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Climate change, cyanobacteria blooms and ecological status of lakes: A Bayesian network approach

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ABSTRACT

Eutrophication of lakes and the risk of harmful cyanobacterial blooms due is a major challenge for management of aquatic ecosystems, and climate change is expected to reinforce these problems. Modelling of aquatic ecosystems has been widely used to predict effects of altered land use and climate change on water quality, assessed by chemistry and phytoplankton biomass. However, the European Water Framework Directive requires more advanced biological indicators for the assessment of ecological status of water bodies, such as the amount of cyanobacteria. We applied a Bayesian network (BN) modelling approach to link future scenarios of climate change and land-use management to ecological status, incorporating cyanobacteria biomass as one of the indicators. The case study is Lake Vansjø in Norway, which has a history of eutrophication and cyanobacterial blooms. The objective was (i) to assess the combined effect of changes in land use and climate on the ecological status of a lake and (ii) to assess the suitability of the BN modelling approach for this purpose. The BN was able to model effects of climate change and management on ecological status of a lake, by combining scenarios, process-based model output, monitoring data and the national lake assessment system. The results showed that the benefits of better land-use management were partly counteracted by future warming under these scenarios. Most importantly, the BN demonstrated the importance of including more biological indicators in the modelling of lake status: namely, that inclusion of cyanobacteria biomass can lower the ecological status compared to assessment by phytoplankton biomass alone. Thus, the BN approach can be a useful supplement to process-based models for water resource management.[1]

1. Introduction

Eutrophication of lakes due to nutrient run-off from the catchments is a major challenge for environmental management world-wide (Schindler, 2012). The consequences of eutrophication for aquatic ecosystem include harmful cyanobacterial blooms (reviewed by Merel et al., 2013) and altered fish communities (Jeppesen et al., 2010). Climate change is expected to reinforce the problems with eutrophication due to i.a. higher water temperature and increased nutrient run-off (Jeppesen et al., 2009). In particular, altered conditions in lakes due to climate change can favour cyanobacteria over other phytoplankton species (Paerl and Huisman, 2008). Therefore, climate change may counteract the effects of mitigation measures for nutrient enrichment, and make it more difficult to obtain management targets for lakes.

Modelling of aquatic ecosystems has been used widely to support water management, and to predict effects of altered land use and/or climate (Gal et al., 2014; Mooij et al., 2010; Recknagel et al., 2014; Trolle et al., 2012). Process-based models for catchments and lakes typically aim at predicting changes in water chemistry (e.g. phosphorus, nitrogen and oxygen) or physical conditions (e.g. transparency, thermal stratification) (e.g., Jackson-Blake et al., 2015). Many lake models also predict chlorophyll *a* (chl-a), which is a proxy of phytoplankton biomass (e.g. Saloranta and Andersen, 2007), and a traditional indicator of water quality. However, the European legislation for water management (the Water Framework Directive – WFD EC, 2000) requires use of more advanced biological indicators for the assessment of ecological status of water bodies. The key indicators of lake eutrophication should represent not only phytoplankton biomass, but also other aspects of the plankton community. Many European countries have therefore included intensity of cyanobacterial blooms as an indicator in their assessment systems (Poikane et al., 2015).

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[1] Abbreviations: BN = Bayesian network; Chl-a = chlorophyll *a*; WFD = Water Framework Directive.

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The relationships between climatic variables, nutrients and cyanobacteria have been thoroughly studied by experiments (e.g. Davis et al., 2009), long-term monitoring (e.g. Nõges et al., 2010) and analysis of time series (e.g. Huber et al., 2012; Wagner and Adrian, 2009) and of multi-lake data sets (Carvalho et al., 2013; Rigosi et al., 2015). However, only a few process-based lake models have so far incorporated such knowledge, according to a recent review (Elliott, 2012). These models are PROTECH (Elliott, 2010; Elliott and May, 2008), PCLake (Mooij et al., 2007), DYRESM-CAEDYM (Trolle et al., 2011), CLAMM (Howard and Easthope, 2002), PROBE & BIOLA (Arheimer et al., 2005) and PROTBAS (Markensten and Pierson, 2007). For example, an application of PROTECH to Esthwaite Water (a relatively shallow English lake), predicted that under scenarios of increased water temperature and decreased flushing rate, cyanobacteria abundance increased, comprised a higher proportion of the phytoplankton and had a longer duration (Elliott, 2010). However, lake models that comprise cyanobacteria have not yet been used in efforts to assess ecological status (*sensu* WFD), to our knowledge.

In this study, we apply a Bayesian network (BN) modelling approach to link future scenarios of climate change and land-use management to ecological status, incorporating cyanobacteria biomass as well as other indicators. A BN provides a framework for summarising large amounts of information (e.g., from process-based models) and for integrating different types of information. It also provides a tool for displaying effects of different scenarios, where the change in each component can be easily visualised. The probabilistic output can readily be interpreted as the risk of failing a certain management target and support decision making. For these reasons, BNs have been increasingly used in environmental modelling (reviewed by Aguilera et al., 2011), and applied in the context of e.g. risk assessment (Lecklin et al., 2011; Moe, 2010), resource management (Barton et al., 2012) and ecosystem services (Landuyt et al., 2013). There are many examples of BN models addressing water resource management (Barton et al., 2005; Borsuk et al., 2004; Castelletti and Soncini-Sessa, 2007; Keshtkar et al., 2013; Martín de Santa Olalla et al., 2007; Molina et al., 2010; Ticehurst et al., 2007; Varis and Kuikka, 1999). Here, we focus on the assessment of ecological status classes of water bodies sensu WFD (High, Good, Moderate, Poor and Bad). The BN methodology typically predicts the probability of different states, and can therefore be particularly suitable for this purpose (Lehikoinen et al., 2014).

As a case study for this BN model we have selected Lake Vansjø in South-East Norway. This lake has a history of high levels of phosphorus and phytoplankton biomass, and has experienced several cyanobacterial blooms (Haande et al., 2011). The lake has been monitored since 1980, and has been subject to modelling by process-based models (Couture et al., 2014; Saloranta and Andersen, 2007) as well as Bayesian networks (Barton et al., 2014 (basin Vanemfjorden); Barton et al., 2008 (basin Storefjorden)). However, this is the first effort to incorporate cyanobacteria in a model for Lake Vansjø, and to link the model to climate change scenarios. The objective of the study is (i) to assess the combined effect of changes in land use and climate on the ecological status of a lake, considering both physico-chemical indicators and phytoplankton, including cyanobacterial blooms, and (ii) to assess the suitability of the BN modelling approach for this purpose.

2. Material and methods

2.1. Study site

The Vansjø-Hobøl catchment (area 690 km^2), also referred to as the Morsa catchment, is located in south-eastern Norway. The Hobøl River drains a sub-catchment of ca. 440 km^2 into Lake Vansjø, which is the catchment's main lake. Lake Vansjø has a surface area of 36 km^2 and consists of several sub-basins, the two largest being the deeper, siliceous basin Storefjorden (eastern basin) and the shallower, calcareous basin Vanemfjorden (western basin). In addition, there are six smaller sub-basins which together represent less than 15% of the lake surface area. The Storefjorden basin water flows into the Vanemfjorden basin through a shallow channel. In this study we have used data from the most impacted basin, Vanemfjorden (national water body code 003-291-L, 59.443°N, 10.755°E). This basin is shallow (mean depth is 3.8 m and maximum depth is 19.0 m) and the water column does not stratify stably. The surface area is 12 km^2, the residence time is 0.21 year and the water body is humic. The phytoplankton growth in this system is probably limited by light, because of the high humic content in the lake and hence low transparency in the water column (Skarbøvik et al., 2014).

The current physico-chemical and ecological status of Vanemfjorden are moderate (Haande et al., 2011), hence it fails the WFD's requirement of good ecological status (EC, 2000). However, the WFD also requires that the current status of a water body should not be worsened. We are therefore also interested in the risk of deterioration from moderate to poor status of Vanemfjorden.

2.2. Data and other information

2.2.1. Scenarios

The future scenarios apply for the period 2030–2052 (i.e., 40 years after the reference period 1990–2012) and are described in detail by Couture et al. (2014). In this study we have used the outcome of a climate scenario, **"Had"**: The global climate model HADCM3 combined with the regional climate model (RCM) HADRM3. This scenario predicts changes in both yearly mean air temperature (+1.6 °C) and yearly precipitation (+78.8 mm). Daily resolution scenario data for surface air temperature and precipitation were derived from a sub-set of the RCM simulations and implemented by scaling the observed weather (1990–2012). The observed temperatures were changed to reflect the increase in both median and variance predicted by the climate models. Precipitation was scaled using a ratio of change approach, multiplying observation by the ratio of observed (1990–2012) over predicted (2030–2052) precipitation. Climate conditions during the reference period are referred to as climate **"Ref"**. The management scenarios are referred to as "**Ref"** = reference (historical data), **"Best"** = best case (water-quality focus), **"Worst"** = "worst case" (economic focus). The "Best" scenario is defined by four criteria: (1) a 10% reduction in agricultural land, which is converted to forest, (2) a 25% decrease in vegetable production, which is converted to grass production, (3) a 25% decrease in P-based fertilizer application, and (4) a 90% improvement in the P-removing performance of WWTPs. Conversely, the "Worst" scenario is defined by (1) a 10% reduction of forest cover, which is converted to agricultural lands, (2) a shift of 25% of the grass production to vegetable production, (3) an increase of P-based fertilizer application by 25%, and (4) a 25% increase in the P load of effluents from scattered dwellings and WWTPs throughout the catchment. More details on the application of these and other scenarios to the catchment and lake process-based models are given by Couture et al. (2014).

2.2.2. Process-based model output

All aspects of catchment and lake process-based modelling are described by Couture et al. (2014). In brief, the effects of the climate and management scenarios on the river hydrology and chemistry were modelled by the catchment models PERSiST (Futter et al., 2013) and INCA-P (Wade et al., 2002), respectively. PERSiST simulated daily runoff in the river system using inputs of catchment characteristics and daily temperature and precipitation time

Table 1
Overview of nodes in the Bayesian network model. Modules are defined in Fig. 2.

