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A Bayesian Networks approach for the integrated assessment of climate change impacts on water quality

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Ai miei nonni…
e a Guillem.

Summary

Climate change is triggering new water management challenges affecting regional and global water quantity and quality. Despite potential impacts of climate change on water availability have been widely studied in the last decades, the implication for concomitant changes in water quality have been just poorly explored. Variations in temperature and precipitation patterns, are likely to have profound effects on those hydrological processes (e.g. runoff, river flow, water retention time, evapotranspiration) that regulate the mobilization of pollutants from land to water bodies however, such signals, can be masked by those of concurring local stressors (i.e. land use, point and diffuse pollution sources).

Breaking down the relative role played by each of these pressures and predicting their combined impacts is necessary to mainstream the implementation of well-targeted adaptation measures supporting sectorial policies and legislations. Accordingly, the adoption of a multi-stressor perspective to water quality assessment is required to drawn realistic base lines and reasonable targets steering future water resource management strategies.

A data driven risk framework based on Bayesian Networks was implemented in the Zero river basin (Northern Italy) to characterize the interlacing between climate change and land use practices and assess their cascading impacts on water quality status (i.e. nutrients loadings). Bayesian Networks were used as meta-modelling tool for structuring and combining the information available by existing monitored data, hydrological models, climate change projections producing alternative risk scenarios to communicate the probability of changes in the amount nutrients (i.e. NO_3^-, NH_4^+, PO_4^{3-}) delivered from the basin under different climate change projections (i.e. RCP 4.5 and 8.5).

Specifically, an Ensemble of temperature and precipitation projections downscaled from available Global and Regional Climate models (i.e. GCMs-RCMs) were directly used to inform the Bayesian Network in order to account for uncertainties across climate change scenarios and river basin responses and to determine the level of confidence of projected water quality alterations between baseline and future climate regimes.

Bayesian Network outputs help in tracking future trends of water quality and in supporting the prioritization of stressors and pollution sources. Overall, developed risk scenarios, can be used as baselines against which test and evaluate existing management and adaptation measures and targets for water quality.

Simulated scenarios show that seasonal changes in precipitation and temperature are likely to modify both the hydrology and nutrients loadings of the Zero River and that diffuse pollution sources play a key role in determining the amount of nutrients loaded while point source have only a marginal effect. Both NH_4 and PO_4 loadings, in fact, are mainly influenced by changes in the climatic and hydrological variables while NO_3 loadings are strongly affected by agronomic practices and land use.

Results have been evaluated through a cross comparison with existing observed data and hydrological models' simulations (i.e. SWAT) available for the case study providing a reasonable agreement.

Motivations and Objectives

Climate change is likely to impose severe impacts on water systems affecting water quantity and quality in several ways (Jiménez Cisneros et al., 2014). However, while climate change impacts on water availability and hydrological risks are quite recognized (Molina et al., 2013; Ronco et al., 2017; Zabel, 2016), the consequences on water quality have been just poorly explored (Bussi et al., 2016; Huttunen et al., 2015; Lu et al., 2015; Whitehead et al., 2008, 2009). Increases in temperature and changes in precipitations will probably affect hydrological processes (e.g. runoff, river flow, water retention time, evapotranspiration) with consequences on the loading and transport of nutrients and other kind pollutants (Alam and Dutta, 2013; Culbertson et al., 2016; El-Khoury et al., 2015; Ockenden et al., 2016). Such signals, however, can be often masked by the effect of other stressors concomitantly acting on water bodies. Integrated into a wider global change concept, climate change is likely to interact with land use , deforestation, urbanization, agriculture exacerbating water quality degradation but very few studies have considered the impact of these factors together (Huttunen et al., 2015).

Risk assessment procedures commonly adopted for water quality assessment, in fact, applied a single stressor approach where each stressor is analysed in isolation (Bussi et al., 2016; Mantyka-Pringle et al., 2014; Xia et al., 2016) neglecting synergic, cumulative or cascading effects (van der Brink, 2016). However, understanding the co-evolution and interrelations between climatic and anthropogenic pressures on water systems and breaking down the relative role played by the single stressor is necessary to provide a realistic picture of risks threatening sustainable water resource management. In addition, predicting the conjoined impact of multiple stressors is required to support the implementation of efficient and well targeted management strategies exploiting potential synergies between climate change adaptation and sectorial water policies (e.g. 2000/60/UE Directive).

A key research challenge is, therefore, the adoption of a more integrated multi-stressor perspective enabling to model in a harmonic way multiple drivers' interaction, account alternative perspectives (i.e. social, economic and environmental objectives and priorities) and effectively deal with the uncertainty characterizing climate change scenarios.

In this context, the thesis aims at developing a multi-stressor oriented approach for the assessment and communication of impacts arisen by the interaction between climatic and anthropogenic stressors on water quality.

Bayesian Networks are proposed as modelling framework to overcome and address some of the main limitations of traditional risk assessment approaches (i.e. single stressors focus, representation of uncertainty) developing a probabilistic risk assessment model considering the interlacing between climate (i.e. changes in temperature and precipitations) and land use (i.e. agriculture, urbanization), and their cascading impacts on water quality parameters (i.e. nutrients loadings).

Final outcomes of the research, include alternative risk scenarios and indicators enabling the communication of the probability (and uncertainty) of water quality alterations under changing conditions thus supporting decision making in the identification of targeted management and adaptation options to ensure the protection of good water status in the future.

Thesis Structure

This thesis is made up of three independent research papers which seek to explore and demonstrate the benefits of adopting Bayesian Networks for the integrated assessments of multiple climatic and non-climatic drivers ‘impact on water quality.

The **first paper** analyses the potential use of Bayesian Networks in dealing with climate change impacts risk assessment and management. Accordingly, it first provides a review of existing Bayesian Networks applications in the field of environmental risk assessment and management. Lately, drawing on the results of the analysis, the paper discusses some of the main advantages and limitations of Bayesian Networks as modelling tool for the implementation of a generic risk framework for the assessment of interactions between climatic and no-climatic stressors.

The **second paper** describes a risk assessment procedure based on Bayesian Networks modelling implemented in the Zero river basin in Northern Italy to link future scenarios of climate change with water quality alterations (i.e. changes in nutrients loadings). Bayesian Networks are employed as integrative tool for structuring and combining information available in existing hydrological models (i.e. SWAT), climate change projections, current land use and agronomic practices, historical observations and expert opinion. The BN is then used toproduce alternative risk scenarios to communicate the probability of changes in nutrients (i.e. NO_3, NH_4, PO_4) delivered from the basin into the lagoon over future scenarios, thus paving the way for the identification and prioritization of most effective management and adaptation strategies to maintain good water quality status under climate change conditions.

Finally, the **third paper** proposes the use of Bayesian Networks to track and communicate uncertainties across a range of climate change projections helping in determining the level of confidence of projected water quality alterations between baseline and future climate regimes. Accordingly, it describes the application of Bayesian Network approach to develop an ensemble of impact scenarios assessing the effect of different climate change projections on the quality of waters of transitional systems (i.e. estuaries). Ensembles of baseline and future temperature and precipitation downscaled from available Global and Regional Climate models (i.e. GCMs-RCMs) are directly used to inform BN and thus to drive simulations of nutrient loadings (i.e. NO_3, NH_4, PO_4) projected under future climate change scenario.

