more degraded downstream sites, respectively. This resulted in 30, 30, 37 and 34 sites sampled in Arges, Fyrisån, Oslo Fjord and Zwalm catchment, respectively.

2.2. Data collection

Stream macroinvertebrates were sampled within a 30 m sampling reach in each site using a Surber sampler (25 × 25 cm, 500 μm mesh net). Sampling effort was standardized for 60 s where the substrate was disturbed to a maximum depth of 10 cm from the surface of the streambed. A total of six replicate subsamples were collected (three from erosional/riffle-run habitats, and three from depositional/run-pool habitats) within each sampling reach and the contents pooled. In the laboratory, the pooled macroinvertebrate sample was sieved (500 μm mesh) and sorted and then preserved in 10-mL tubes with 96% ethanol to reach a final concentration of 70%. Samples were identified under a stereomicroscope to the lowest possible level using the identification keys (Dall and Lindegaard, 2001; de Pauw and Vannevel, 1991; Dobson et al., 2012; Edington and Hildrew, 2005; Hubendick, 1949; Lillehammer, 1988; Nilsson, 1996; Nilsson, 1997; Pattée and Gourbault, 1981; Richoux, 1982; Sahlen, 1996; Tachet et al., 1980; Ulmer, 1909; Wallace et al., 2003; Zwick, 2004). Subsequently, we calculated the Average Score Per Taxon index (ASPT) with family-level macroinvertebrate data using the calcBMWP function in the R package biotic for each site (Briers, 2016; Burdon et al., 2020). The ASPT index was calculated as the ratio of the score obtained in the Biological Monitoring Working Party (BMWP) index to the number of taxa scored in the sample. A higher ASPT value indicates a better ecological condition (Armitage et al., 1983). The samples were collected in September of 2017, May of 2018, end of January–March of 2018 and May–June of 2018 in Arges, Fyrisån, Oslo Fjord and Zwalm catchment, respectively. These periods were chosen due to practical reasons and the accessibility of the rivers. Nevertheless, studies have shown that samples taken in any season are likely to provide consistent estimates of ASPT (Armitage et al., 1983; Callanan et al., 2008; Odume, 2017).

In each site, the reach-scale vegetation in the riparian zones was surveyed adjacent to the sampling reach at 50 m length of each bank. The vegetation was classified as score 1–5 (Table 1). Detailed information on riparian survey methods is given in Burdon et al. (2020).

Segment-scale riparian characterization of each site was obtained from GIS data in a polygon of 300 m upstream of the sampling sites (i.e. the recorded coordinates) with 50-m width on each stream bank. We calculated the percentages of each land use category: arable/agriculture, forest and shrub, pasture and grassland, and urban and industrial areas. The geographic information system (GIS) data sources were Bodembedekkingskaart (BKK), a 1-m resolution land cover dataset (Agentschap Informatie Vlaanderen, 2019) for the Zwalm catchment, Copernicus, a 20-m resolution forest cover dataset (European Union et al., 2020) for the % forest and shrub of the three catchments and Corine, a 30-m resolution land cover dataset

Table 1
Description of each score class.

Classes	Description
Score1	Short grazed pasture grasses to stream edge or impervious surfaces
Score2	Invasive weedy shrubs gorse, blackberry, broom, or mainly high grasses or low shrubs 0.3–2 m
Score3	Deciduous tree dominated; small tree dom. (2–5 m); or forest plantation with <25% cover of >5 m trees or natural grassy vegetation
Score4	Regenerating forest or woodlot evergreens with >25% cover sub-canopy (>5 m) trees but <10% canopy trees (>12 m); or > 25% natural grassy vegetation
Score5	Maturing forest including >10% cover canopy trees (>12 m); or 100% natural wetland or natural grassy vegetation

(European Union and European Economic Area (EEA), 2012) for the % area of the remaining land uses of three catchments.

The land use of the whole catchment upstream of the sites were also determined using the GIS dataset BKK (Agentschap Informatie Vlaanderen, 2019) for the Zwalm catchment and Corine (European Union and European Economic Area (EEA), 2012) for Arges, Fyrisån and Oslo Fjord catchments.