Module	Node name	Unit	No. of values	Node states					
				1	2	3	4	5	6
1	Management			Ref	Worst	Best			
1	Climate			Ref	Had				
1	Year			1990–1995	1996–2001	2002–2007	2008–2012		
1	Month			May	Jun	Jul	Aug	Sep	Oct
1	Season			May–Jun	Jul–Aug	Sep–Oct			
2	Irradiance	$\mu mol/m^2\,s$	251,280[a]	0–100	100–150	150–200	200–300		
2	Secchi (pred.)	m	251,280	0–2	2–2.6	2.6–5			
2	Total P (pred.)	μg/L	251,280	0–20	20–25	25–30	30–39	39–50	50–80
2	Chl-a (pred.)	μg/L	251,280	0–5	5–10.5	10.5–15	15–20	20–25	25–60
2	Temp. (pred.)	°C	251,280	0–10	10–15	15–19	19–30		
3	Secchi (obs.)	m	191	0–2	2–2.6	2.6–5			
3	Total P (obs.)	μg/L	250	0–20	20–39	39–80			
3	Chl-a (obs.)	μg/L	250	0–10.5	10.5–20	20–60			
3	Temp. (obs.)	°C	195	0–19	19–30				
3	Cyano	μg/L	103	0–1000	1000–2000	2000–6000			
3	CyanoMax	μg/L	103[b]	0–1000	1000–2000	2000–6000			
4	Status Secchi			HG	M	PB			
4	Status Total P			HG	M	PB			
4	Status Chl-a			HG	M	PB			
4	Status Cyano			HG	M	PB			
4	Status Phys-chem.			HG	M	PB			
4	Status Phytoplankton			HG	M	PB			
4	Status of lake			HG	M	PB			

[a] The number of values in Module 2 is generated by simulation of weekly values during May-Oct for 23 years with 60 different parameter sets for 6 scenarios.
[b] CyanoMax has only 9 unique values (one for each year of observation).

series. INCA-P produced daily predictions of discharge and material transport in the river (concentration of suspended solids, soluble reactive P and total P (TP)), which were then passed to the lake model. The successive effects of the scenarios on the physical conditions and the concentration of different P fractions in the lake were modelled by the process-based model MyLake (Saloranta and Andersen, 2007). In MyLake, phytoplankton has a constant C:P ratio of 106:1 and an organic-P:Chl-a ratio of 1:1, such that particulate organic P is a proxy for Chl-a (Saloranta and Andersen, 2007). The MyLake model was automatically calibrated against monitoring data from the years 2005–2012, using a probabilistic Bayesian inference calibration scheme. In this scheme each parameter was given a prior and a posterior distribution, within the framework of a self-adaptive differential evolution learning scheme (DREAM), implemented in Matlab (Starrfelt and Kaste, 2014). The MCMC algorithm was run along eight chains until convergence, monitored visually, was obtained. Four hundred iterations were saved and used to determine posterior parameter distribution. An envelope of 60 parameter sets of equal likelihood was sampled to generate a set of 60 model realisations with daily resolution for 23 years (1990–2012). The variability among these sets (median and interquartile space) was discussed by Couture et al. (2014). For the BN model, all 60 realisations of the process-based models are used as input and considered a source of uncertainty. Specifically, the following outcome of the lake model was used as nodes in the BN model (see Table 1): surface water temperature (henceforth referred to as "temperature"), Secchi depth, total P (TP) and Chl-a. Secchi depth (SD) was calculated using the light extinction coefficient (η) calculated by MyLake and the relationship $\eta = 1.7/SD$ (French et al., 1982). Temperature and concentrations were averaged for depths 0–4 m (to match the monitoring data). In addition we included surface irradiance at noon (an input variable for MyLake), to represent seasonal change in addition to temperature. For each variable, values for one day per week were selected (to match the sampling frequency of the monitoring data).

2.2.3. Lake monitoring data

The main data source for this study was the data series from Lake Vansjø, the basin Vanemfjorden (see Table 1 and Fig. 1). All data were downloaded from NIVA's monitoring database (http://www.aquamonitor.no). The following data were included in this study: water temperature (years 1993–1996, 2005–2012), Secchi depth (2000–2001, 2005–2012), total P (1990–2012), Chl-a (1990–2012) and biomass of cyanobacteria (2004–2012). Integrated water samples from 0 to 4 m were collected for the chemical and biological analyses. Only data from the months of May to October were included (following the national classification system; section 2.2.4). From 2005 all variables were measured weekly, except for cyanobacteria, which were measured bi-weekly.

In addition, the larger dataset EUREGI was used for evaluation of the model (as described in section 3.3). The EUREGI lake dataset results from the regional eutrophication survey in Norway in 1988 (Oredalen and Faafeng, 2002). The dataset includes quantitative analyses from more than 400 lakes, sampled minimum 4 times. The locations are selected in order to cover the broadest possible gradient of human influence. Parameters that typically represent eutrophication (TP and Chl-a) range over two orders of magnitude in this dataset. Eutrophic lakes are overrepresented regarding the proportion of area covered by these lakes; nevertheless, the dataset contains more oligotrophic than eutrophic lakes. Almost 75% of the lakes are clear-water lakes, of which the majority is calcium-poor lakes. The remaining 25% are humic lakes; this group has equal proportions of calcium-poor and calcium-rich lakes. In total 599 samples from EUREGI were used in this study; samples that comprised values for water temperature, Chl-a and cyanobacteria.

2.2.4. National classification system for lakes

The status assessment in this study is based on the main eutrophication indicators and their combination rules in the Norwegian lake classification system,[2] with status class boundaries defined for the lake type L-N8 (lowland, large, shallow, siliceous/moderate alkalinity, humic). Three of the indicators in the classification system were obtained from MyLake model predictions, and included in this study: seasonal averages of

[2] http://www.vannportalen.no/Revidert_klassifiseringsveileder140123_VZIS-.pdf.file.

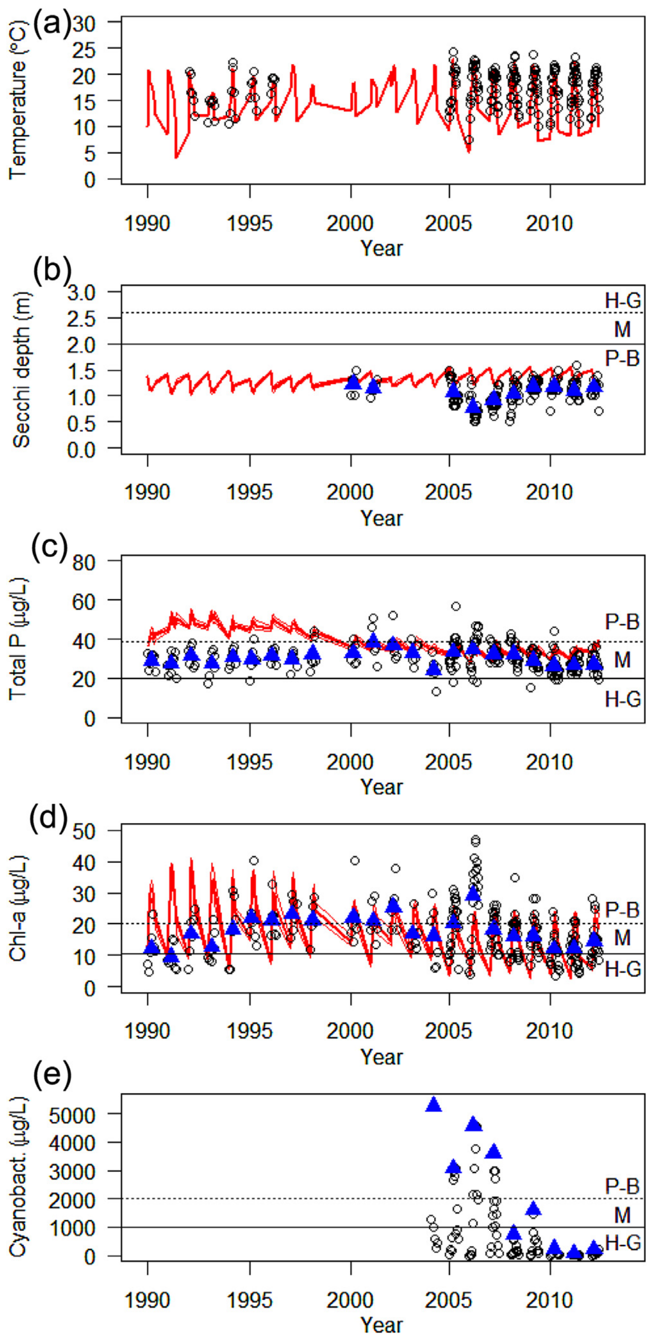

Fig. 1. Observed (open black circles) and predicted (red curves) values of (a) temperature, (b) Secchi depth, (c) total P, (d) chl-a and (e) cyanobacteria. Predicted values are median values (with 25 and 75 percentiles) of 60 runs of the process model MyLake with different parameter combinations (see section 2.1.1). (Predicted values for cyanobacteria are not available from this model). Blue triangles represent seasonal mean values for Secchi depth, total P and chl-a, and seasonal maximum value for cyanobacteria (corresponding to the node CyanoMax). Horizontal lines indicate the boundaries between ecological status classes: High-Good (H-G), Moderate (M) and Poor-Bad (P-B).

Secchi depth, TP and Chl-a. According to the classification system, physico-chemical indicators (here: Secchi depth and TP) should be combined by averaging. Phytoplankton status should in principle be assessed by four indicators: Chl-a, total phytoplankton biomass, PTI (a measure of sensitive vs. tolerant taxa; (Ptacnik et al., 2009)) and the yearly maximum of cyanobacterial biomass. All four indices can be calculated from the monitoring data, but they are all correlated, and only one can be predicted by MyLake (Chl-a). We therefore chose to include only one additional phytoplankton index in the BN, namely the yearly maximum of cyanobacteria (termed "CyanoMax"). Combined phytoplankton status should be obtained as follows: if CyanoMax have worse status than chl-a, then the two indicators should be averaged; if CyanoMax has equal or better status than chl-a, then CyanoMax should be ignored. Thus, including cyanobacteria can only result in worse or equal status of phytoplankton compared to the status determined by chl-a alone. Finally, while the overall ecological status of the lake is determined primarily by biology (here: phytoplankton), it can be compromised by physico-chemical elements.

If the status set by biology is High or Good, and the physico-chemical status is worse than the biological status, then the overall ecological status should be reduced by one class (i.e., from High to Good or from Good to Moderate). (More details are given in Appendix A). The full classification system comprises several more indicators including both physico-chemical quality elements (e.g. Total N) and biological quality elements (BQEs; macrophytes, benthic invertebrates and fish). In this study, however, we included only the indicators that could be predicted by MyLake or that could be linked to MyLake predictions with high confidence (i.e., cyanobacteria).

2.3. *Bayesian network modelling*

For constructing the BN model, we followed recent guidelines for use of BN in ecological modelling (Marcot et al., 2006; Pollino and Henderson, 2010): (1) Defining the objective of the model and its final node (here: ecological status of the lake); (2) generating a conceptual model (nodes and arrows) based on knowledge from the literature and on expert knowledge; (3) establishing the model states and quantifying the relationships. The BN model was developed and run in the software Hugin Expert, version 8 (http://www.hugin.com).

2.3.1. *Model structure*

In a BN model, each node (variable) is typically defined by a discrete probability distribution across a number of alternative states (i.e., intervals or categories). This structure enables different types of information to be linked by conditional probability tables (CPT) (see Table 2 and section 3.1). Although continuous variables may also be included in a BN with certain restrictions, this type of nodes are not considered here. All nodes with outgoing arrows are termed "parent nodes", while all nodes with incoming arrows are termed "child nodes". In a CPT, the probabilistic dependencies between a child node and its parents are defined. When the model is run, probability distribution of the child node is updated accordingly, given the states of the parent nodes, following the Bayes' theorem for conditional probability calculation (Koski and Noble, 2009). The probability distributions in the CPTs can represent the natural variability in the system as well as any other type of uncertainty concerning the relationship between the variables. In our model the main sources of variability are (1) the temporal variation in the predicted and observed time series (within the specified time intervals) and (2) uncertainty in the predictions of the process-based models that are included in the BN. The complexity of a BN grows exponentially with the number of nodes and arrows; therefore it is often desirable to limit the number of nodes (Varis and Kuikka, 1999). The computing capacity of computers have increased to the extent that even relatively complex and big networks can be built and run (Lehikoinen et al., 2013), but more complex BNs nevertheless require more data or other information than simpler ones. In this study, we aimed at including only the nodes that were necessary to (i) run the model according to selected scenarios, (ii) represent particular processes that were important

Table 2
Examples of conditional probability tables (CPT) for each module of the BN model. Each column contains the probability distribution of a child node for a given combination of states of the parent nodes. The bottom row ("Experience") contains the total count of observations for each combination of parent nodes.