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Paper 1-Reviewing Bayesian Networks potentials for climate change impacts assessment and management: a multi-risk perspective[1]

Introduction

Climate change risk assessment represents a challenging task for environmental management due to the inherent complexity of socio-ecological systems, the multiplicity of processes and the high degree of uncertainty, variability and randomness involved (Döll and Romero-Lankao, 2017; Gallina et al., 2016).

Multiple climatic and non-climatic stressors interact, inducing impacts which can be highly correlated (i.e. cumulative, synergic or antagonistic effect) or strongly dependent (i.e. cascading or triggering effects) one each other (Gill and Malamud, 2014, Kappes et al., 2012; Liu et al., 2014). Neglecting these interactions can lead to an underestimation of the overall risk and further to inefficient or controversial risk management strategies (i.e. maladaptation, unexpected environmental impacts, increase vulnerability or exposure toward other kind of stressors)(Liu et al., 2014). An effective risk management should be built on a good understanding of all relevant threats affecting the target of interest thus enabling decision makers and practitioner to develop efficient adaptation plans based on a robust prioritization of risk reduction measures (Komendantova et al., 2014).

However, due to the differing characteristics of hazards, few quantitative models that suite a fully multi-risk perspective exist. Most climate change studies still are predominantly mono-disciplinary, designed to consider impacts triggered by individual shocks (i.e. hazards) and analysing mono-causal and mono-temporal cause-effect relationships (Gallina et al., 2016).

At the same time, considering uncertainty as a pervasive issue in climate change, it should be included as a key component of each risk assessment model.

Despite this, most of risk assessment models still rely on the traditional definition of risk considering the probability of an event and its negative consequences (UNISDR, 2009). Instead, deep uncertainty about future risk could be better addressed by risk scenarios

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describing the range of plausible future environmental and socio-economic conditions (Döll and Romero-Lankao, 2017; Stirling, 2010; Willows and Connell, 2003).

The aforementioned considerations clearly suggest that climate change risk assessment and management, required a shift from traditional risk assessment based on a single stressor approach, toward a more challenging multi risk and adaptive paradigm (Döll and Romero-Lankao, 2017; Landis et al., 2013a).

New approaches should be included in the current environmental risk assessment and management procedures considering the adoption of integrated models (i.e. Bayesian Networks (BNs), System Dynamics (SD), Agent-Based Models (ABMs), Artificial Neural Networks (ANNs) and Expert Systems) able to: incorporate multiple stressors and endpoints (i.e. social, economic and environmental objectives and priorities); ii) deal with uncertainty; iii) take into account the effect of policy and adaptation in changing final system states (Hamilton et al., 2015; Kelly et al., 2013).

Bayesian Networks (BNs) in the last decade have become a recognized tool to deal with environmental problems and decision making under uncertainty (Varis and Kuikka, 1997) and some authors (Catenacci and Giupponi, 2010; Döll and Romero-Lankao, 2017; Hart and Pollino, 2008; Landis et al., 2013a; Pollino and Hart, 2008), suggested their use for risk assessment.

Bayesian Networks (BNs), also known as Bayesian Belief Networks (BBNs) or Belief Networks, are probabilistic graphical models representing a set of random variables and their conditional interdependencies via a Directed Acyclic Graph (DAG) (Pearl, 1988) thus using probabilistic expressions to describe the relationships among system components (Borsuk et al., 2004). BNs, originally emerged from research into artificial intelligence (Charniak, 1991; Heckerman et al., 1995; Jensen, 1996; Pearl, 2011), have been applied with a risk assessment perspective to many different environmental issues (e.g. Integrated Water Resource Management, ecology, maritime spatial planning, fishery, agronomy)(Barton et al., 2008; Borsuk et al., 2004, 2003; Bromley et al., 2005;; Farmani et al., 2009; Gudimov et al., 2012; Henriksen et al., 2007; Lecklin et al., 2011; Renken and Mumby, 2009; Stelzenmüller et al., 2010; Zorrilla et al., 2010). However, the application of BNs in the context of climate change still represent a limited explored field if compare with others where their use has exponential growth during recent years. Only very few studies which explicitly apply BNs to assess and manage climate change impacts on natural resources (i.e. water scarcity and deterioration, soil erosion, biodiversity loss, eutrophication, sea-level rise) can be found in literature (Catenacci and Giupponi, 2013; Dyer et al., 2011; Gutierrez et al., 2011; Kotta et al., 2010; Molina et al., 2013; Tighe et al., 2007).

The purpose of the present work is, therefore, to discuss the application of BNs to improve climate change risks assessment and management. The paper wants to explore to what extent BNs can be useful to enhance environmental risk assessment, through the analysis of multi-stressors issues in several case studies mainly related to natural hazards, sustainable resources management and pollution prevention in view of climate change.

Finally, it describes the use of BNs for the environmental management of climate change impacts, providing some insights of their functionalities for risks prioritization, uncertainty communication and to support practitioners in the selection of optimal adaptation measures at the regional and local scale. To do so, a systematic analysis of existing literature is presented in Section 1. In Section 2, main advantages and limitations of BNs are discussed according to each steps of the general framework of multi-risk assessment and management (Figure 1) thus providing a sort of "road map" for the integration of BNs also in climate change risk assessment and management procedures.

1. Reviewing Bayesian Networks applications

According to the aim of the present work, a set of case studies dealing with BNs applications in the field of environmental modelling and management were selected and analysed.

To facilitate a comparative analysis and discussion, case studies have been categorized according to specific features (i.e. model objectives, model structure, model parametrization, model evaluation, scenarios analysis, stakeholders involvement, representation of spatial and temporal dynamics) recognized as fundamental steps within a BN development process (Kragt, 2009; Pollino et al., 2007; Pollino and Henderson, 2010). Table 1 provides a summary of reviewed cases studies dealing with the sustainable management of natural resources (i.e. disaster risk reduction, climate change adaptation, integrated water management) which will be extensively described and discussed in the following sections.

Table 1 List of reviewed case studies dealing with BNs applications

Reference	Model objectives and scales			Model conceptualization			Model parametrization		Model Evaluation	Scenario analysis		Dynamics		SH involvement
	Model aim	Application context	Spatial scale	Type of stressor	Multiple stressors	Climate change scenario	Structure Learning	Parameter learning		Use of scenarios	Type of scenarios	Spatial	Temporal	
(Nadim and Liu, 2013)	To estimate the risk for buildings associate with earthquake-triggering landslides	RA, RM	LOC	GEO	X		E	E	SA	Predictive	Alternative management measures			
(Qiu et al., 2014)	To forecast the chain reaction path and losses due to a crisis event	RA	LOC	HYDRO	X		E	D	D	Predictive	Alternative risk scenarios			
(Liu et al., 2014)	To model the probability of a tsunami triggered by a rockslide	RA, RM	LOC	HYDRO	X		E	D	MOD	Predictive	Alternative management measures			
(Grêt-Regamey and Straub, 2006)	To assess the damage of avalanches in mountain regions	RM	LOC	HYDRO			E	D	MOD, SA	Predictive	Alternative risk scenarios	X		
(den Heijer et al., 2012)	To estimate the impact of extreme storm events on coastal shoreline	RM	REG	GEO	X		E	D	D	Predictive	Alternative waves scenarios			
(Balbi et al., 2015)	To estimate the benefit of improving existing Early Warning Flood System	RM	LOC	HYDRO			E	E	MOD, SA	Predictive	Alternative performance of Early Warning System	X		
(Stelzenmüller et al., 2010)	To assess the consequences of marine planning objectives	RM	REG	ANTHR CLIM	X		E	D	SA	Diagnostic	Alternative marine planning scenarios	X		
(Helle et al., 2015)	To provide a cost-benefit analysis of oil spill reduction measures	RM	REG	ANTHR			E	E, D	NO VAL	Predictive	Alternative management scenarios			
(Franco et al., 2016)	To evaluate effects of anthropogenic and climate change disturbances on coral reef	RM	REG	ANTHR CLIM	X		E	D	SA, D	Predictive	Alternative anthropogenich disturbances			
(de Santa Olalla et al., 2005)	To assess the impact of water abstraction on groundwater systems	RM	REG	HYDRO			SH	D, E	E	Predictive	Alternative water abstraction regimes			X
(Keshtkar et al., 2013)	To assess the sustainability of catchment management	RM	REG	CLIM	X		SH	D, E	E	Predictive	Alternative management scenarios			X