2.3. Model development

A Bayesian belief network (BBN) model was developed to analyze and predict the response of the ASPT index to the reach-scale and segment-scale effects of riparian conditions as well as the catchment land use. A BBN is a type of probabilistic graphical model that comprises two structural components: a causal network, often referred to as the directed acyclic graph (DAG), and conditional probability tables (CPTs) that quantify the relations among the variables in the causal network. The DAG consists of a set of nodes, representing the system's variables of interest, and a set of arrows, indicating the causal relationships among these variables. Each node has a finite set of states with probabilities defining the likelihood that a particular state is manifested. The probability distribution over the states of a node X is determined by the realized states of its preceding or parent nodes, using the conditional probability P(X|parents(X)) described in Bayes' theorem (Puga et al., 2015). These conditional probabilities are tabled in the model's CPTs and quantify the strengths of the relationships between the network's variables. A detailed model description and statistical background can be found in Jensen and Nielsen (2007).

The causal relations were defined between ASPT and the reach-scale and segment-scale predictors of riparian condition and catchment land use, detailed above in Section 2.2. Subsequently, the variables were organised in a causal network. A multi-scaled approach was implemented in the model, i.e. variables at different spatial scales were considered. The subcatchment-scale variable represents the dominant land-use distribution (%) in the full upstream catchment of the site. The segment-scale variables consist of the average riparian width of trees (m) and percent area of trees in a polygon of 300 m upstream of the sampling sites with 50-m width on each stream bank as well as the ASPT upstream of the sites. However, the upstream ASPT of a site was indicated as a missing observation if there was no direct upstream site that was sampled. The reach-scale variable consists of the buffer vegetation. The CPTs for each node were populated based on the collected field data with 122 observations (after removing 9 inconsistent data) using Netica's (Norsys Software Corporation, 2017) expectation-maximization (EM) algorithm (Gupta and Chen, 2011).

2.3.1. Thresholds

The ASPT at each site is expressed in three discrete ecological condition categories: good, moderate, and bad (Table 2). The land use of each site was categorized based on the most dominant land use category: grassland (or pasture) interlaced with residences, forest and agriculture (i.e. arable). To categorize the mean riparian width of trees and the area of trees, we plotted a scatter plot of the two variables as a function of ASPT with a line of best fit. We identified the ASPT score where a sudden change of line direction was observed. These scores were slightly adjusted so that the CPTs of the

Table 2
ASPT scores and water quality classes based on Ganguly et al. (2018) and (Ochieng et al., 2020).

Water quality category	ASPT score	BBN states
Waters with excellent quality	>5.4	Good
Waters with good quality or no obvious distortions	4.8–5.4	
Waters with regular quality, potentially eutrophic	4.3–4.8	Moderate
Waters with poor quality	3.6–4.3	Bad
Waters with bad quality	3.0–3.6	

ASPT node were optimally trained. As a result, the mean tree width was categorized into 0–20 m (low), 20–40 m (medium), and 40–100 m (high). The percent area of trees was categorized into 0–25% (low), 25–40% (medium), and 40–100% (high).

2.4. Model evaluation

2.4.1. Sensitivity analysis

The Netica software (Norsys Software Corporation, 2017) is an easy-to-use program for developing BBNs and was used to calculate the sensitivity of the ASPT node to findings in all other nodes of the network. Sensitivity analysis measures the degree to which a model variable influences the variable of interest within the model (Marcot et al., 2006; Sun and Müller, 2013), which is quantified through variance reduction. A higher variance reduction value indicates a higher influence on the target variable of the network. Sensitivity analysis identifies important variables within the network and can help to assess the behaviour of the model.

2.4.2. Model validation

The model was separately tested by each of the country's data to evaluate the applicability of the model in each country using three performance metrics: Cohen's kappa, correctly classified instances (CCI), and spherical payoff (SP).

Cohen's kappa (κ) is a descriptive statistics to quantify the agreement between two raters (Cohen, 1960). A Cohen's kappa value of less than 0 indicates less than chance agreement, 0.01–0.20 indicates slight agreement, 0.21–0.40 indicates fair agreement, 0.41–0.60 indicates moderate agreement, 0.61–0.80 indicates substantial agreement, and 0.81–0.99 indicates almost perfect agreement (Viera and Garrett, 2005). A Cohen's kappa value above 0.4 is considered to indicate a reliable model (Dakou et al., 2007).

CCI is commonly used to evaluate the performance of ecological models (Everaert et al., 2011; Goethals et al., 2007). CCI is calculated by the number of correctly classified instances divided by the total number of observations in the test dataset (Kohavi and Provost, 1998). A CCI that exceeds the no-information rate (i.e. percentage of the largest class in the training set) can be deemed acceptable (Kuhn and Johnson, 2013). In our study, the no-information rate was 80%. The limitations of CCI as a model performance metric include the index's inability to differentiate between small and large class disagreements and its inability to take into account the uncertainties associated with the predictions of a BBN.