(a) CPT (the first 8 columns) for Chl-a (predicted) conditional on management, years, irradiance and water temperature. The full table contains 3 (management scenarios) x 4 (year intervals) x 4 (irradiance intervals) x 4 (temperature intervals) = 192 columns.

Management	Reference							
Years	1990–1995							
Irradiance	0–100				100–150			
Temp. (pred.)	0–10	10–15	15–19	19–25	0–10	10–15	15–19	19–25
Chl-a (pred.)								
0–5	0.013	0.012	0	0	0.124	0.067	0.004	0
5–10.5	0.104	0.106	0.117	0.117	0.588	0.180	0.065	0.092
10.5–15	0.066	0.020	0.017	0.017	0.148	0.223	0.082	0.042
15–20	0.297	0.085	0.000	0.000	0.036	0.026	0.033	0.000
20–25	0.313	0.264	0.104	0.104	0.050	0.168	0.018	0.000
25–60	0.206	0.512	0.763	0.763	0.055	0.337	0.798	0.867
Experience	3015	2445	540	0[a]	420	1200	1980	480

(b) CPT for Cyanobacteria conditional on Chl-a (observed) and water temperature (observed).

Chl-a (obs.)	0–10.5		10.5–20		20–60	
Temp. (obs)	0–19	19–25	0–19	19–25	0–19	19–25
Cyano						
0–1000	1	1	1	0.923	0.333	0.323
1000–2000	0	0	0	0.077	0.333	0.290
2000–6000	0	0	0	0	0.333	0.387
Experience	20	1	22	13	3	31

(c) CPT for CyanoMax conditional on Cyanobacteria and Season.

Cyano	0–1000			1000–2000			2000–6000		
Season	May–Jun	Jul–Aug	Sep–Oct	May–Jun	Jul–Aug	Sep–Oct	May–Jun	Jul–Aug	Sep–Oct
CyanoMax									
0–1000	0.618	0.724	0.667	0	0	0	0	0	0
1000–2000	0.088	0.138	0.111	0.167	0.167	0	0	0	0
2000–6000	0.294	0.138	0.222	0.833	0.833	1	1	1	1
Experience	34	29	27	6	6	2	1	12	2

(d) CPT for Status of lake conditional on status of phytoplankton (PP) and status of physico-chemical (PC) variables. HG = High-Good, M = Moderate, PB = Poor-Bad.

Status PP	HG			M			PB		
Status PC	HG	M	PB	HG	M	PB	HG	M	PB
Status Lake									
HG	1	0	0	0	0	0	0	0	0
M	0	1	1	1	1	0	0	0	0
PB	0	0	0	0	0	1	1	1	1

[a] Assumed probability distributions inserted where no observations were available.

for the cyanobacteria and other phytoplankton and (iii) assess the effects of the scenarios on the status indicators.

A BN is usually not a dynamic model, meaning that it does not have a time dimension. Instead, the predictions of a BN can represent the probability of realising different outcomes during a specified period. The BN in our study represents the whole period for which the MyLake model was run (1990–2012). However, there has been substantial changes in the concentrations of TP and chl-a during this period (Fig. 1c and d), which could be useful to account for in the BN. We therefore included a node "Year" that divided the 23-year time span into 4 periods of 5–6 years; this way the effects of the different scenarios on water quality (i.e., the CPTs) could be estimated separately for these periods, and the BN could be run for selected periods. (The default setting of the Year node was a uniform probability distribution, corresponding to running the BN for the whole 23-year period). Moreover, a node "Month" was included to account for seasonal changes in the water quality.

The BN model developed in this study (Fig. 2) comprises four modules, corresponding to the four sources of information described above.

Module 1 contains all the parent nodes, representing the climate and management scenarios, as well as the nodes representing specific periods (years and month).

Module 2 links these scenarios to the output from the process-based models, i.e. the predicted effects on physico-chemistry in the lake.

Module 3 links these model predictions to the observed time series for a set of physical, chemical and biological variables, and furthermore provides a link from two of these variables (chl-a and water temperature) to the observed cyanobacterial biomass. In addition, the yearly maximum of cyanobacteria ("CyanoMax") is set equal to the highest observed cyanobacteria biomass across all samples in a given year. Thus, each observation of Cyano is associated with a CyanoMax from the same year, but possibly from a different month.

Module 4 links each of the physico-chemical and biological indicators to the lake classification system. This enables prediction of the probability of different status classes for each indicator as well as for the overall ecological status of the lake.

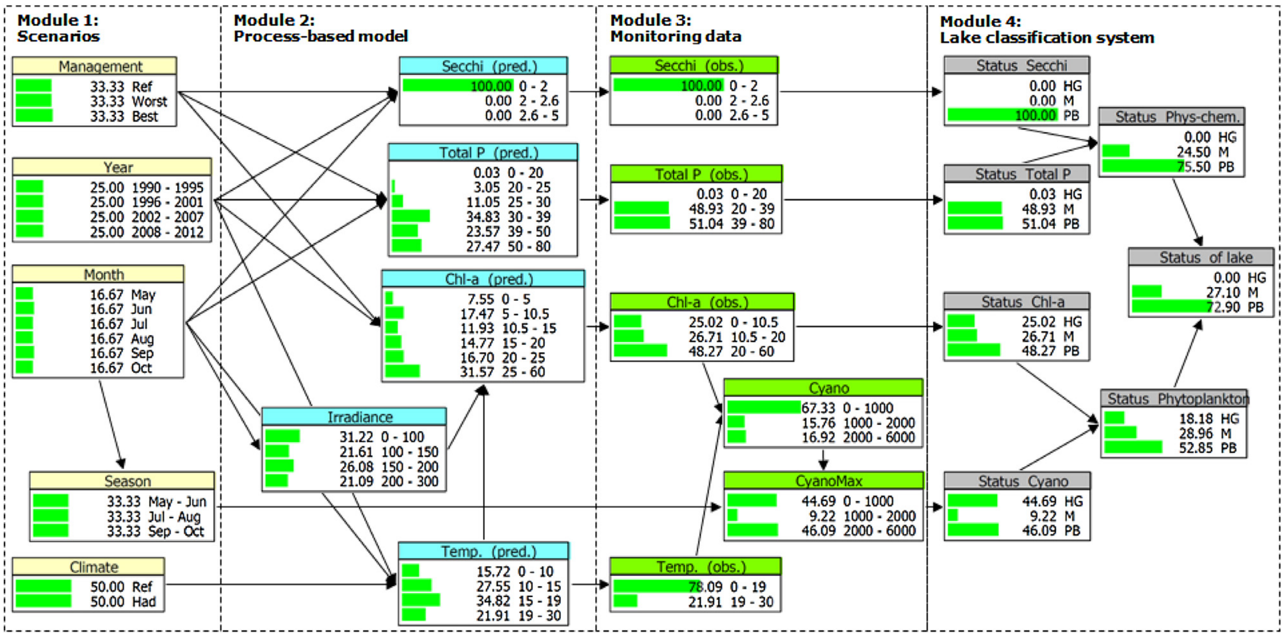

Fig. 2. Structure of the Bayesian Network (BN) model for ecological status of Lake Vansjø, basin Vanemfjorden. The model consists of four modules: (1) Climate and management scenarios (2), output from the process-based lake model MyLake; (3) monitoring data from Lake Vansjø (1990–2012); (4) the national classification system for ecological status of lakes. The prior probability distribution for each node is displayed both as horizontal bars and by percentages (the first column in each node), across the states (the second column). The set of arrows pointing to one node represents the conditional probability table for this node. Status classes: HG = High-Good (required by the WFD), M = moderate, PB = Poor-Bad.

The causal links between the nodes (i.e., the arrows and their directions) can be determined in different ways. For nodes that are based on data, it is possible to let the software estimate suggest a set of arrows and their directions given specific criteria. Nevertheless, we chose to develop the structure based on knowledge and theory about causal relationships among the nodes. For the nodes in Module 2, regression tree analyses were performed to explore which parent nodes had significant effect on the child nodes. The analyses were performed with the packages *rpart* (Therneau et al., 2015) and *party* (Hothorn et al., 2006) in the software R (R Core Team, 2015). All indicator nodes varied with year and with month. The node Management had significant effects on all indicator nodes predicted by MyLake (Secchi, TP and Chl-a). Water temperature affected Chl-a, but not Total P. The node Irradiance was included as a parent for Chl-a, because of the particular importance for phytoplankton growth. The purpose was to distinguish between effects of Irradiance and Temperature; both variables varied during the year, but only Temperature was affected by Climate. TP and Chl-a were strongly correlated, as is commonly observed in lakes (Phillips et al., 2008), and therefore both variables could have been a

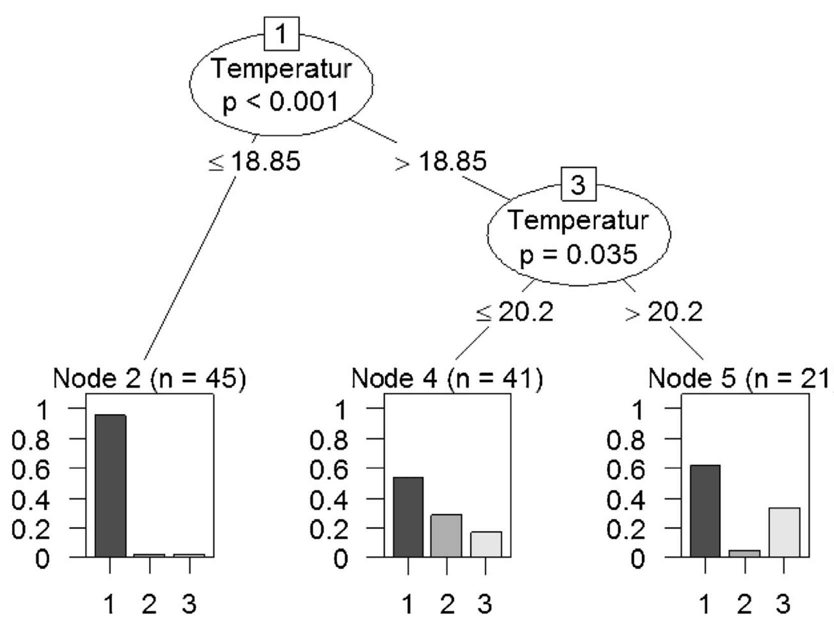

Fig. 3. Regression tree for effects of temperature on the variable CyanoMax (seasonal maximum of cyanobacteria biomass). The numbers on the branches (18.85 and 20.2) show the significant breakpoints along temperature gradient. The bar plots in each resulting node show the probability distribution of CyanoMax across the three status classes: 1: High-Good (<10.5 µg/L), 2: Moderate (10.5–20 µg/L), Poor-Bad (≥20 µg/L). n = number of observations in each node.

suitable parent node for Cyanobacteria. We chose Chl-a as the parent node, because this variable has lately been reported to be a better predictor of cyanobacteria biomass than the more commonly used TP (Ptacnik et al., 2008).

2.3.2. Node states and prior probability distributions

Continuous variables must be discretised into intervals (states) for use in discrete nodes in a BN. The number of states for each node is typically kept low, because the model complexity also grows quickly with the number of states. In this study, therefore, we tried to minimise the number of states, while still obtaining a model with sufficient sensitivity to respond to the scenarios. An overview of the states of all nodes is given in Table 1.