Reference	Model objectives and scales			Model conceptualization			Model parametrization		Model Evaluation	Scenario analysis		Dynamics		SH involvement
	Model aim	Application context	Spatial scale	Type of stressor	Multiple stressors	Climate change scenario	Structure Learning	Parameter learning		Use of scenarios	Type of scenarios	Spatial	Temporal	
(Chan et al., 2012)	To assess the effect of river flows on fish abundance	RM	REG	ANTHR CLIM	X		E	D, E	SA, D	Predictive	Alternative water abstraction regimes	X		X
(Spence and Jordan, 2013)	To estimate the effect of nitrogen inputs on freshwater wetland ecosystem services	RA	REG	ANTHR			E	D	SA, D	Predictive	Alternative nitrogen inputs			
(Molina et al., 2013)	To estimate the impact of climate change and land use on groundwater systems	RA, RM	LOC	ANTHR CLIM	X	X	E	D		Predictive	Alternative climate change and land use change scenarios		X	
(Giordano et al., 2013)	To assess conflicting uses in groundwater resources	RM	REG	ANTHR			E	D, E	E, SA	Predictive	Alternative management policies	X		
(Landuyt et al., 2014)	To assess ecosystem services delivery of pond under different management scenarios	RM	LOC	ANTHR			E	D, E	SA	Predictive	Alternative pond management scenarios			
(Gutierrez et al., 2011)	To assess the probability of shoreline changes as response to sea-level rise changes	RM	REG	GEO	X	X	E	D	D	Predictive	Alternative climate change scenarios	X		
(Varis and Kuikka, 1997)	To assess the impact of climate change on water quality	RM	LOC	CLIM	X		E	E	E	Predictive	No scenarios			X
(Tighe et al., 2007)	To assess climate change pressures on natural resources	RA	LOC	CLIM	X	X	E	D, E	SA, E	Predictive	Alternative climate change scenarios	X		
(Kotta et al., 2010)	To assess the interactive effect of eutrophication and climate change on sea water quality	RA	REG	CLIM	X	X	E	D	NO VAL	Predictive	Alternative climate and land use change scenarios			
(Dyer et al., 2011)	To assess the effect of climate change on flow regime and water attributes	RA	REG	CLIM	X	X	D	D	NO VAL	Predictive	Alternative climate and regulation scenarios	X		
(Catenacci and Giupponi, 2013)	To assess the effectiveness of adaptation measure to sea level rise	RM	LOC	HYDRO		X	E	E	SA, E	Predictive	Alternative adaptatation measures			

RA=risk assessment, RM=risk management; LOC=local, REG=regional; ANTHR=anthropogenic, CLIM=climatic, GEO=geological, HYDRO=hydrological; E=expert, D=eata, SH=stakeholders; SA= sensitivity analysis, MOD= models, NO VAL=no validation

1.1 Model objectives, systems and scales

The process of a BN model development starts with the definition of the models' objectives and the context of its application (Pollino and Henderson, 2010). Within the analyzed literature, two main contexts of applications can be identified: risk assessment and risk management. In most of case studies (de Santa Olalla et al., 2005; den Heijer et al., 2012; Gutierrez et al., 2011; Kotta et al., 2010; Qiu et al., 2014; Varis and Kuikka, 1997) BNs are employed for environmental risk assessment in order to provide a more or less quantitative or qualitative estimate of risk related to specific stressors on well-defined targets. With this aim, for instance, Dyer et al. (2011) built a model to assess the probability of exceeding defined thresholds for water quality attributes (i.e. nitrogen, phosphorus, dissolved oxygen, pH, turbidity) related to climate change projections for different regions of Ginninderra (Australia).

In some cases BNs have been specifically designed for risk management assessment with the objective of evaluating adaptation or management strategies effectiveness in control the probability of adverse events or conditions (Balbi et al., 2013; Catenacci and Giupponi, 2013; Nadim and Liu, 2013; Stelzenmüller et al., 2010).

Balbi et al. (2015) developed a BN to estimate the benefits (i.e. avoided fatalities, injuries and post-traumatic stress disorder) of improving the existing Early Warning System for flood in the Sihl valley (Switzerland). In the same way, Catenacci and Giupponi (2013) evaluated the effectiveness of two alternative adaptation measures (i.e. saltmarshes restoration, beach nourishment) to contrast the negative effect of sea level rise in the Grado-Marano Lagoon (Northern Italy).

In the listed applications, BNs have been applied most widely at regional and local scales to model processes taking place at very different spatial (e.g. aquifer, river basin, coast, ecosystem, region) and temporal (e.g. daily, monthly, annual, decadal) levels.

1.2 Model conceptualization

The model conceptualization aims at identifying the causal structure of the model and, consequently, requires the development of an influence diagram in which all the most relevant components of the system (i.e. stressors, processes, vulnerabilities, endpoints) and their casual relationships and interdependences are included and represented (Pollino and Henderson, 2010). The causal structure of the model, should represent as much as possible the reality of the system and thus the choice between alternative model structures can be fundamental. In fact, it is entirely possible to develop alternative model structures that are totally plausible but produce completely different results (Pshenichny et al., 2009). It is the case of complex and heterogenous environments, where interactions between systems components are largely unknown. In such situations, the use of multidisciplinary expert systems and knowledge-based models is crucial to reach a shared vision and a consensus on the most appropriate model configuration.

Within the reviewed case studies BNs have been applied to assess the effect of both environmental and anthropogenic stressors on a variety of natural and semi-natural endpoints (i.e. rivers, transitional systems, coastal zone, agricultural and urban areas) using a heterogeneous set of indicators (i.e. ecological, social and economic). For what concern environmental stressors most of case studies are dealing with geological (i.e. earthquakes, avalanches, landslides) (den Heijer et al., 2012; Grêt-Regamey and Straub, 2006; Nadim and Liu, 2013; Qiu et al., 2014) and hydrological hazards (i.e. flood, drought, storm surges, sea-level rise, coastal erosion) (Balbi et al., 2015; Catenacci and Giupponi, 2013; Gutierrez et al., 2011; Tighe et al., 2007) however few methodologies consider the alteration of climatic variables (i.e. temperature, precipitation, winds)(Kotta et al., 2010; Molina et al., 2013 Varis and Kuikka, 1997) as primary stressor and assess their impacts in changing systems conditions (i.e. water quality and availability). Anthropogenic stressors are usually considered together with environmental ones and include mainly water abstraction, changes in land use, and pressures derived by other human activities (i.e. agriculture, fishing, transportation, tourism and recreational activities) (de Santa Olalla et al., 2005; Molina et al., 2013). Stelzenmüller et al., (2010) however, considers only anthropogenic stressors (i.e. fishing, oil and gas infrastructures, aggregate dredging) derived by different marine planning objectives to assess how their cumulative impact can affect marine environments and ecosystems.
With some exceptions (Balbi et al., 2015; Catenacci and Giupponi, 2013; de Santa Olalla et al., 2005), which focus on single stressors, most of case studies follow a multi-stressors approach

considering the presence of multiple cumulative or cascading threats affecting the same system or region. Qiu et al. (2014), for instance, employed BN to assess the risk of buildings exposed to landslides triggered by earthquakes. They exploited BNs features to forecast the cascade of effects associated with a crisis event simulating the reaction path of emergency which can be induced by a typhoon-rainstorm-flood chain.