SP is a performance metric that accounts for prediction uncertainty while evaluating model performance (Marcot et al., 2006). SP is represented by Eq. (1) where n is the number of cases in the test file, P_{ic} is the predicted probability of the correct state for case i, P_{ij} is the predicted probability of state j for case i and m denoting the total number of states of the target variable. SP ranges from 0 to 1, with higher values denoting better model performance (Norsys Software Corporation, 2013).

$$SP = \frac{\sum_{i=1}^{n} \frac{P_{ic}}{\sqrt{\sum_{j=1}^{m} P_{ij}^2}}}{n} \tag{1}$$

2.5. Model simulations

In each land use type, 18 scenarios were formulated as a basis for model simulations (Table 3); that is, model simulations were performed by setting

Table 3

List of scenarios.

Scenario	Tree width node	Area trees node	Buffer vegetation node
1	High		
2	Low		
3	High	High	
4	High	Low	
5	Low	High	
6	Low	Low	
7	High	High	Score 5
8	High	High	Score 3
9	High	High	Score 1
10	High	Low	Score 5
11	High	Low	Score 3
12	High	Low	Score 1
13	Low	High	Score 5
14	Low	High	Score 3
15	Low	High	Score 1
16	Low	Low	Score 5
17	Low	Low	Score 3
18	Low	Low	Score 1

Fig. 3. Graphical representation of the sensitivity analysis results of the Bayesian Belief Network (BBN) model represented as percentage variance reduction of the target variable average score per taxon (ASPT).

a 100% probability for the corresponding state of a given node indicated in Table 3 in each scenario. For instance, the state "high" of the *tree width* node was set to a probability of 100% in Scenario 1, while a probability of 100% was set for the state "high" of the *tree width* and *area trees* nodes and state "Score 5" of the *buffer vegetation* node in Scenario 7. Additionally, each land use type was indicated by setting a 100% probability for a given land use type (i.e. agriculture, grassland or forest). Subsequently, the probability distribution of the ASPT node was recorded after the simulation of each scenario. These model simulations provided information on the effect of riparian conditions at different scales on the ecological condition, expressed as ASPT.

3. Results

3.1. The BBN model

The model consisted of 6 nodes with downstream ASPT as the target variable. Three spatial scales of riparian variables are implemented in the model: subcatchment, segment and reach scale (Appendix A). The model indicated that 12.9%, 21.2% and 65.9% of the sites had bad, moderate and good ecological water quality, respectively (Fig. 2). Seventy-six percent of the upstream sites had good ecological water quality. Seventy-five
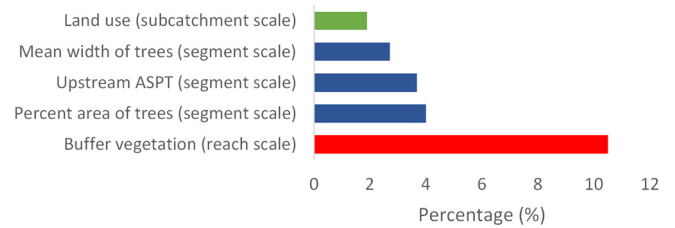
percent of the sites were dominated by forest land use. More sites have high mean width of trees while most sites have approximately the same percentage of low and high area of trees. About 50% of the sites were classified as score 2 and 5 in terms of reach-scale buffer vegetation.

3.2. Model evaluation

Reach-scale riparian variables strongly influenced the ASPT score (Fig. 3). This was followed by the segment-scale variables: percent areas of trees, upstream ASPT score and mean width of trees. The subcatchment land use had the least influence on the ASPT score. Validation by country revealed an acceptable Cohen's kappa mean value of 0.41 and correctly classified instances (84.5%). Among the case study catchments, the Zwalm catchment (Belgium) had a very good Cohen's kappa score (0.75) followed by the Arges (Romania) with a score of 0.47 (Table 4, Tables S1–2). ASPT classes were poorly predicted in the Norwegian and Swedish case study catchments. For both case studies, the model incorrectly classified sites with moderate and bad ASPT classes into good class (Tables S3–4). The spherical payoffs among the case studies were comparable.