For all status nodes (Module 4), the five ecological status classes were lumped into three states (High-Good, Moderate and Poor-Bad). The corresponding indicator nodes in Module 3 (Monitoring data: Secchi, Total P, Chl-a and CyanoMax) were discretised into three intervals, with borders determined by the class boundaries of the national classification system (see Table A1a–d). Observed temperature was divided into two intervals, determined by a regression tree analysis (Fig. 3): A breakpoint in the effect of temperature on cyanobacteria was estimated at 19 °C (above which there was a higher probability of high cyanobacteria concentrations). For the corresponding variables predicted by MyLake (Module 2), the large amount of simulated data allowed discretisation with higher resolution: predicted Total P, Chl-a and Temperature were given 6, 6, and 4 states respectively. The states from the corresponding variables in Module 3 were used as a starting point; then the state(s) with the highest proportion of the observations were split into two or more intervals to obtain a more even probability distribution. For example, the TP state 30–39 μg/L was split into 3 intervals (20–25, 25–30 and 30–39) while the state 39–80 μg/L was split into two intervals (39–50 and 50–80). The years (Module 1) were grouped into four 5- or 6-year periods (1990–1995, 1996–2001, 2002–2007 and 2008–2012). The months were grouped into three 2-months periods in a separate node "Season" (May-June, July-August and September-October); the purpose to obtain a parent node for CyanoMax with fewer states than the Month node.

All prior probability distributions are displayed in Fig. 2 (and in Supplementary data). The prior probability distributions were defined as follows. For parent nodes representing scenarios and time intervals (Module 1), equal probability was assumed for each state. This was simply a starting point for running the model, and is not meant to represent our beliefs or knowledge. For each subsequent child node, the prior probability distribution was determined by their CPT in combination with the prior probability distributions of their parent nodes. Hence, the prior probability distributions of all child nodes throughout the BN represent all the different scenario combinations with equal probability.

3. Calculation

3.1. Construction of conditional probability tables

The discrete probability distributions in the CPTs are also obtained by different approaches in the different BN modules. Table 2 contains examples of CPTs for each module, while all CPTs are included in Supplementary data.

In Module 2 (Process-based model output), the conditional probability distribution of each child node was therefore calculated as the frequency distribution of this variable across each of its parent nodes in the reference scenario for both climate and management, for all 60 realisations of MyLake pooled together. For example, for predicted chl-a, the probability of the lowest chl-a interval (0–5 μg/L) under a given combination of states of the parent nodes (e.g. Management = Reference, Year = 1990-1995, Irradiance = 0-100 and Temperature = 0-10) was determined by the count of predicted chl-a values obtained in this interval for this particular combination of states of the parents nodes (40) divided by the total number of observations for this combination (3015). I.e., the probability is 40/3015 = 0.013 (the upper left cell in Table 2a). Thus, the probability distribution in this column arises from the variability between the 60 MyLake model realisations as well as from the temporal variability during the period 1990–1995. In cases where a given combination of parents' states in the reference scenario did not occur in the count data (Experience = 0 in the CPT), values based on expert judgement were inserted to allow the model to run. For example, for Total P (obs.), the count was zero for the lowest interval of Total P (pred.) (Table B1a); here an assumed probability distribution based on the neighbour column was inserted. For the nodes in module 2, where the CPTs had a high number of columns, columns with Experience = 0 were populated with probability distributions from the neighbour column (see example in Table 2a). (Testing showed that the assumed probability distributions in such cases had negligible effects on the posterior probability distributions of the child nodes).

In Module 3 (Monitoring data), likewise, the links from the predicted MyLake outcome to the observed monitoring data were based on the joint frequency distributions of the two variables. The observed data were paired with the corresponding predicted data for the same week, and the concentration intervals were compared (Table B1). The CPT for the Cyano node was calculated from the observations of Temperature, Chl-a and Cyanobacteria from the same date.

The CPT for CyanoMax (the maximum of Cyano for each year) was obtained by counting the number of observed Cyano in each concentration interval and each season, and calculating the frequency distribution across the corresponding CyanoMax intervals for all of these observations. For example, out of the 34 observations of Cyano concentration below 1000 μg/L in the May-June season, 10 observations (probability 0.29) came from a year where the CyanoMax in the same year exceeded 2000 μg/L. The total number of cyanobacteria samples (90) was relatively low for calculating the 9 frequency distributions in the CPT of Cyano (and of CyanoMax; Table 2c and d). We therefore complemented the temporal data for the target lake with the larger spatial dataset from the regional dataset EUREGI (described in section 2.2.3).

In Module 4 (Ecological status), each of the four indicators (Secchi, TP, Chl-a and Cyano) has a status node where the three states (High-Good, Moderate or Poor-Bad) correspond to the three intervals of the parent node. For these nodes, the CPT is set to 1 for each cell with matching states and 0 for all other cells (Table A1a–d). For the subsequent nodes (Physico-chemical status, Phytoplankton status and Lake status), the implementation of the combination rules into the CPTs is described in Appendix A.

3.2. Running the BN model

A BN model can be run by altering the probability distribution of one or more nodes (e.g., selecting one management scenario) and thereby updating the probability distribution in all the nodes that are linked by CPTs throughout the network (e.g., the status of the lake). A common way to run the model is to "set evidence" for one or more of the parent nodes, i.e. to select one of the states (assign 100% probability for this state) (Fig. 4). In this study, the main model runs (the 6 scenarios) were performed by setting evidence for each combination of the management and climate node states, and recording the posterior probabilities in the child nodes. In addition, for the purpose of model evaluation, alternative model

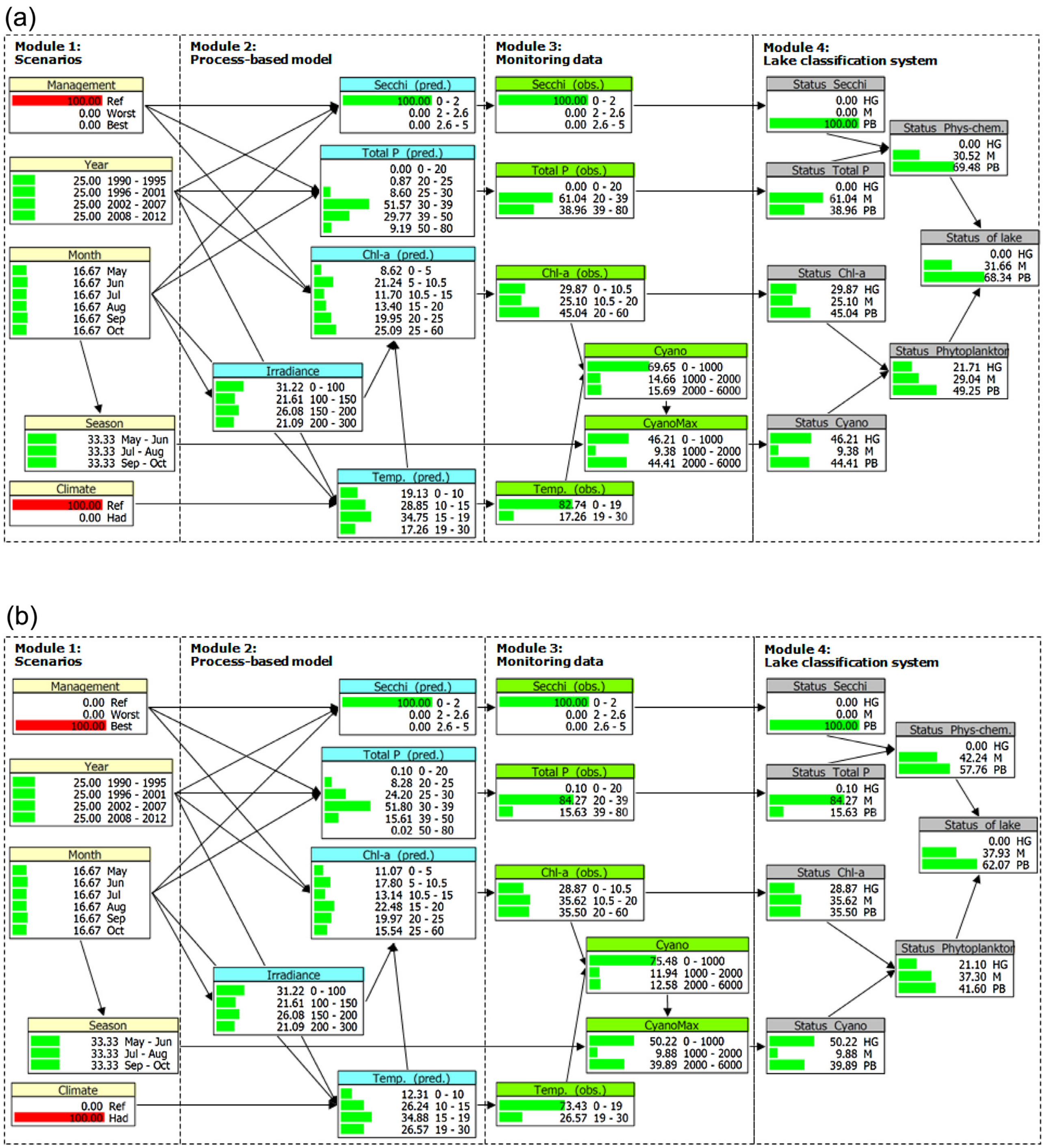

Fig. 4. Examples of BN model predictions (posterior probability distributions) for two scenarios. (a) Scenario with current climate (Ref) and reference management (Ref). (b) Scenario with future climate (Had) and "best case" management. Note the shift to higher probability of HG status for most of the nodes under the latter scenario. For more details, see Fig. 2.

runs were performed by setting evidence for other selected nodes in the network (see next section).

3.3. Model evaluation

Model evaluation is an important step in good modelling practice, but evaluation of Bayesian network models is often neglected (Aguilera et al., 2011). Ideally, one part of a dataset should be used for "training" (model calibration) while another part is reserved for evaluation by comparison with model predictions (Chen and Pollino, 2012). However, the data on the most crucial component of this model – Cyanobacteria – could not be divided without compromising the calibration (construction of CPTs; see Table 2b). Moreover, predictions based on future scenarios could not be compared to real data. Other, more qualitative forms of model evaluation have been suggested (Chen and Pollino, 2012; Marcot, 2012), such as applying different combinations of inputs and examining the resulting probabilities throughout the network, to test whether the behaviour of the model is consistent with current understanding about the system. Here, we identified three critical parts of the model and inspected the sensitivity of the model to alterations of these parts.

(1) *The link from process-based model predictions to observed data*. The correspondence between predicted and observed values is captured in the CPTs for the monitoring data (Table B1). As a rough evaluation based on the proportions of matching states in these CPTs, the goodness-of-fit of the MyLake model predictions can be characterised as good (temperature), intermediate (chl-a) and less good (TP), respectively. A detailed assessment of the MyLake model predictions and explanations for the deviations are given by Couture et al. (2014). To assess the influence of the prediction vs. observation uncertainty on the model performance, we ran two versions of the model: one version that was based on the process-based model predictions without accounting for the mismatch with observations (version 1) and another that incorporated this uncertainty in the CPTs (version 2).
(2) *The CPT for cyanobacteria*. Due to the limited number of cyanobacteria observations (Table 2b), to reserve a subset of the cyanobacteria data for evaluation purposes would not be meaningful. Instead, we used the independent EUREGI dataset (see section 2.2.3) to construct an alternative CPT for cyanobacteria (model version 3, based on version 1) and compared the outcome of this version with that of version 1.
(3) *Effects of water temperature*. A critical component of this BN is the effect of water temperature on cyanobacteria. Moreover, since the conditional probabilities used for calculating posterior probabilities for cyanobacteria are based on very few observations for some of the parent state combinations (Table 2b), it is important to check that these CPTs do not provide spurious results. We therefore inspected more closely relationship between temperature, Chl-a and cyanobacteria by setting evidence (fixating probabilities) for the nodes Temperature and Chl-a. In addition, the effect of Season was checked.