Most of case studies do not take into account the effect of climate change (Balbi et al., 2015; de Santa Olalla et al., 2005; den Heijer et al., 2012; Nadim and Liu, 2013; Qiu et al., 2014; Stelzenmüller et al., 2010; Varis and Kuikka, 1997). Few studies (Catenacci and Giupponi, 2013; Gutierrez et al., 2011; Kotta et al., 2010; Molina et al., 2013; Tighe et al., 2007), instead, are explicitly designed to explore the potential impacts of climate change which is considered as one of the main drivers. Among these, however, very few used climate change projections provided by climate models to inform the BN (Gutierrez et al., 2011; Molina et al., 2013; Tighe et al., 2007).

1.3 Model parametrization

The parametrization of a BN requires the assignment of states (i.e. potential values or conditions the variable can assume) to each variable of the system and the computation of conditional probabilities representing the strength of relationships between systems components (Kragt, 2009; Pollino and Henderson, 2010).

Across the reviewed literature, various sources of information have been employed to define states and extrapolate conditional probabilities including directly observed data, probabilistic or empirical equations, outputs from model simulations or elicitation from expert knowledge.

When using observed data, conditional probabilities are learned directly from the dataset of monitoring or field observations, calculating the probability based on the frequency of observed conditions. In case of scarcity of observed data, outputs from models can be used to generate large amount of information to cover many cases as requests by scenarios setting (Cain, 2001b). The use of models becomes particularly useful, especially when dealing with climate change modelling and, more in general, with future scenarios for which directly observations are not available.

Molina et al. (2013), for instance, employed outputs provided by a chain of regional climate models, rainfall-runoff, groundwater and agro-economic models forced with different climate change projections (e.g. A1B, A2) and land use scenarios to parametrize a Decision Support Tool for sustainable groundwater management.

When data learning cannot be applied because data or measures are missing or totally lacking, experts or stakeholders elicitation can be employed. Each knowledge source present some limitations which can affect the rigor and credibility of the model and therefore the best approach would be represented by the integration of different methods, at different level of accuracy and details (Pollino and Henderson, 2010).

Only few of analysed methodologies, represent good practices in this sense, integrating multiple information and knowledge sources (Chan et al., 2012; de Santa Olalla et al., 2005; Keshtkar et al., 2013; Molina et al., 2013; Tighe et al., 2007). Among them Tighe et al. (2007), employed climate change projections provided by regional climate models, historical observations, expert judgment and literature information in an integrative fashion in order to assess multiple climate pressures on the state of natural resource in the Macquire River Delta Valley (Australia).

1.4 Model evaluation

After the model has been structured and trained, it requires to be evaluate in order to assess if it purses the objective for which it was designed and if the results are consistent with the outcome of other similar models (Kragt, 2009). According to Pollino and Henderson (2010), two main types of validation methods can been identified: the data-based validation and the qualitative evaluation.

The data-based evaluation measures the predictive accuracy of the model by means of error rates comparing the frequency of the predicted node state (i.e. the node with the highest probability) with a test or an independent set of observed data. In cases where suitable dataset are not available, a qualitative model evaluation can be performed using expert judgement or comparing results with peer reviewed literature or similar model results (Kragt, 2009).

Within the reviewed case studies, only two models have been validated using observed data (den Heijer et al., 2012; Gutierrez et al., 2011) while others (de Santa Olalla et al., 2005; Tighe et al., 2007; Varis and Kuikka, 1997) have not been validated or just provided a qualitative evaluation of the model highlighting that validation, as for other risk modelling techniques, remains a weak point.

In addition, sensitivity analysis can be used to test the sensitivity of model outputs to variation in model input parameters and thus allowing to identify which are the most relevant variables but also to verify and correct model structure and parametrization (Borsuk et al., 2004; Marcot et al., 2006; Newton, 2009). Most of the analyzed methodologies include sensitivity analysis (Balbi et al., 2015; Catenacci and Giupponi, 2013; Nadim and Liu, 2013; Stelzenmüller et al., 2010; Tighe et al., 2007) which, however, is performed using different type of measures (e.g. variance reduction, Entropy or Shannon's measure of mutual information (Pearl, 1988)) according to the model objective and evaluation purposes. Tighe et al. (2007) applied the latter to identify which are the variables (i.e. climate change, river flow, water quality) that strongly influence the state of health of marshes.

1.5 Scenario analysis

Once trained and evaluated, the BN model can be used for scenarios analysis allowing to assess the relative changes in outcomes probabilities associated with changes in input variables (i.e. predictive function) or to define the state in which state input variable should be to obtain the desired outcome (i.e. diagnostic function). Most of the case studies applies scenarios analysis for predictive function perturbing the state of input variables according, for instance, to information provided by climate change (Catenacci and Giupponi, 2013; den Heijer et al., 2012; Gutierrez et al., 2011; Kotta et al., 2010; Molina et al., 2013; Tighe et al., 2007) and land use projections (Kotta et al., 2010; Molina et al., 2013) or future management and adaptation scenarios (Balbi et al., 2015; Catenacci and Giupponi, 2013; de Santa Olalla et al., 2005). Giupponi and Catenacci et al., (2013) performed scenarios analysis to estimate the effectiveness of two different adaptation strategies (i.e. saltmarshes restoration, beach nourishment) in reducing the losses induced by sea level rise. To do so, the authors developed a total of nine different scenarios by imposing different relative sea level increase (i.e. +30, +50, +100 cm) and different scenarios of measures implementation changing the probabilities distribution of input nodes' states. The same approach has been used by Gutierrez et al., (2011) to estimate the effect of different climate change scenarios on shore line change rates.

Finally, Molina et al. (2013) tested the effect of different scenarios on the recovery time of sustainable groundwater level in dry regions. Scenarios were developed starting from the outputs of an ENSEMBLE of Regional Climate Model (RCMs) and changing the states of input variables according with different combination of climate variables and land use features.

Among the analyzed applications just Stelzenmüller et al., (2010) applied scenarios analysis with a diagnostic function. Specifically, she fixed the state of the final cumulative impacts (i.e. output variables) obtaining new "posteriori" probabilities distribution in the input nodes variables (i.e. fishing, sediment extractions, oil and gas infrastructures) to understand which changes in intensities of human activities would be required to achieve the desired level of cumulative impacts according with Maritime Spatial Planning (MSP) objectives and targets.

Few studies (Varis and Kuikka, 1997) do not exploited the scenarios analysis function of BNs and provided just a scenario representing current or baseline conditions.