3.3. Model simulations

The model simulations suggest that grassland and agricultural subcatchment-scale land use follow similar patterns with slight differences in the probability distribution of ASPT states (Fig. 4a–b). Simulations on forest-dominated land use showed a higher probability of a good ecological state in comparison to the other dominant land uses (Fig. 4c). Scenario 10 indicates equal probability distribution of the ASPT states, implying
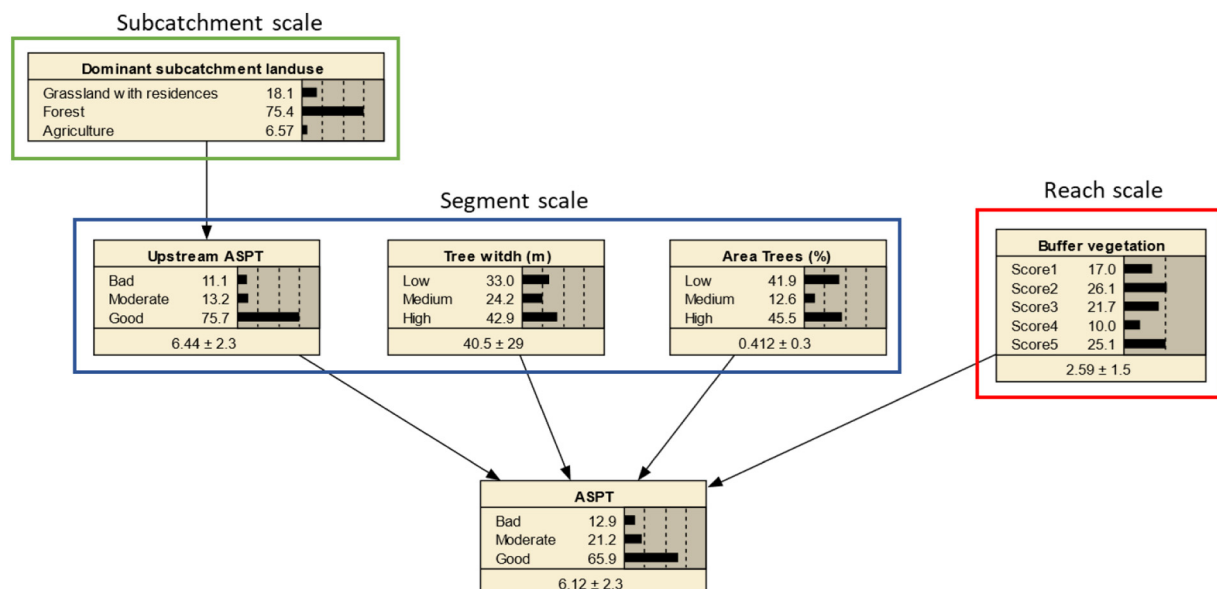

Fig. 2. BBN model to predict the ecological condition expressed as average score per taxon (ASPT) in the four European catchments.

Table 4
Model validation per country.

	CCI (%)	Cohen's kappa	Spherical payoff
Sweden	79.3	0.21	0.84
Romania	92.6	0.47	0.89
Norway	81.2	0.19	0.89
Belgium	84.8	0.75	0.90
Mean	84.5	0.41	0.88
Standard deviation	5.9	0.26	0.03

uncertainty of model predictions. This is due to the absence of an observation in the data with wide tree area and reach-scale buffer vegetation classified with score 5, that is, this specific observation does not exist in any of the sampled locations. Reach-scale buffer vegetation of score 3–5 generally results in the highest probability of a good ASPT score (Scenario 8, 11, 13, 14 and 16). However, the highest probability of a good ASPT state was also attained in a riparian zone with reach-scale buffer vegetation of score 1 but with a very wide and large area of trees at the segment-scale area (Scenario 9). In contrast, a site with a narrow width of riparian trees and a small area of trees with score 1 predicts a high probability of a bad ASPT score (Scenario 18). Low probability of good ASPT was observed in narrow width of riparian trees and a small area of riparian trees in combination with a reach-scale buffer vegetation of score 3 in a grassland- and agriculture-dominated land use (Scenario 17). These sites are more likely classified as bad or moderate quality class. Riparian zones with a wide width of riparian trees and a large area of riparian trees predict high chances of obtaining a good ASPT class (Scenario 3, Fig. S2). In contrast, riparian zones with a narrow width of riparian trees and a small area of riparian trees predict high chances of a bad ASPT class (Scenario 6, Fig. S2).