4. Result and discussion

4.1. Effects of management and climate scenarios on lake status

The results reported in this section are based on version 1 of the BN (defined in section 3.3; the choice of the version is explained in section 4.2). The model outcome of this version is equal to the outcome of the MyLake model (TP and Chl-a) as reported by Couture et al. (2014). The BN model has achieved new results in three main ways: (1) including the Cyanobacteria component in the model, as well as Secchi depth, (2) assessing the probability distribution of status classes for the four indicator variables, and (3) using the combination rules of the national classification system to assess the overall lake status. In this study we focus more on the resulting status classes (High-Good, Moderate and Poor-Bad) than on the exact values of the indicators.

The climate scenario had a limited effect of the Temperature node (see Fig. 4): the probability of "a warm year" (>19 °C water temperature during May-October) increased from 17% to 27%. All subsequent climate change effects in the BN are based on this increase.

Secchi depth values, both observed and predicted (MyLake), were in the Poor-Bad status during the whole time series (Fig. 1a). Accordingly, this indicator had a 100% probability of Poor-Bad status, for the references scenario as well as for all other scenarios (Fig. 5a). Hence, the effects of the different scenarios on Secchi depth are not given more attention here. Nevertheless, the Secchi depth status affected the Physico-chemical status (Fig. 5c) and thereby potentially the overall lake status (Fig. 5g). Therefore, inclusion of the Secchi depth node is important for obtaining a more correct overall status assessment.

For TP, the best-case management increased the probability of obtaining a better status (Fig. 5b and d). The probability of good or high status was <0.1% for all scenarios. The probability of moderate status, however, increased from 61% under reference management to 84% with the best-case management, and decreased to only 1.5% with the worst-case management. In the combined physico-chemical status assessment (Fig. 5c), which included both Secchi depth and TP, the probability of moderate status was halved compared to the assessment for TP alone. This result reflects the fact that the CPT for the physico-chemical status node (Appendix A) weighted the contributions from TP and Secchi equally.

The status indicated by Chl-a was better than the status of TP, with 30% probability of good (or high) status under the reference scenario. This can be explained by the poor light conditions in the lake: a Secchi depth of 1–1.5 m and no stable stratification is probably causing the phytoplankton to be continuously mixed to depths beyond the photic zone. Hence, the phytoplankton is light-limited, and not able to utilize the available P for optimal growth. Chl-a status was affected by the climate scenarios as well as by the management scenarios (Fig. 5d). Under current climate conditions, best-case management increased the probability of obtaining good or high status to 35% with the best-case management, while worst-case management decreased it to 18%. Climate change slightly reduced the probability of good or high status in each case.

The status probability distribution of CyanoMax (Fig. 5e) differed from the distribution of Chl-a: CyanoMax had high probability of both the best and the worst status but a low probability of the intermediate status. This strongly bimodal distribution of CyanoMax reflects the tendency of cyanobacteria to occur in either very low or very high abundance (blooms) (Fig. 1e). Nevertheless, the status of Cyanobacteria responded to the management and climate scenarios in a similar way to Chl-a. In other words, reducing nutrient concentrations counteracted the increased cyanobacterial risk associated with higher temperatures, in agreement with the conclusion of Rigosi et al. (2015).

The status distribution of the combined Phytoplankton node (Fig. 5f) was more affected by the Chl-a node than by the Cyanobacteria node, as could be expected from the combination rule (section 2.2.4). Notably, the Phytoplankton node had generally worse status than either of its two parent nodes. The probabilities of good or high status were 22%, 25% and 13% (for Reference, Best and Worst management respectively) under current climate, and 18%, 21% and 10% under climate change. This result is consistent with the combination rule for phytoplankton: including Cyanobacteria in the assessment can only worsen (or not affect) the combined Phytoplankton status.

In the overall lake status assessment (Fig. 5g), the best possible status was Moderate, due to the influence of the physico-chemical node. In general, the probability of moderate (or better) status (e.g., 32% in the Reference scenario) was closer to the physico-chemical node (31%) than to the phytoplankton node (51%); i.e. the lake status was worse than indicated by phytoplankton alone. This result reflects the whole-lake combination rule, which selected the worse status (or a compromise) whenever the status of the two parent nodes differ. Nevertheless, the whole-lake status also showed negative impact of climate change, which was inherited from the Phytoplankton node (since climate change impacts on physico-chemistry were not incorporated in this BN). Hence, all of the four indicator nodes (Secchi depth, TP, chl-a and cyanobacteria) played important roles in the overall assessment of lake status under the management and different scenarios.

The ecological status of Vanemfjorden assessed by the BN (35% probability of Moderate and 65% probability of Poor-Bad for the reference scenario; Fig. 5g) was somewhat worse than the most

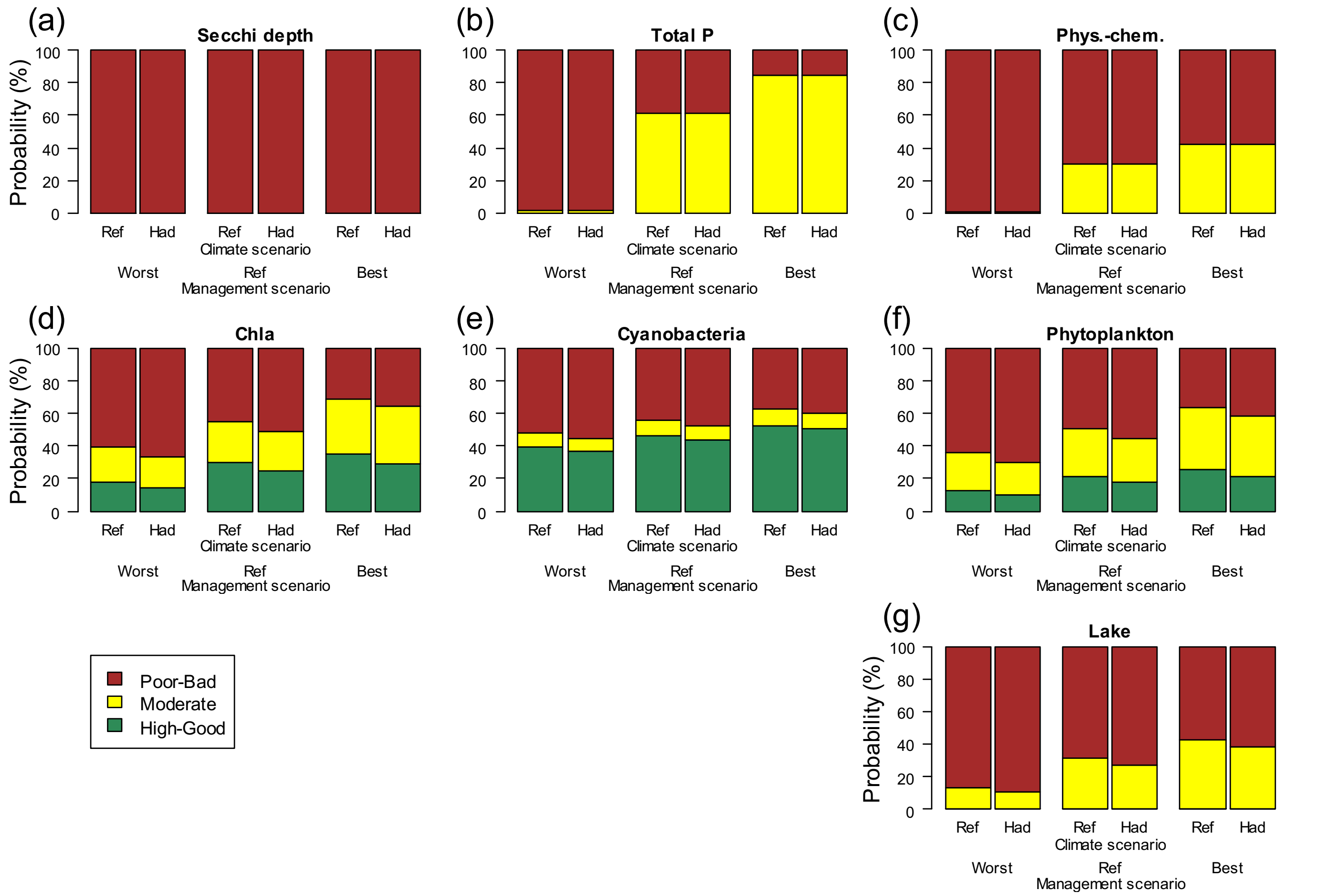

Fig. 5. Effects of climate and management scenarios on the probability distribution of status classes for all nodes in the module "Lake classification system" (Fig. 2). The climate scenarios are reference ("Ref") and HadRM3 ("Had); the management scenarios are economy focus ("Worst"), reference ("Ref") and water-quality focus ("Best"). The distribution of status classes (High-Good, Moderate and Poor-Bad) for Secchi depth (a) and total P (b) are combined in the plot "Physico-chemical" (c), while the results for Chl-a (b) and Cyanobacteria (e) are combined in the plot "Phytoplankton" (f). Finally, the results for Physico-chemical and Phytoplankton are combined in the plot "Lake" (g).

recent official ecological status assessment, which is in the middle of the Moderate class (Haande et al., 2011). This can be explained by differences in the selection of data for the assessment (where the data selected for the BN were constrained by the link to the MyLake output). Firstly, the official status is based on data from 2004 and 2010 only, while the BN also includes data from years prior to 2004, during which conditions were worse (Fig. 1c–d). Secondly, the previously published assessment did not consider Secchi depth, which imposed Poor-Bad status, but instead included Total N, which was associated with Moderate status. Thirdly, it did not include cyanobacteria (which could have reduced the phytoplankton status), but instead included macrophytes (which were associated with Moderate status).

The effects of climate change considered in this study were limited to water temperature and effects on phytoplankton. Higher water temperature is likely to affect other biological groups as well, especially fish (Hering et al., 2013; Jeppesen et al., 2012), which have so far not been monitored in Vanemfjorden. The climate change scenario also comprised increased precipitation, which was included in the process-based models for the catchment and lake (Couture et al., 2014), but precipitation has not yet been incorporated explicitly as a node in the BN. Increased precipitation has the potential to influence ecological status in several ways. For example, increased run-off of nutrients from agriculture is likely to give higher TP concentrations (Jeppesen et al., 2009). On the other hand, increased flushing of the lake may reduce the concentration of phytoplankton and in particular of cyanobacteria, which tend to have slower growth rate than other phytoplankton (Carvalho et al., 2011; Elliott, 2012). Such contrasting effects of altered precipitation patterns could be considered in a more advanced version of this BN.