1.6 Stakeholder involvement

According to Bromley et al. (2005), good practices in BNs modelling would require stakeholders' involvement during all the steps of the model development: from model conceptualization to validation and scenarios analysis. Despite these recommendations, just few of the reviewed case studies (Chan et al., 2012; de Santa Olalla et al., 2005; Keshtkar et al., 2013; Varis and Kuikka, 1997) formally involved interested stakeholders in the process, thus using BNs as a fully participative tool for environmental assessment and management (Bromley, 2005). In most studies, in fact, stakeholders are mainly involved in the phase of model conceptualization (de Santa Olalla et al., 2005; Keshtkar et al., 2013) while they are generally ignored during the other stages of model development.

de Santa Olalla et al. (2005) developed a BN to support the fulfilment of EU Water Framework Directive (Directive 2000/60/EC) requirements for groundwater resources. Relevant stakeholders (i.e. water users, local authorities) were identified performing a preliminary social network analysis and involved during the entire process of model development, testing and updating by means of participatory recognized techniques (i.e. participative workshops, surveys). Conclusions highlight that, because of the high level of stakeholder involvement, the probability of adoption of proposed solutions and management options has increased.

1.7. Spatial and temporal dynamics representation

BNs are limited in the representation of spatial and temporal dynamics (Pollino and Henderson, 2010). Accordingly, just few case studies consider possible changes of variables states in time or space across the timeframe and region of analysis (Balbi et al., 2015; Gutierrez et al., 2011; Molina et al., 2013; Stelzenmüller et al., 2010; Tighe et al., 2007). Tighe et al. (2007) included spatial nodes within the network to provide a more spatially explicit assessment of climate change impact on flows, water quality and ecology of Macquerine river and marshes (Australia). Specifically, the additional nodes are based on measures coming from gauging stations at different locations along the river and are used to build a subnetwork for river flow which rely on respective monitored data. In this way, the model, once run fixing the states of the spatial nodes, allows to associate the outcome to the specific location (i.e. gauging station). Others authors (Balbi et al., 2015; Grêt-Regamey and Straub, 2006; Gutierrez et al., 2011; Stelzenmüller et al., 2010) instead, coupled BNs with Geographical Information Systems (GIS). In this way is possible to exploit spatially explicit dataset to characterize BNs nodes and to visualize the output in a spatial manner (e.g. risk mapping).

The aforementioned approaches, however, only allow reproducing static changes trough space and time while neglecting dynamics and feedback effects. Among the reviewed application, only Molina et al. (2013) developed a dynamic model able to account also for dynamic changes trough time by applying an extension of conventional BNs (i.e. Dynamic Bayesian Networks, DBNs). Molina et al. (2013) developed a DBNs model to estimate the effect of climate change and land use scenarios for the future period 2070-2100 on groundwater recharge rates. Through DBNs modelling different stationary networks, each representing a discrete time steps, can be then linking together and information can be updated based on the output of the previous time steps thus allowing a more dynamic representation of space and time.

2. Potentials and limits of BNs for climate change multi-risk assessment and management

The assessment and management of environmental and climate impacts from a multi-risk perspective can be seen as an extension of common environmental risk assessment and management frameworks (EPA, 1998) in which particular effort have to be posed to the identification and quantification of stressors interactions (Dawson, 2015; Gallina et al., 2016). Artificial Intelligence based models (e.g. Artificial Neural Networks (ANN), Bayesian Networks (BN) and fuzzy modelling approaches), integrating different system processes into a unified framework, are already commonly applied in environmental applications (Kourgialas et al., 2015; Liu et al., 2010; Pshenichny et al., 2009; Zabeo et al., 2010), and can be used to frame and quantify risk interactions under changing conditions.

This kind of methods, in fact, can be designed to tackle complex environmental problems characterized by non-linear behaviour and hampered by large uncertainties. Fuzzy modelling, especially, result particular suitable in analysing new emerging risks which are still not well understood due to the lack of experience data (Zabeo et al., 2010). Fuzzy approaches recognize the uncertainty and lack of knowledge using available data or expert systems to describe cause-and-effect relationships, assess the degree of risk exposure and rank key risks in a consistent way. Most variables are described in linguistic terms, making fuzzy models more intuitively similar to human reasoning (Shang and Hossen, 2013). However, relying most on expert knowledge they are strongly dependent on the human perspective and perception of the system failing in providing a strong quantitative assessment of risk and making the validation of results difficult.

From the other side, Artificial Neural Networks (ANNs) allow relatively accurate and quantitative predictions of risk (Kourgialas et al., 2015). ANN, simulating the neural network behaviour of the human brain, are powerful learning tools capable of identifying complex non-linear relationships between input and output variables without prior knowledge of the internal structure of the system (Elgaali and Garcia, 2007). Often, however the value of ANNs as risk assessment tool has been argued claiming that they apply a sort of “black box” approach in which cause-effect paths are difficult to be detected and communicated to users. Furthermore, ANNs are a deterministic tool and, consequently, features such as uncertainty, variability or randomness are difficult to assess through this tool.

Bayesian Networks have the capability and flexibility to use and integrate different sources of information, from detailed models to qualitative experiential understanding, in order to derive the conditional probability distribution between variables.

In this way, BN can be used as integrative tool in which different kind of methods can be coupled overcoming the shortcomings of single approaches and improving the risk assessment procedure.

Fuzzy approaches, for instance, can be integrated in BNs modelling to discriminate between alternative model structures thus reducing structural uncertainty and encapsulating expert knowledge and rules to improved systems understanding. At the same way, ANNs results simulations can be used to extrapolate probabilistic relations between systems variables in the network improving the quantitative description of specific processes taking place in the system.

Moreover, BN can act as integrative tool always maintaining an intuitive graphical structure which, making clear the underlaying cause-effect relationships and assumptions ensure a transparent communication of results to stakeholders and end users.

Based on these considerations, in the following sections, an analysis of advantages of applying BNs as integrated modelling tool for environmental risk assessment and management of climate change impacts is provided. Specifically, drawing on the case studies analysis, main potentials of BNs are described and discussed in relation with the fundamental steps of a generic multi-risk assessment framework (Dawson, 2015) which is a chronological and iterative process as described in Figure 1. Finally, some of the major drawbacks which could represent barriers for BNs application in the climate change impact assessment and management field are presented.