4. Discussion

4.1. Model outcome

Our study indicates that reach-scale riparian attributes, particularly the vegetation condition had the strongest effect on ASPT among the variables considered while the segment-scale riparian variables and the subcatchment-scale land use had a moderate and the low influence on ASPT, respectively. The model outcome generally followed similar patterns as observed in previous studies, i.e. ecological condition is positively related to the quality and extent (e.g. width, area) of the riparian vegetation (Burdon et al., 2020; Damanik-Ambarita et al., 2018; Gericke et al., 2020). Based on our results, it can be inferred that ecological condition is enhanced when the reach-scale riparian vegetation is at least deciduous tree dominated; small tree dominated (2–5 m); or forest plantation with <25% cover of >5 m trees or natural grassy vegetation, and when the area of riparian trees is large (>40%) or riparian width of trees is wide (>40 m). Furthermore, the results of our model imply that a minimum riparian vegetation score of 3 is required for all stream sections to achieve a high probability of good ecological condition. Other studies, akin to our investigation, have documented the benefits of riparian forest on aquatic invertebrates and the underpinning mechanisms. Riparian forest buffers retain nutrients and reduce soil erosion (Blankenberg and Skarbovik, 2020; Groh et al., 2020; Singh et al., 2021), and regulate temperature (Reiter et al., 2015; Singh et al., 2021) which are beneficial to aquatic organisms (Collier and Smith, 2000; Quinn et al., 2004; Vought et al., 1995). However, the positive effects of riparian vegetation can be overruled by other factors (e.g. presence of wastewater) that are not included in our model (Damanik-Ambarita et al., 2016; Mercado-Garcia et al., 2019; Musonge et al., 2020; Mutinova et al., 2020). In our study, we only focus on riparian attributes as the aim was to simulate the effects of riparian variables on the ecological condition. Furthermore, due to the limitations of the BBN model and the data, it is challenging to add additional nodes directly connected to the ASPT node. On the other hand, keeping the model simple facilitates the understanding of model simulations and output.

4.2. Strengths and limitations of the model

The model developed in this study is relatively simple in terms of structure and number of input variables. Despite this, the model was able to implement various simulations which allow the understanding of the effect of riparian conditions on the ecological condition. The input variables in the model were also selected so learners could potentially comprehend these variables easily and be able to estimate the ecological condition based on observations in their study area. That is, one can conveniently predict the ecological conditions based on ASPT quality classes at a given site, given the riparian conditions and the dominant land use. Incorporating difficult-to-assess variables in the model will most likely be challenging for the learners to understand. For instance, although the overall riparian condition score (e.g. Riparian Condition Index, cf. Burdon et al. (2020)) provides an overall indication of the reach-scale riparian quality, it cannot be directly estimated by learners as it consists of 13 riparian attributes such as shading of water, buffer width, buffer intactness, land slope and vegetation composition. In this respect, keeping the model simple is potentially advantageous for learning purposes (Allison and Tharby, 2015; Carroll, 1999). Model simplicity facilitates the straightforward interpretation of model simulations and predictions, enabling effective learning (Allison and Tharby, 2015; Carroll, 1999; Fink, 2013; Krumsieg et al., 1996).

The number of nodes in the BBN model and states in each node are limited by not only the amount of data but also the number of instances containing a combination of different parent states. It is however possible that the combinations of certain states are rare within the catchments. For example, it is uncommon to observe the presence of an excellent reach-scale vegetation quality (i.e. score 5), a large area and narrow width of riparian trees in the reach-scale area. The absence of certain instances or observations in the data causes uncertainties in the model predictions (e.g. Scenario 10). On the other hand, as these instances are rarely occurring in the case study sites, the predicted outcome is not crucial. Nevertheless, to improve the model's predictive performance, a large and diverse dataset is needed to populate the conditional probability table (CPT). The dataset must not only contain a high number of instances/observations but also should comprise an adequate number of instances to train every parent state combinations in the CPTs (Landuyt et al., 2013). Cain (2001) recommended having at least 20 instances for all parent state combinations in the CPTs. Thus, developing a more accurate model with a large number of states and nodes might require a large dataset not only with a large number of observations but also a sufficient number of observations to train every parent state combinations in the CPTs.