4.2. Model evaluation

4.2.1. The link from process-based model predictions to observed values

The accuracy of the MyLake model predictions varied highly among the different indicator variables. The model performance is discussed in detail by Couture et al. (2014); here we only consider the accuracy at the level of node states (intervals) and focus on the implications for the BN model. For Secchi depth, the match between prediction and observation was 100%, because all predictions and observations were in the same interval (0–2 m). For water temperature the match was generally good (Table B1c), although the highest observed temperatures (19–25 °C) were frequently underestimated by MyLake (as 15–19 °C). This negative bias in the prediction of temperature may have contributed to the mismatch between predicted and observed Chl-a (Table B1b). Although the precision of predicted Chl-a was rather low (43% of the observed values predicted to the correct interval), the accuracy was good in terms of the balance between underestimations (28%) and overestimations (29%). TP was less well predicted: although the precision (66%) was higher than for chl-a, the accuracy was lower: 10% underestimations vs. 23% overestimations. The underestimations are mostly from the period 1990 to 1999 (Fig. 1c), i.e. before the calibration period of MyLake (2005–2012). A better match could have been obtained by using only data from the calibration period, but the range of predicted values in this period was narrow compared to the whole time series (e.g., predicted Total P was only in moderate status). Moreover, our intention was to make use of as much data as possible for filling in the CPTs.

Accounting for the mismatch between predicted and observed values in the CPTs (Table B1) had clear consequences for the BN model predictions (BN version 2, Fig. B1). For TP (Fig. B1b), the BN no longer predicted a positive effect of better management on the probability of moderate status, but instead a weak increase in the probability of poor-bad status. For the combined physical-chemical indicator (Fig. B1c) there was no obvious response to the management scenarios. The Chl-a variable (Fig. B1d) and thus the combined phytoplankton indicator (Fig. B1f) displayed similar responses to the management scenarios as in the default BN version (Fig. 5d and f), but the effects of the scenarios were much weaker. This is consistent with the high accuracy and low precision of predicted Chl-a from the process-based model. The total lake assessment was most dominated by the phytoplankton node (as determined by the classification rules), but the physical-chemical indicator contributed with additional uncertainty. In the BN version 2, the overall lake assessment for the reference scenario (Fig. B1g) was close to the default version (Fig. 5g), but there was almost no effect of the management or climate scenarios. This is a common problem for BN models that incorporate several sources of uncertainty: nodes further down the causal chain have greater predictive uncertainty (Borsuk et al., 2004; Marcot et al., 2006).

Our decision not to include the mismatch between MyLake predictions and observations in the default BN version can be justified by the fact that this uncertainty should already have been accounted for in the calibration of MyLake. The resulting 60 parameter sets were instead included as a source of uncertainty in the BN. Incorporating the prediction – observation mismatch as an additional source of uncertainty would not only make the BN model non-responsive to the scenarios, but also introduce a systematic error for TP.

4.2.2. The CPT for cyanobacteria

A minority of the EUREGI observations were from lakes with high degree of eutrophication; only 45 out of 559 observations were in the highest Chl-a interval (vs. 34 out of 90 observations from Lake Vansjø). Likewise, the number of cyanobacteria observations in the highest interval was relatively low: 22 out of 559 (vs. 13 out of 90 from Lake Vansjø). Nevertheless, the EUREGI dataset gave similar probability distributions in the CPT for cyanobacteria (Table B2) to those from Lake Vansjø (Table 2b-c). Consequently, model version 3 with CPT from the EUREGI dataset predicted effects of climate and management scenarios on ecological status of cyanobacteria (Fig. B2e) that were very similar to the default model version (Fig. 5e). The fact that an independent, large-scale dataset gave similar CPTs and consequently very similar model predictions as the original data from Lake Vansjø strengthened our confidence in the cyanobacteria component of the model.

4.2.3. Effects of water temperature

Since the future climate scenario had a limited effect of the Temperature node (probability of "a warm year" increased from 34% to 44%), we investigated more closely how the phytoplankton nodes responded to changes in water temperature in the model. One way to inspect the temperature effects in the BN was to select the warmest months, July-August ("summer"). The full model is based on all data from May to October, because this is a criterion in the national assessment system for ecological status. However, since there is large seasonal variation in many of the variables, selecting only summer months would reduce the temporal variation, and might therefore improve the precision of the model (i.e., result in narrower probability distributions of the indicators). We therefore compared the default model outcome (Fig. 5) with the corresponding results from summer months (Fig. B3). (To simplify the comparison we have displayed the result in terms of status classes, although it is not strictly correct to base the status assessment of summer values only). Lower probability of Moderate or better status can be seen for all indicators, except cyanobacteria; this is likely because Cyanobacteria status is based on the seasonal maximum, which is less sensitive to the selection of months. This result shows that the model behaves as expected regarding seasonal variation in temperature and in indicator variables.

Further inspection of the water temperature effects was performed by setting evidence for "a warm year" (100% probability of temperature $\geq 19\,^{\circ}$C) vs. "a cold year" ($<19\,^{\circ}$C) (Fig. B4). The temperature effect was stronger for Chl-a than for cyanobacteria: from a cold to a warm year, the probability of moderate or better Chl-a status dropped from 58% to 24% (worst management) and from 70% to 48% (best management). The corresponding probabilities for cyanobacteria were a drop from 64% to 47% (worst management) and from 71% to 60% (best management), but this response included both the direct effect of the temperature node and the indirect temperature effect through the Chl-a node. Furthermore, we fixed the Chl-a node at PB, M or HG status under cold and warm year, respectively (Fig. B5a). The additional temperature effect on cyanobacteria was most evident when Chl-a was in moderate status (Fig. B5b). This result is in line with the conclusion by Rigosi et al. (2015), that the cyanobacteria concentrations of mesotrophic lakes were particularly sensitive to warming. This temperature effect on cyanobacteria had a small, but noticeable effect on the total phytoplankton status (Fig. B5c). Although this effect was small, it shows that the BN generated reasonable results.

4.3. Assessment of the BN approach for modelling of ecological status

Overall, the BN model satisfied our objective: to integrate information from scenarios, process-based models, monitoring data – especially cyanobacteria, and the lake classification system. The BN approach gives a possibility to account for mismatch between process-model predictions and observations for certain variables, by incorporating this uncertainty in their CPTs (cf. Table B1) and evaluating its consequences. Since the selected model (version 1) does not account for the mismatch between MyLake prediction and observations, the results predicted by the BN should not be interpreted in terms of absolute probability values. Nevertheless, the qualitative effects of the scenarios on the different indicators predicted by the BN should be valid.

The components involving cyanobacteria gave reasonable results, and had importance to the overall assessment. Our confidence in these components was strengthened by the comparison with an independent dataset (Fig. B2); at the coarse scale of the ecological status (rather than exact concentrations), the results were very similar. This implies that our approach can be used for other lakes that are at risk of algal blooms. For lakes with more limited data on cyanobacteria than Lake Vansjø, we show that filling the data gaps using cyanobacteria observations from other lakes in combination with expert knowledge on lake type, local conditions etc. is a viable option. Rigosi et al. (2015) demonstrated this possibility: using physicochemical, biological, and meteorological observations collated from 20 lakes located at different latitudes and characterized by a range of sizes and trophic states, they constructed a BN to analyse the sensitivity of cyanobacterial bloom development to different environmental factors and to determine the probability that cyanobacterial blooms would occur. The ability to utilize other available datasets for answering management questions is a strength of the BN approach, given the financial constraints of most agencies (Wilson et al., 2008).

A complete ecological status assessment should in principle include three more biological quality elements (BQEs), namely macrophytes, benthic invertebrates and fish (EC, 2000). Such an assessment is likely to have resulted in even worse status, due to the "one-out, all-out" combination rule of the WFD (EC, 2005). This rule states that the ecological status should be determined by the BQE with lowest status, meaning that including more BQEs inevitably leads to a stricter or equally strict assessment. The more pessimistic outcome of the one-out, all-out rule compared to other combination rules was also demonstrated by Lehikoinen et al. (2014), who used a BN for analysing the probability of reaching good ecological status of coastal waters in the Gulf of Finland. When there is high uncertainty associated with the data, assessments based on this combination rule tend to underestimate the ecological status (Moe et al., 2015). A probabilistic result such as the outcome of a BN can be helpful, giving a more nuanced and more informative result than only a single status class (Gottardo et al., 2011).

Compared to existing process-based models for ecological status of rivers and lakes, the BN approach provides an opportunity to include biological elements, as demonstrated by our study. Even when data are sparse, theory or expert knowledge on selected biological indicators can be used as a first step to construct causal links (CPTs) between abiotic and biotic responses. Since the WFD requires that assessments are based primarily on biology (EC, 2000), this is clearly an added value for use of models in water management in Europe. Moreover, the WFD requires that potential impacts of climate change are considered in the next set of river basin management plans (EC, 2009). Although much knowledge is available on effects on climate change on ecosystems, including specific effects on biological quality elements in lakes (Moe et al., 2014), incorporating such information in predictive models is a challenge. The BN methodology can facilitate the use of such knowledge, manifested as expert judgement of probabilities under given climatic scenarios. Furthermore, a BN model may be relatively easy to understand for end users who do not have any modelling background {Borsuk et al., 2012 #138}. Therefore, BNs are promising tools for supporting informed decision making and thus the work of water managers.

There are of course also several limitations associated with the BN methodology in the context of environmental management. The fact that the non-dynamic network cannot contain loops puts constraints on the ecological processes that can be modelled; phosphorus and phytoplankton dynamics in lakes are typically dominated by feedback processes (Saloranta and Andersen, 2007). For example, high phytoplankton biomass can reduce the Secchi depth; on the other hand, lower Secchi depth can limit further phytoplankton growth due to light limitation. In our study, such feedback loops were handled by dynamic models (INCA-P and MyLake), while the BN summarised the outcome of the catchment and lake process. Moreover, the accumulation of uncertainty with the length of the network implies that it can be difficult to draw conclusions from the final output nodes (Borsuk et al., 2004). Other challenges associated with the use of BNs have been discussed previously (Landuyt et al., 2013; Uusitalo, 2007; Varis and Kuikka, 1999).

The current BN model can be further developed in several ways. An important improvement would be to reduce the predictive uncertainty of the catchment-lake model chain (i.e. INCA-P and MyLake). A more quantitative sensitivity analysis of the model, such as calculation of entropy reduction, can help identify nodes to which the final output is particularly sensitive (Chen and Pollino, 2012). A more complete representation of climate change in the BN would include effects of changed precipitation patterns (cf. Lehikoinen et al., 2014), and potentially other meteorological or hydrological variables. Inclusion of Total N in the BN would make the assessment of physico-chemical status more complete. The total N concentration also seems to play a role in favouring certain N-fixating cyanobacteria taxa (order Nostocales, e.g. *Anabaena*), especially in late summer/autumn after N has been depleted. Effects of nutrients and other environmental variables on *Anabaena* biomass in a reservoir were recently analysed by another BN model (Williams and Cole, 2013): reduced levels of N and/or P had negligible impact on the phytoplankton in their study, while high water temperature and stratification increased the risk of Anabaena blooms. Anyway, to model effects of climate or management scenarios on Total N in our BN would require that this variable is first incorporated in the process-based lake model. Finally, a dynamic version of the BN could be considered (Molina et al., 2013; Nicholson and Flores, 2011), which might better handle feedback processes.

In this study we used an external, larger dataset for evaluation by constructing an alternative CPT for cyanobacteria and comparing the results with the default model version. External datasets can also be used in a more integrated way for estimation of CPTs. However, differences in lake type factors such as water colour and alkalinity may be even more important than the TP concentration (Carvalho et al., 2011). A hierarchical Bayesian regression model would be a suitable method for estimating relationships for a target lake while "borrowing information" on this type of relationship from a larger set of lakes, and simultaneously accounting for differences in lake type (Kotamäki et al., 2015). Inclusion of more biological quality elements would also be desirable; primarily macrophytes, for which some data exist (Haande et al., 2011). Future monitoring in Lake Vansjø might provide some more biological data also for macrophytes and fish. However, new biological elements for which few observations are available will be associated with high uncertainty. The model structure in its current version is rather simple and general, and should be feasible to adapt for other lakes or other aquatic ecosystems. The model can be considered over-fitted to Lake Vansjø, since the estimation of probability distributions is based solely on data from this case study. Application of this model to other ecosystems should involve calibration and validation of the model with relevant data.