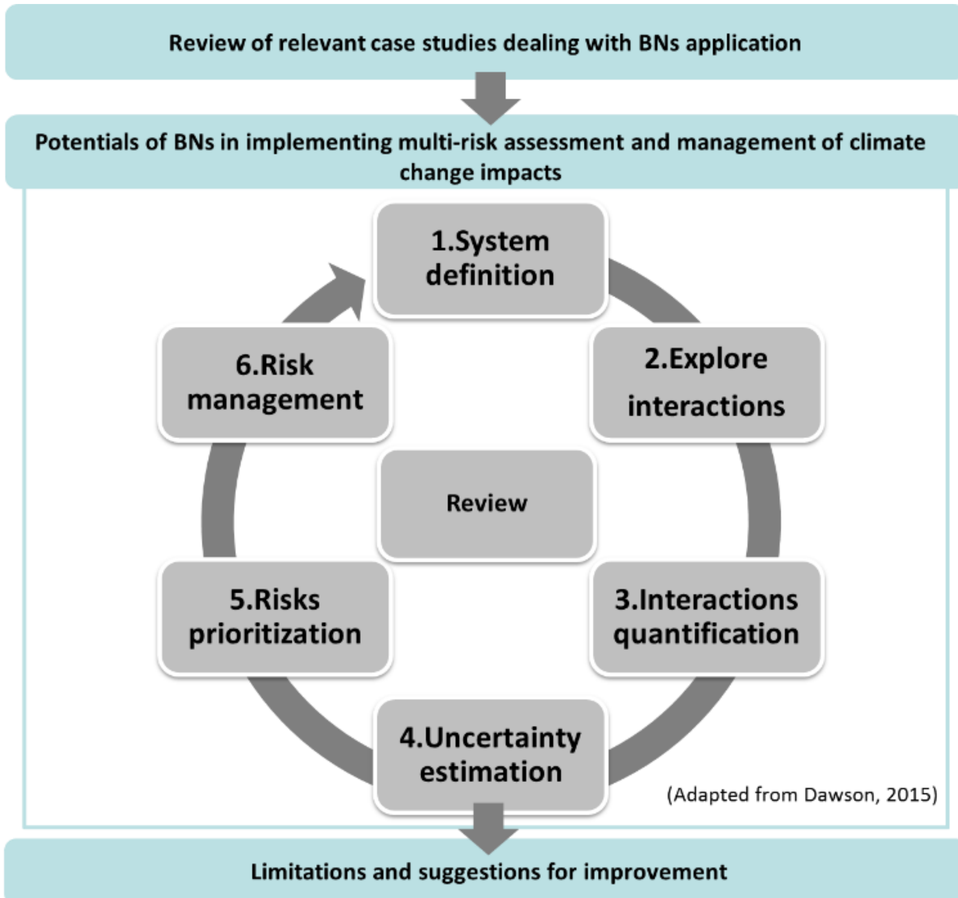

Figure 1 Overall approach adopted for the review and discussion of potentials and limits of Bayesian Networks for climate change multi-risk assessment and management.

2.1 Potentials

2.1.1 System definition

Any environmental risk assessment procedure requires, preliminarily, to establish the context of the analysis bounding the problem on appropriate time and spatial scales and identifying the systems structures and relevant assessment endpoints (Dawson, 2015; Pollino and Hart, 2008). Assessment endpoints provide an explicit representation of values or characteristics of the system that need to be protected and, therefore, translate the risk assessment objectives into measurable attributes which can be modelled (EPA, 1998). In the context of climate change impacts assessment, they can be represented by either ecological or human systems, characteristics, processes, values or activities which can be potentially affected or altered by climate related events (IPCC, 2014).

Given the multi-disciplinarily of the issue and the multitude of actors involved, reaching a consensus on the structure of the systems and relevant endpoints to be included in the analysis can be not straightforward. In such situations, the use of multidisciplinary expert systems and the involvement of representative groups of actors is crucial to reach a share vision of the system. BNs allow a strong integration between very different information sources ensuring that expert knowledge can be included together with quantitative data to better understand system structure and relevant processes involved (Kelly et al., 2013).

Moreover, through BNs, multiple assessment endpoints can be integrated within the same framework allowing considering multiple perspectives and dimensions (e.g. economic, social and environmental), thus ensuring a comprehensive analysis of risk.

In this way, the network can be used to estimate the optimal tradeoff between different and, in some cases, contrasting objectives. The potential to promote an informed discussion on tradeoffs (e.g. balancing water requirements for productivity and the ecosystem) and opportunities enhances the prospect for less controversial outcomes and an higher acceptance of the results (Pollino and Hart, 2008).

2.1.2 Explore interactions

The multi-risk analysis requires the characterization of all systems variables, interactions and processes relevant to the objectives and endpoints in the selected timeframe and spatial unit (Dawson, 2015; Gill and Malamud, 2014; Pollino and Hart, 2008). According to Gallina et al. (2016), when dealing with climate change impacts this can result particularly challenging as it naturally requires a multidisciplinary approach taking into account multiple perspectives and dimensions (e.g. economic, social and environmental) (McCann et al., 2006). Multidisciplinary may, to some extent, represents a demanding task in risk assessment: the joint involvement of different expertise requires the development of frameworks which are understandable and acceptable by all involved specialists, including decision makers. Moreover, different data sources adopt different unit of measures which can be not directly aggregable and comparable.

The conceptual model's structure of BNs can help in the understanding of such complex systems (Aguilera et al., 2011). Many variables (i.e. stressors, vulnerabilities, risks) and their interrelationships can be incorporated, in form of nodes and arcs, under the same network. Through their graphical structure BNs provide an effective conceptualization of different possible interactions between variables and assessment endpoints including cumulative, synergic or antagonistic effects, cascading and triggering events. In this way, it is possible simultaneously to capture and communicate the breadth of the problem, allowing to include also indirect effects (e.g. lag effects, indirect impacts), as well as focusing on key processes at the local scale. BNs support the integration of knowledge coming from various disciplines and spheres permitting very different variables to be assembled in a systematic manner (Düspohl et al., 2012; Haapasaari and Karjalainen, 2010) and expressed using the same unit of measure (i.e. probability distribution). In this sense, BNs represent an effective tool to integrate existing information and, at the same time, a common platform where different domains (i.e. environmental, economic, social) can interact in a more effective fashion (Rahikainen et al., 2016).

2.1.3 Interactions quantification

A fundamental aspect translating a risk assessment into a multi-risk assessment lies on the quantification of interdependency between systems variables (i.e. cumulative, synergic or antagonistic, cascading effects) which are likely to influence the final risk level (Dawson, 2015; Gill and Malamud, 2014).

Ideally, this quantification should be wholly quantitative however due to the differing characteristic of hazards, multiple sources of vulnerability and incomplete information about their relation this is rarely possible (Liu et al., 2015, 2014). Commonly used models for multi-risk analysis, mostly rely on past information, neglecting considerations about future climate and socio-economic scenarios and, consequently, resulted scarcely applicable for climate change analysis where condition could differing substantially from actual ones (Gallina et al., 2016). In addition, current multi-risk assessment practices are based on deterministic models where relationships evaluation is limited to those that are readily quantified while rarely uncertainty or variability are represented (Liu et al., 2014).

In BNs, as relations between variables are express as conditional probability, interactions are quantified in a probabilistic form and the likelihood of an event given the occurrence of another can be quickly derived. The use of probability to express risk components' dependencies means that these can be quantified using both quantitative (i.e. empirical models, physical analyses or historical data, climate change models) and qualitative (i.e. expert elicitation) information. It makes possible to explore multi-risk also in cases when little information are available, uncertainty are high and the relationships are not easily expressible using mathematical notations (Pearl, 2011). A larger number of multi-risk scenarios, considering different combination of variables interactions, can be explored. In this way, it is possible to assess the consequence of chain of impacts induced by events that, despite being characterized by few information at the actual state of knowledge, could become more frequent in the future. At the same time, the uncertainty and probability of each of these scenarios are provided such as users can have a realist idea of those which are the most probable in term of occurrence. Another, interesting potential use of BN for the quantification of interactions between variables is the possibility of using Dynamic Bayesian Networks (DBNs) (explained in detail in Section 1.8 and Section 3.2.1) to account also for time-depended dependencies. In contrast to BN, DBNs allows probabilistic inferences in dynamic domains enabling to monitor and update the system as time proceeds (Mihajlovic and Petkovic, 2001). Introducing DBNs, would be possible, for instance, to predict the behavior of system variables in response to states changes in previous time steps and even to model the effect of consecutive or triggering events.

2.1.4 Uncertainty estimation and communication

An effective communication of risk and associated uncertainty is essential when developing models to support decision making. Given the high uncertainty associated with climate change projections, it is necessary that decision makers are informed about the range of possible outcomes (i.e. best/worst scenarios) to ensure that decisions taken are based on robust quantitative estimates (Burgman, 2005; Power and McCarty, 2006).