We recommended using the model only in the Belgian and Romanian catchments, and that slight caution is advised when applying the models to the Norwegian and Swedish catchments. To improve the predictive performance of the model for the Norwegian and Swedish sites, the model might need to be trained with additional data from both case studies. For example, an additional node to accommodate the local-specific conditions might increase model performances. The Norwegian case study catchment has significant urban areas downstream of the catchment which may have played a role in the model's predictive performance. Specifically, some of the Norwegian sites were heavily polluted while having a good riparian condition (Kupilas et al., 2021; Mutinova et al., 2020), which potentially truncated the positive link between riparian vegetation and ASPT in our models. Specifically, Kupilas et al. (2021) suggested that the positive effect of riparian vegetation on fish abundances seemed to be limited by other factors, as a number of sites with a good riparian condition had low fish densities, or, in some cases, no fish present. They expected that other human impacts aside from urbanization, such as source pollution interferes with, and, in some cases, completely disrupts, stream-riparian buffer interactions, thereby limiting their potentially positive effects on fish populations. On the other hand, the Swedish catchment had several features that could affect model performance. The intermittent flows of the forested reference streams during the summer preceding sampling might partly explain why these sites deviate from the expected ecological condition (Burdon et al., 2020). Another factor is that the model may have overpredicted the results
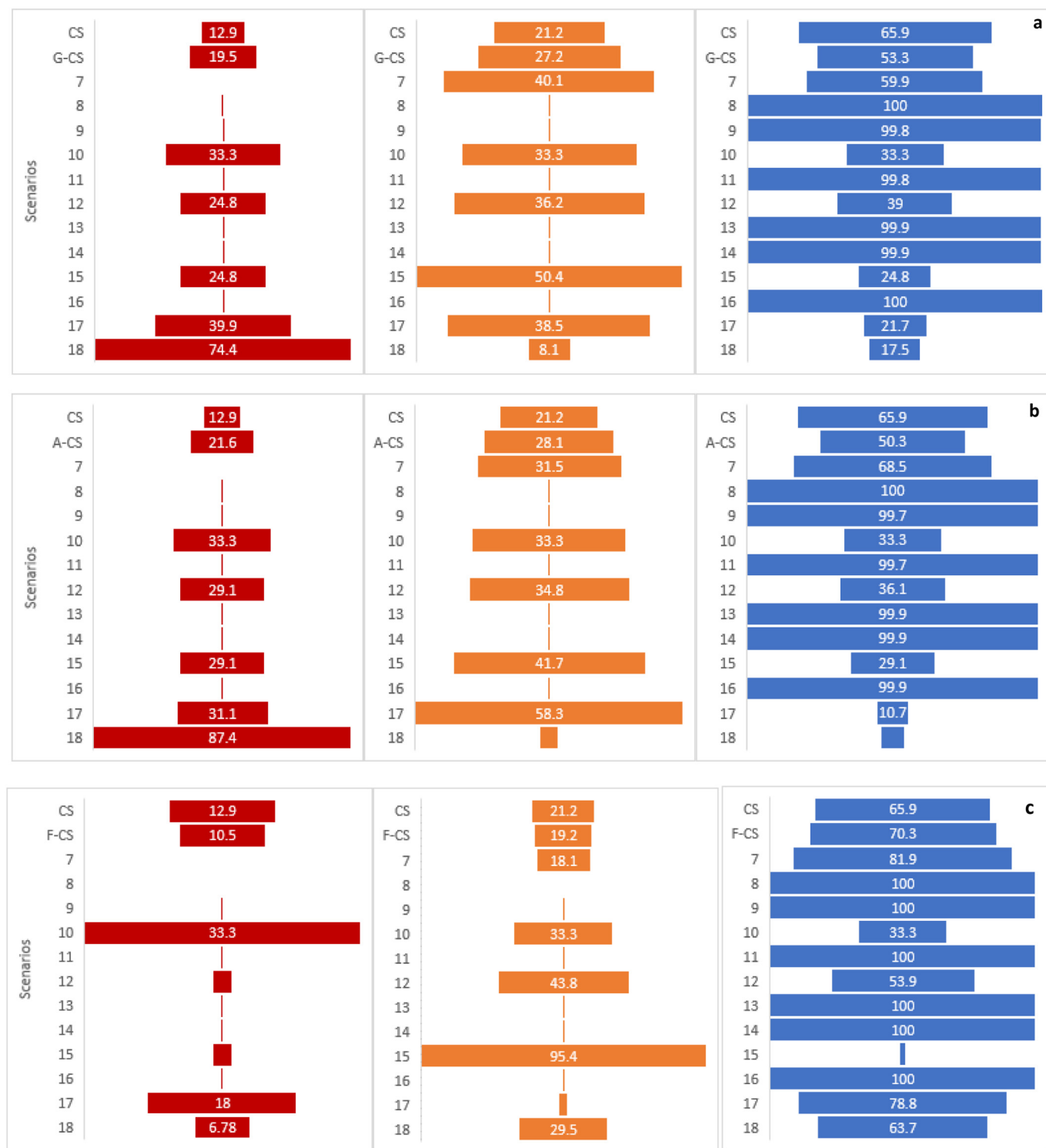
Fig. 4. Model simulations for Scenarios 7–18 for grassland with residences (a), agriculture (b) and forest (c) with current conditions (CS), current conditions for grassland with residences, agriculture and forest-dominated land use (G-CS, A-CS, F-CS, respectively). Red, orange and blue bars represent the probability of ASPT with bad, moderate and good classes, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