4.4. Conclusions

In summary, the Bayesian network approach was able to model effects of climate change and management on ecological status of a lake, by combining scenarios, process-based model output, monitoring data and the national lake assessment system. The BN model showed that the benefits of better land-use management were partly counteracted by future warming under these scenarios. Most importantly, the BN demonstrated the importance of including more biological elements, namely cyanobacteria, in the modelling of lake status. Thus, the BN modelling approach can be a useful supplement to more traditional process-based models for lakes, which only rarely include cyanobacteria or other biological groups.

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Appendix A. Implementation of combination rules of the national classification system

Implementation of combination rules of the national classification system

For the combined Physico-Chemical status, the classification system requires averaging of the two variables Secchi and TP, which is not straight-forward in a probabilistic model. When both indicators had the same status, the combined status was the same with 100% probability. The averaging was implemented by assigning 50% probability of both High-Good and Moderate status when one indicator was in High-Good status and the other was in Moderate status, and likewise for Moderate and Poor-Bad status (Table A1e). When one indicator was High-Good and the other Poor-Bad, the combined status was Moderate with 100% probability. For the combined Phytoplankton status, a similar solution was used, with some exceptions: when the status of Cyano was better than or equal to the status of Chl-a, the combined status was set equal to the status of Chl-a (Table A1f). The overall lake status (Table 2d) was set equal to the phytoplankton status when the physico-chemical status was equal or better, and to one lower state when the physico-chemical status was worse.

Appendix B

Figs. B1–B5 .
Tables B1 and B2.

Table A1
Conditional probability tables for the national classification system for ecological status of lakes (see Fig. 2, Module 4). (a) Status Secchi, (b) Status Total P, (c) Status Chl-a, (d) Status Cyano, (e) Status Phys-Chem, (f) Status Phytoplankton. (For the node Status of Lake, see Table 1e). HG = High-Good, M = Moderate, PB = Poor-Bad.

(a)

Secchi	0–2	2–2.6	2.6–5
Status Secchi			
HG	0	0	1
M	0	1	0
PB	1	0	0

(b)

Total P	0–20	20–39	39–80
Status Total P			
HG	1	0	0
M	0	1	0
PB	0	0	1

(c)

Chl-a	0–10.5	10.5–20	20–60
Status Chl-a			
HG	1	0	0
M	0	1	0
PB	0	0	1

(d)

CyanoMax	0–1000	1000–2000	2000–6000
Status Cyano			
HG	1	0	0
M	0	1	0
PB	0	0	1

(e)

Status Total P	HG			M			PB		
Status Secchi	HG	M	PB	HG	M	PB	HG	M	PB
Status Phys-chem.									
HG	1	0.5	0	0.5	0	0	0	0	0
M	0	0.5	1	0.5	1	0.5	1	0.5	0
PB	0	0	0	0	0	0.5	0	0.5	1

(f)

Status Chl-a	HG			M			PB		
Status Cyano	HG	M	PB	HG	M	PB	HG	M	PB
Status Phytoplankton									
HG	1	0.5	0	0	0	0	0	0	0
M	0	0.5	1	1	1	0.5	0	0	0
PB	0	0	0	0	0	0.5	1	1	1

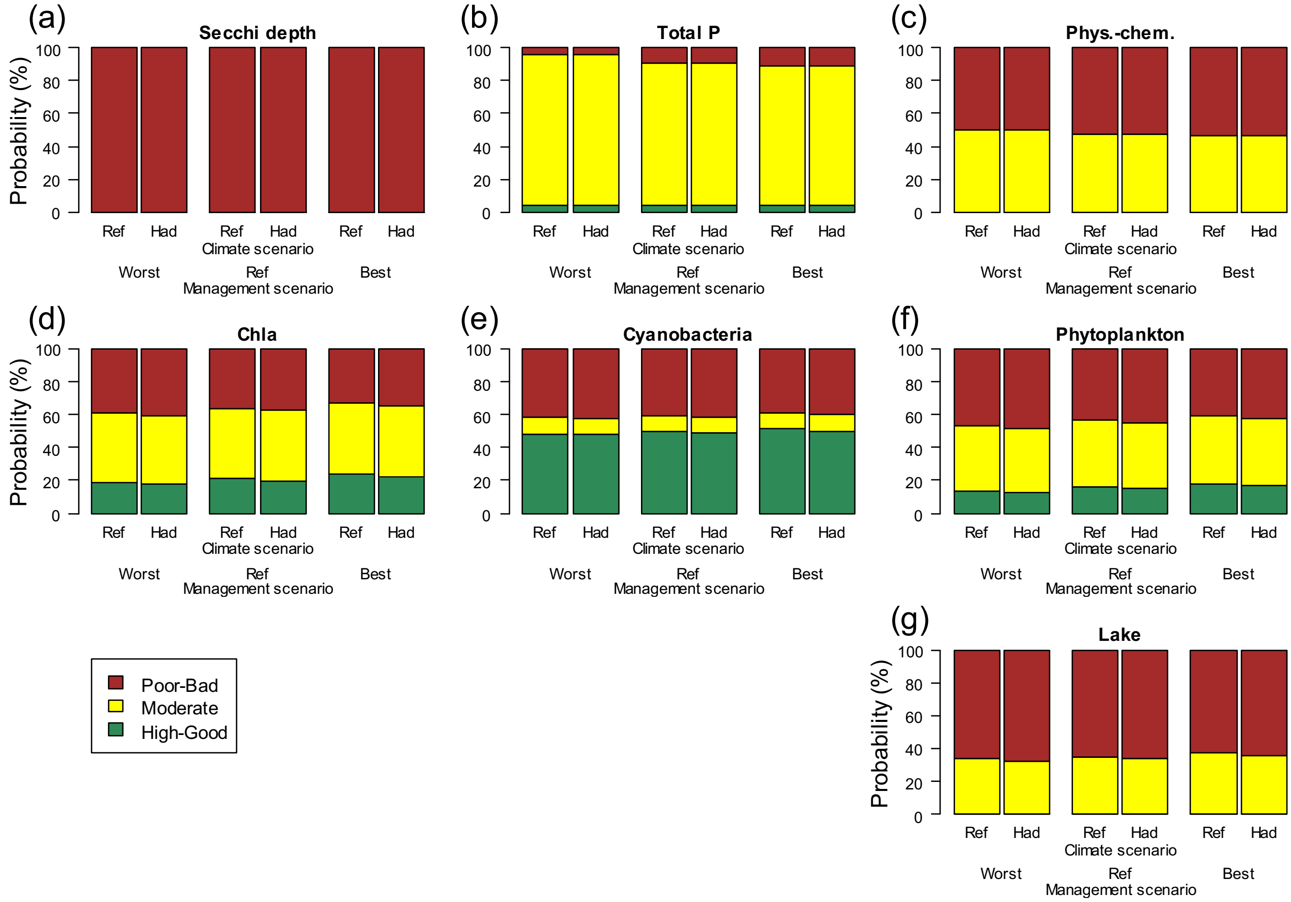

Fig. B1. Effects of climate and management scenarios on the probability distribution of status classes for all indicator nodes, when the mismatch between process-based model predictions and observations is accounted for by the conditional probability tables (Table B1). For more details and for comparison with the default model, see Fig. 5.

Table B1
Conditional probability table for the nodes that link predicted to observed data: (a) Total P, (b) Chl-a, (c) (water) temperature. Asterisk indicates a match between predicted and observed values. For Secchi depth, all predicted and observed values were in the same state (0–2 m). For more explanation, see Table 2.

(a)

Total P (pred.)	0–20	20–25	25–30	30–39	39–50	50–80
Total P (obs.)						
0–20	*0.800	0.075	0.022	0.039	0.053	0.044
20–39	0.200	*0.717	*0.887	*0.838	0.887	0.923
39–80	0	0.209	0.091	0.123	*0.060	*0.033
Experience	0[a]	254	1977	10689	2701	879

(b)

Chl-a (pred.)	0–5	5–10.5	10.5–15	15–20	20–25	25–60
Chl-a (obs.)						
0–10.5	*0.492	*0.281	0.327	0.164	0.098	0.126
10.5–20	0.389	0.486	*0.344	*0.480	0.402	0.415
20–60	0.119	0.232	0.329	0.356	*0.501	*0.459
Experience	1652	3017	1729	2779	4455	2868

(c)

Temp. (pred.)	0–10	10–15	15–19	19–30
Temp. (obs.)				
0–19	*1	*1	*0.513	0
19–30	0	0	0.487	*1
Experience	775	3596	4933	2636

[a] Assumed probability distributions inserted where no observations were available.

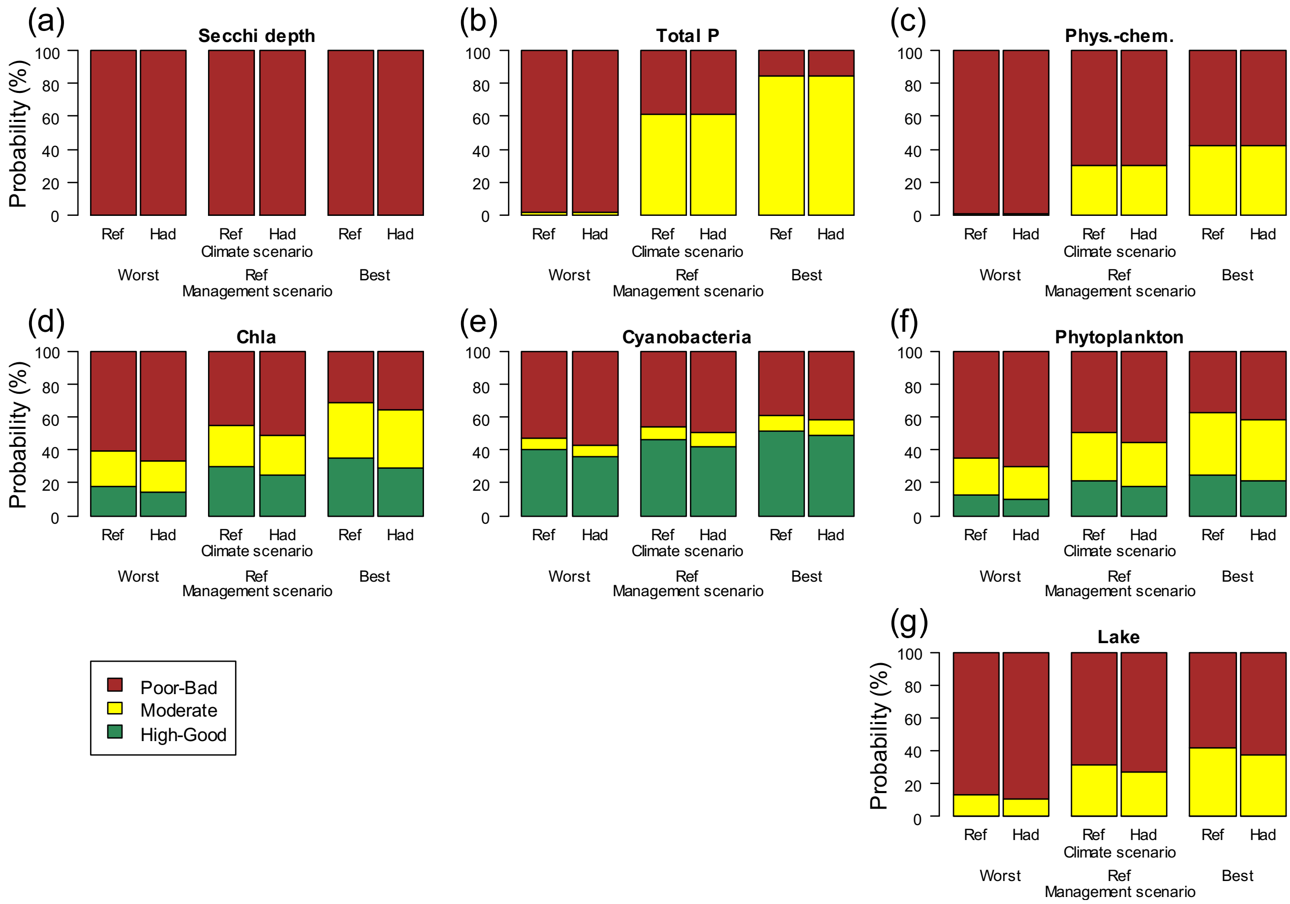

Fig. B2. Effects of climate and management scenarios on the probability distribution of status classes for all indicator nodes, when the conditional probability table for Cyanobacteria is based on the alternative larger dataset EUREGI (see section 2.2.3). For more details and for comparison with the default model, see Fig. 5.