Commonly decision makers are averse to uncertainty and, especially in climate change management issues, it can represent a major barrier for engagement and commitment (Morton et al, 2011). For this reason uncertainties should be communicate as an inevitable component of risk and in a way that can be easily understood also by a no-scientific community to avoid misjudged information and to prevent overconfidence in management responses (Uusitalo, 2007). When applying BNs for risk assessment, results are presented in form of risk scenarios representing a range of possibilities of what the future could be, each with a probability attached. In this way, uncertainty and risk are represented and communicated in a way which is quantifiable and well recognizable also by a non-expert. BNs, as probabilistic model, are designed to deal with uncertainty: uncertainty in the inputs is recognized and propagates trough the model determining uncertainty in the outputs. Users can easily track which are the main sources of uncertainty affecting the model (e.g. lack of knowledge, natural variability, subjectivity of expert judgements) and identify, if and where, it can be reduced improving the performance of the assessment. Finally, thanks to their graphical structure and the transparency in input information, the assumptions and uncertainties lying behind the model can be better communicate increasing the likelihood that the outputs will be accepted and, consequently adopted, in decision making and risk management (Pollino et al., 2007). BNs networks can be informed, for instance, using multi-model ensembles that rely on the outputs of multiple climate or impact models (e.g. hydrological, ecological models), thus facilitating the assessment and communication of uncertainty characterizing the analysed hazards and risks.

2.1.5 Risks prioritization

Risks prioritization is a key component of risk assessment and management as it provides the guidance for the implementation of appropriate risk reduction strategies and support the optimal allocation of available adaptation resources. This steps aims at evaluating environmental and climate risks identified in the previous phases based on their magnitude, uncertainty, relevance for stakeholders, to identify the most relevant ones that should be considered when developing adaptation strategies (Döll and Romero-Lankao, 2017).

BNs, being causal models, can assists risk prioritization driving the understanding of pathways of hazards and vulnerabilities relations, how they change over space and time, and what it means in terms of probability and likelihood of adverse effects in a straightforward and understandable manner (Molina et al., 2016; Pollino and Henderson, 2010; Pollino and Hart, 2008). As suggested by Pollino and Hart (2008), once the structure and the relationships driving the model have been established, priority stressors and risks can be identified performing sensitivity analysis (Section 1.4).

Sensitivity analysis, in fact, can be used to explore the behaviour of the system and to identify variables which have the greatest influence on model endpoints. Through sensitivity analysis, it is possible to detect how the variation in the output of a model (i.e. risk level) can be apportioned to different variations in the inputs (i.e. hazards and vulnerability changes) and therefore to track relevant causal pathways between variables.

In this way, the outcomes of risk prioritization can be useful to identify which factors and variables should be targeted by risk management to effectively reduce the probability of undesired events and to select the opportune typology of responses to put in place (i.e. hazards mitigation, vulnerability or exposure reduction).

Finally, sensitivity analysis depicts the key variables which should be included in a more quantitative risk assessment procedure and those which can be removed from further consideration as their contribution on final risk level is irrelevant.

2.1.6 Risk management

Focusing on the most relevant risks identified in the previous phase, risk management involves the identification of measures and assessment of their effects in minimizing the probability of adverse events induced by multiple and interacting factors. Measures can be evaluated considering several criteria including costs, benefits and trade-offs among options.

Specifically, climate change risk management is based on the development of adaptation or management scenarios, where the effect of alternative options is simulated to identify what measures can lead to a envisioned risk reduction under different climate change scenarios and other external stressors (Döll and Romero-Lankao, 2017).

BNs can be used to guide decision makers in the testing of individual or set of interventions (e.g. alternative management decisions or policies, adaptation or risk mitigation measures) through a quick and straightforward process. The effect of measures can be examined by assigning a fixed distribution to the input variable of interests (i.e. those directly affected by the interventions) and to determine how probabilities distribution of the output variables change in response. As results are expressed as probability distributions, for each alternative, decision-makers can have a realistic prediction of the chances of achieving desired outcomes and an evaluation of its uncertainty. Moreover, to make the results more explicit and clear for users, decision and utility nodes can be incorporate within the network (Pollino and Henderson, 2010). Decision and utility nodes have the advantage that they can be associated with deterministic costs and benefits analysis (Düspohl et al., 2012; Inman et al., 2011) making the impacts of several management actions comparable also in economic terms and thus supporting the identification of the set of optimal measures (e.g. the mitigation of most relevant risk at the lower cost).

2.1.7 Monitor and review

Given the high uncertainty surrounding climate change, an adaptive approach to the whole process of multi-risk assessment and management is strongly required (Döll and Romero-Lankao, 2017; Landis et al., 2013b).

The outputs of the risk assessment and management should be continually reviewed and updated throughout and after the process to: i) include improved knowledge to reduce uncertainty; ii) track changes in variables interactions as results of changes within the system; iii) determine if predicted effects are realized over the time; iv) monitor how the systems is reacting to the implemented adaptation measures.

BNs are highly flexible and adaptable to changing conditions and, being constructed through an iterative process, well fit the implementation of the adaptive management principle (Pollino and Henderson, 2010). As soon as the new knowledge and evidences (e.g. observations, field data, model results, scenarios) become available they can be used to update evidences and uncertainty thus increasing the robustness of risk assessment outcomes (Failing et al., 2004).

In this way, new climate change scenarios can be included as input for the process allowing to test system responses to a wider range of climatic combinations and to adjust management efforts over time.

As results of iterative review, the model structure can also be adapted and extended including for instance, additional variables to capture emerging properties or removing variables that, with projected changes, may become irrelevant for final risk estimates.

2.2 Limitations

Besides highlighting several potentials of BNs as risk assessment tool, the reviewed applications allowed to depict also some of their main limitations and drawbacks. These limitations, have been extensively discussed by several authors (Aguilera et al., 2011; Catenacci and Giupponi, 2010; Düspohl et al., 2012; Phan et al., 2016; Pollino and Henderson, 2010; Uusitalo, 2007) and include: i) the big amount of data required for model development; ii) the limited capacity of BNs of dealing with continuous variables; iii) the knowledge bias in expert elicitation; iv) the growing complexity of the computational effort in case of complex systems.

Two other drawbacks of BNs models, however, are those representing major challenges and limiting their application for climate change impact assessment and management: their scarce representation of temporal and spatial dynamics and the difficulty of performing a quantitative validation of model results. Both aspects, together with practical solutions for improvement, are described and discussed in the following sections.

2.2.1 Scarce representation of temporal and spatial dynamics and feedback loops

As highlighted in Section 1.7, BNs are limited in the representation of spatial and temporal dynamics. It represents a problem for climate change applications as environmental and socio-economic systems involved are characterized by dynamics which are strongly unpredictable and varying across space and time (Moore et al, 2009). As reported in some of the analysed application (Balbi et al., 2015; Gutierrez et al., 2011; Molina et al., 2013; Stelzenmüller et al., 2010; Tighe et al., 2007), different methods can be adopted to overcome this limitation. One straightforward solution is to include a spatial/temporal node in form of an additional input variable into the network which can be then parametrized using information associated with specific geographical location (e.g. gauging and monitoring stations) or time period (i.e. a specific year or climatic period). The model, once run fixing the states of the temporal-spatial nodes, allows to associate outcomes to the specific location or time.

Another widely used practice consist in coupling BNs with Geographical Information Systems (GIS) in order to exploit the capabilities of GIS to quantify specific nodes and to visualize outputs in a spatial manner (Balbi et al., 2015; Grêt-Regamey and Straub, 2006; Gutierrez et al., 2011; Stelzenmüller et al., 2010).