due to the large forest areas, thus underestimating the local impact of agriculture and overpredicting the ASPT scores in many sites.

The model was developed to assess and predict the responses of a macroinvertebrate-based index on the different riparian attributes at varying scales as proof of principle and used ASPT to demonstrate the principle. Nevertheless, responses to chemical indicators such as nutrients could provide useful information to stakeholders. In this context, the model can be reapplied to other variables such as nutrients across catchments. However, developing this model might be challenged by the fact that relevant chemical variables may differ among case study catchments due to differences in type of sources and loads of these stressors (Hering et al., 2015). For instance, the downstream Norwegian streams are heavily impacted by urbanization (Kupilas et al., 2021; Mutinova et al., 2020). The Belgian case study catchment, although is mainly dominated by agriculture-pasture land use,

is interlaced with residences in which about 40% of the untreated wastewaters are directly discharged into the streams (Boets et al., 2021; Forio et al., 2020a). The Swedish case study catchment, on the other hand, is moderately impacted by agricultural activities (Burdon et al., 2020; Sargac et al., 2021). Lastly, the Romanian case study catchment is least impacted by stressors in comparison to all case study catchments (Burdon et al., 2020; Popescu et al., 2021). In this respect, a catchment-specific model might be needed to assess the responses of chemical variables on the different riparian attributes.

One of the disadvantages of the model is the use of discrete values, often resulting in information loss (Aguilera et al., 2010; Landuyt et al., 2013). One option is to increase the number of states within a node; however, this may lead to a large conditional probability table (CPT) and the presence of missing data in many or some parent state combinations in the CPTs. This is particularly the case in the BBN model developed in our study. Adding more states within the nodes only resulted in additional untrained parent state combinations in the CPTs, resulting in poorer model performance (Uusitalo, 2007). Likewise, connecting additional nodes in the ASPT node will result in bulky CPTs which will again lead to additional unlearnt state combinations. The BBN model developed in our study is to some extent limited by the data used to train the CPTs. To improve model performance, the model should be trained with not only data with a high number of instances but also with a sufficient number of instances in each parent state combination.

4.3. BBN model as a learning tool

The simulations in the developed BBN model can provide information on the changes in ecological condition as a response to the riparian conditions and dominant land use. Thus, learners such as stakeholders can perform queries and be able to obtain different types of inferences: diagnostic and predictive (Fig. S3). The BBN model can be run in a diagnostic mode by inserting the evidence in the output node and indicate the causes (see Fig. S3a). On the other hand, when the evidence is inserted in one of the input variables of the models, a predictive mode is run (see Fig. S3b), providing effects of input changes (Landuyt et al., 2017). The simulations in our study implement a predictive mode. These queries allow the learners to determine the causes or effects of certain conditions through diagnostic or predictive inferences, respectively, which enhances their understanding of the effects of riparian vegetation.

Information on model uncertainty is paramount for model users and learners to understand the uncertainties associated with a particular scenario and ultimately management strategies. Notably, quantitative indication of uncertainties is incorporated in the BBN model and these values are indicated in various ways (Landuyt et al., 2015). As an illustration, we use Scenario 3 for the land use type grassland with residences (SI Figs. 2, 4a). In this case, the expected ASPT value was 6.3 (standard deviation was 2.2) indicating good quality. However, this standard deviation is less informative because the distribution of the ASPT node is skewed. Another quantification of uncertainty is through the quantification of the probability of the most probable state. The most probable state (i.e. good quality) has a 70.5% probability across all case study sites in this case. This information indicates that Scenario 3 provides 70.5% certainty of good ecological condition. In contrast, Scenario 4 for the land use type grassland with residences (SI Figs. 2, 4b) has a 45.6% probability of the most probable state (i.e. good quality).