Table B2
Conditional probability table for the two cyanobacteria nodes based on the alternative, larger dataset (EUREGI, see section 2.2.3): (a) Cyano, (b) CyanoMax (corresponding to Table 2c and d, respectively). For more information, see Table 2.

(a)

Chl-a (obs.)	0–10.5		10.5–20		20–60	
Temp. (obs.)	0–19	19–30	0–19	19–30	0–19	19–30
Cyano						
0–1000	0.993	1	0.949	1	0.444	0.111
1000–2000	0.007	0	0.051	0	0.111	0.222
2000–6000	0	0	0	0	0.444	0.667
Experience	454	19	39	2	36	9

(b)

Cyano	0–1000			1000–2000			2000–6000		
Season	May–Jun	Jul–Aug	Sep–Oct	May–Jun	Jul–Aug	Sep–Oct	May–Jun	Jul–Aug	Sep–Oct
CyanoMax									
0–1000	0.882	0.964	0.870	0	0	0	0	0	0
1000–2000	0.076	0.034	0.087	0.5	0.889	0	0	0	0
2000–6000	0.042	0.003	0.043	0.5	0.111	0	1	1	1
Experience	119	384	23	2	9	0	5	16	1

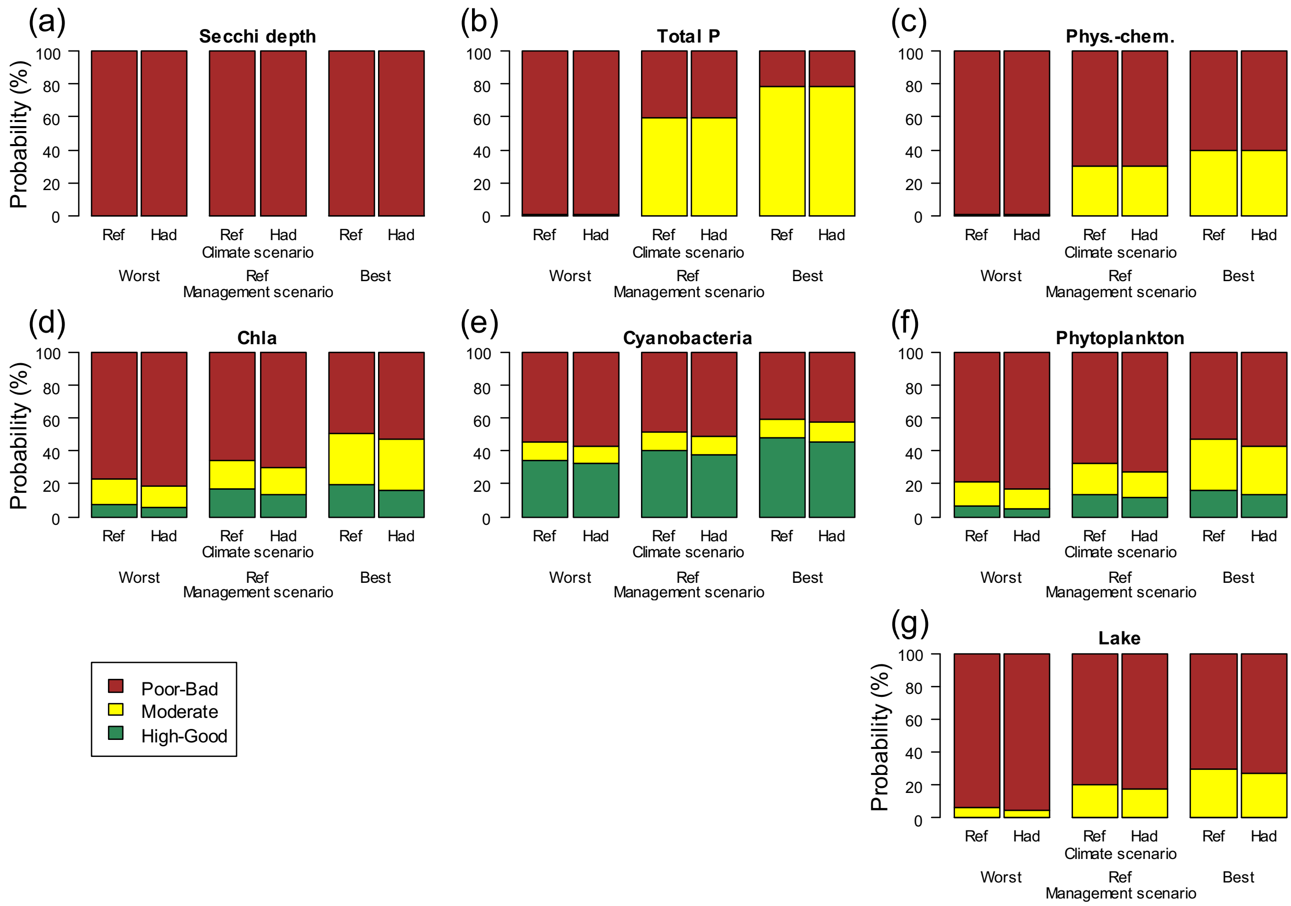

Fig. B3. Effects of climate and management scenarios on the probability distribution of status classes for all indicator nodes, when the model is run only for the warmest months (July–August). For more details and for comparison with the default model, see Fig. 5.

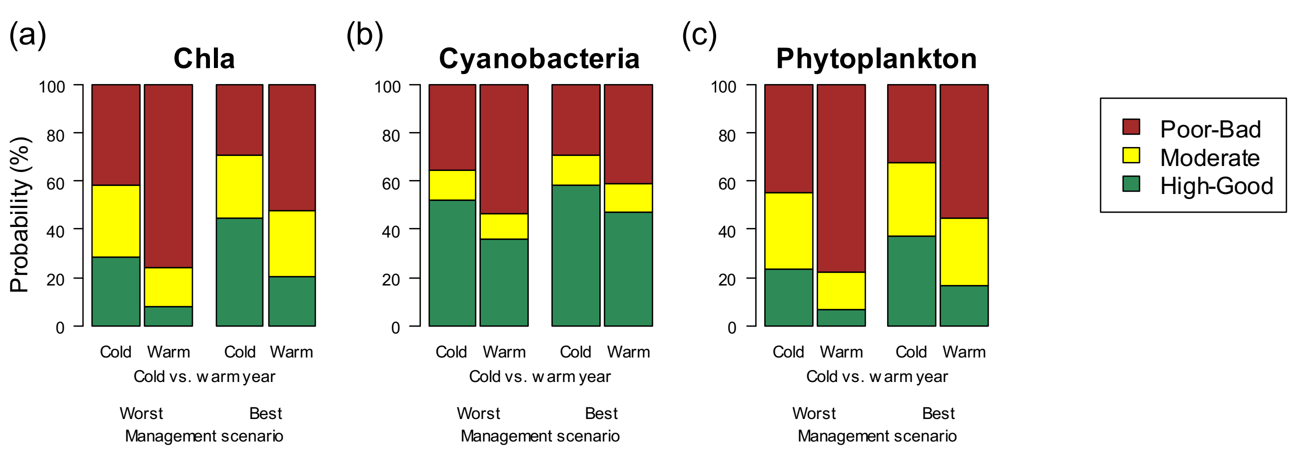

Fig. B4. Effects of high vs. low water temperature (above vs. below 19 °C, respectively) under different management scenarios (worst vs. best) on the probability distribution of status classes for Chl-a (a), Cyanobacteria (b) and Phytoplankton (c). For more details and for comparison with the default model, see Fig. 5.

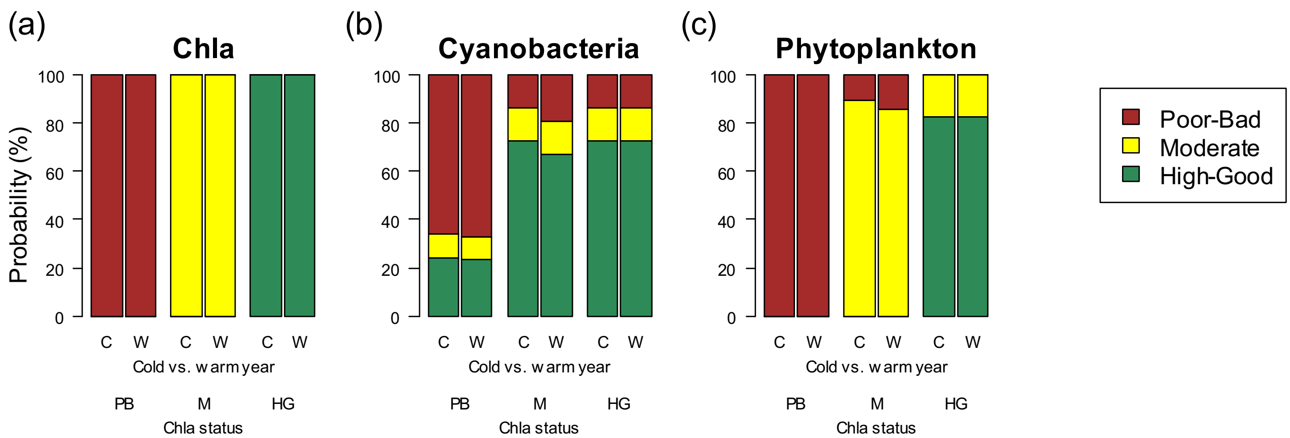

Fig. B5. Effects of high vs. low water temperature (above vs. below 19 °C, respectively) under different scenarios of chl-a status (Poor-Bad, Moderate or Good-High) on the probability distribution of status classes for Chl-a (a), Cyanobacteria (b) and Phytoplankton (c). For more details and for comparison with the default model, see Fig. 5.

Appendix C. Supplementary data

The file Supplementary Data.pdf contains tables with prior probability distributions for all parent nodes and conditional probability distributions for all child nodes. The probability distributions are given as counts rather than proportions. The file is generated from the BN model by the software Hugin.

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolmodel.2016.07.004.

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