One of the main advantages of the model is the short simulation time. It takes less than a second to obtain results from each model simulation. Users or learners, in general, prefer models that provide fast outcomes (Cheng et al., 2014; Han et al., 2018; Mouton et al., 2009). Furthermore, the model does not require additional data to perform simulations in comparison to other model types (Grützner, 1996).

The model was developed as a potential learning tool. According to Sterman (1994), effective learning methods must include tools that evoke participants' knowledge and simulation tools that improve scientific reasoning skills. Moreover, using these tools in stakeholder workshops and

dialogues is beneficial in achieving the learning goals (Pahl-Wostl, 2007). As the involvement of stakeholders has been proven valuable in water management (Tengberg et al., 2021), these tools contribute to the success of water protection, preservation and restoration. The model developed in our study is potentially valuable as a learning tool because it provides evidence-based learning outcomes, is relatively simple, interactive and is therefore engaging, which are useful in stakeholders workshops (Allison and Tharby, 2015; Carroll, 1999; Fink, 2013). Furthermore, the model provides information on the current environmental issues, raising stakeholders' awareness of environmental problems. Nevertheless, this study is only a first step and the model itself needs to be tested by stakeholders.

Singh et al. (2021) stressed the significance of stakeholders' participation in managing riparian zones. It is therefore of utmost importance that they are involved in the decision-making process (Cansino-Loeza and Ponce-Ortega, 2021) and the learning tools can be used to inform stakeholders of possible decision outcomes. However, stakeholders often have varying interests which are based on either economic, environmental or socio-cultural objectives (Cansino-Loeza and Ponce-Ortega, 2021). In addition, their decision preferences are generally influenced by their vested interest. A learning tool that provides trade-offs between these objectives is valuable in multi-stakeholders learning dialogues. Our model only focuses on one objective, that is, ecological condition. The model setup might be less interesting for stakeholders who are more concerned with outcomes related to economic and socio-cultural objectives. Thus, a trade-off tool is valuable for multi-stakeholders learning dialogues. The Bayesian belief network model can potentially be set up as a trade-off tool (Forio et al., 2020b) by adding other target nodes related to economic or socio-cultural objectives. In our study, the model was only focused on assessing the effect of riparian attributes on the ecological condition (i.e. the target node in our model which was expressed as ASPT classes). However, the model can be adapted to provide trade-offs between different objectives by restructuring and collecting the needed data for populating the CPTs.

5. Conclusions

We constructed a Bayesian Belief Network (BBN) model to simulate and assess the effects of riparian vegetation on stream macroinvertebrates, specifically on the Average Score Per Taxon index (ASPT), indicating ecological condition (Fig. 1) as a proof of principle. Among the riparian attributes at different spatial scales, the reach-scale attributes had the most influence on the ecological condition (i.e. expressed as ASPT), followed by the segment-scale attributes and lastly the subcatchment-scale attributes. The model simulations indicated that a higher probability of ecological condition, was achieved when the reach-scale riparian vegetation was at least deciduous tree dominated; small tree dominated (2–5 m) or forest plantation with <25% cover of >5 m trees or natural grassy vegetation. The main advantage of the Bayesian belief network (BBN) model as a learning tool is its simplicity, which allows the straightforward interpretation of model simulations and predictions, facilitating the learning process. Furthermore, key characteristics of the BBN model are its fast simulation, interactivity and ability to explicitly indicate uncertainty of model outcomes, stimulating learning. Limitations of the model are the use of discrete values, potentially resulting in the loss of information, and the challenges in adding more nodes in the BBN model and states in each node as these additions require not only more observations in a dataset but also more instances for all parent state combinations. Despite these drawbacks, the model is potentially a valuable learning tool to support stakeholders' workshops and dialogues in water management implementation and synthesis.

CRediT authorship contribution statement

Marie Anne Eurie Forio: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Francis J. Burdon:** Methodology, Formal analysis, Validation, Investigation, Data curation, Writing – review & editing. **Niels De Troyer:** Investigation, Resources, Writing – review &

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.152146.

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