Despite the aforementioned approaches allow conferring to the BNs' outcome a more spatially and temporally explicit flavour, they only permit to reproduce static changes trough space and time while ignoring dynamics and feedback effects. If the process or system under analysis requires a dynamic representation trough time and space Dynamic Bayesian Networks (DBNs) can be used (Molina et al., 2013; Pollino and Henderson, 2010). DBNs are an extension of conventional Bayesian Networks relying on the Object Oriented Programming paradigm (OOP)(Koller and Pfeffer, 1997). DBNs act breaking up timeframe of analysis into relevant time slices (i.e. discrete time-steps) and reproducing the same structural copy of the network for each time slice. Networks associated with different time step are then linked by instance nodes which enable the exchange of information between different networks.

Despite the potential of DBNs is quite attractive, especially from a multi-risk assessment point of view, their application can result tedious due to the complexity involved which require a certain level of expertise in statistics to be managed. For this reason, very few examples of DNBS modelling can be found in literature (Molina et al., 2013)

2.2.2 Quantitative validation

Another limiting aspect of the application of BNs as risk assessment tool is the difficulty to provide a strong quantitative validation of the network results. As for other kind of models, the best way for validation would be represented by a comparison with an independent set of observed data. However, as described in the analysed literature, it is not always feasible especially when dealing with complex systems characterized by multiple stressors and variables, where large dataset is commonly lacking or difficult to be retrieved.

BNs are usually developed in an integrative way including different and heterogeneous information sources (i.e. experts, data, models results) making the validation of the whole network a very difficult or even impossible task (Barton et al., 2008; Uusitalo et al., 2016). For this reason, in fact, quantitative validation is commonly limited to data-derived portions of the network or to single parameters (Molina et al., 2013) while, for others, validation is restricted to indirect methods (i.e. expert evaluation, comparison with previous studies).

BNs validation became even more complex and problematic in the context of predicting future risks, where, the observations and experiences are not available and the true outcome will be revealed only in the future (Uusitalo et al., 2016). In such cases, an alternative validation can be performed using outputs of model's simulation (i.e. climate or hydrological models), forced with the same climate change scenarios, as comparative dataset.

Conclusions

The paper provides a review of BNs applications in the field of sustainable resources management and natural hazard with the aim to explore the potential use of BNs as modelling tools to improve current climate change risk assessment and management procedure. The results highlight that, despite BNs have been applied to a large variety of problems and contexts (i.e. water resource management, oil spills, transport of pollutants, hydrological hazards), their application in climate change studied is still limited. Among the reviewed applications, very few previous studies (Catenacci and Giupponi, 2013; Dyer et al., 2011; Gutierrez et al., 2011; Kotta et al., 2010; Molina et al., 2013; Tighe et al., 2007) make explicit use of BNs to deal with the assessment of climate change impacts on natural resources (i.e. water quality and availability, soil erosion, biodiversity). These studies however mainly used qualitative and narrative scenarios to inform the BN, while very few integrated quantitative projections coming from climate change models within the analysis.

The reviewed applications also reveal BNs could represent a powerful tool to help in addressing some of the main limitations of traditional approaches to environmental risk assessment such as the single stressor assessment focus and the representation of uncertainty.

BNs, in fact, provide a stochastic assessment of risk based on probabilistic causal-effect relationships quantification which enable the modelling of multiple stressors and endpoints in the same integrated framework. In this way, the probability of impacts chains induced by the interactions between multiple stressors can be evaluated in a quick and systematic manner taking advantage of the integration of qualitative and quantitative information coming from different knowledge domains (i.e. environmental, social, economic). The probabilistic expression of knowledge in BNs directly incorporates uncertainty, which represent a pervasive problem in climate change researches. Through BN, the large amount of information provided by climate and impact models can be effectively integrated and summarized supporting the quantification and transparent communication of uncertainties related with climate change projections and scenarios.

Together with BNs potentials as risk assessment tool, some of their limitations and drawbacks are also discussed including, among all, the scarce representation of temporal and spatial dynamics as well as the difficult incorporation of feedback loops.

In literature some of these limitation has been overcome by coupling, for instance, BNs with GIS (Grêt-Regamey and Straub, 2006; Stelzenmüller et al., 2010) or by developing DBNs (Molina et al., 2013).

Both solutions represent innovative fields to be explored in future researches to boost BNs use in climate change applications and allowing the representation of spatial and temporal dynamics of risk and vulnerabilities, as well as the communication of results in a spatially explicit manner.

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Paper 2-A Bayesian Network approach for the assessment of climate change impacts on nutrients loadings in transitional waters

Introduction

Climate change, in combination with other anthropogenic stressors (i.e. urbanization, agriculture, population grown), may affect the availability and quality of water in multiple ways (Jiménez Cisneros et al., 2014). Accordingly, a deep understanding of expected impacts is required to support adaptation processes. Furthermore, a sustainable water resources management requires approaches that can be applied under uncertain and changing conditions. Despite potential impacts of climate change on water availability have been widely studied in the last decades (Molina et al., 2013; Marcos-Garcia et al., 2017; Ronco et al., 2017; Zabel, 2016), the implication for concomitant changes in water quality have been just poorly explored (Bussi et al., 2016; Huttunen et al., 2015; Lu et al., 2015; Pulido-Velazquez et al., 2015; Whitehead et al., 2008).

In Mediterranean climate regions, the high seasonal variability alternating dry and wet period is likely to have profound effects on those hydrological processes (e.g. runoff, river flow, water retention time, evapotranspiration) that regulate the mobilization of nutrients and other kinds of pollutants from land to water bodies (Alam and Dutta, 2013; Culbertson et al., 2016; El-Khoury et al., 2015; Ockenden et al., 2016). Likewise, increased temperature can accelerate the mineralization of organic matter in the soil (Eghball et al., 2002). Consequently, the availability of inorganic forms of nitrogen and phosphorus increases and favourite their erosion. Furthermore, decrease in precipitation can reduce river flow and nutrient loadings but at the same time can alter their dilution in the receiving water body (Whitehead et al., 2009). Finally, increased winter precipitation and the occurrence of summer extreme events can increase the runoff and associated wash-off of fertilizers (Jeppesen et al., 2009; Sterk et al., 2016; Whitehead et al., 2009).

Despite the fact that all these alterations are likely to affect nutrients availability and loadings, the magnitude, timing and seasonality of these changes are still largely unknown (Jiménez Cisneros et al., 2014)

Moreover, procedures commonly applied to assess negative impacts on water resources are based on process-based models in which relationships between model variables are

expressed using mathematical equations with deterministic values (Jackson et al., 2000). Despite these approaches have the advantage of providing a strong quantitative modelling of impacts, they fall short in dealing with the uncertainty characterizing climate change scenarios and in incorporating the effect of human decisions on the system, thus reducing their usefulness for management and adaptation. Consequently, it results in their low use for management and adaptation. In fact, when dealing with natural resource management, , understanding the average processes is not always sufficient, while decision-makers are increasingly more interested in having a realistic picture of all possible outcomes (Burgman, 2005; Power and McCarty, 2006) and uncertainties (O'Hagan, 2012).
For this reason, probabilistic models (i.e. Bayesian Networks) which directly incorporate and account for uncertainty through all stages of the modelling, are increasing in popularity in environmental resource management under changing conditions (Catenacci and Giupponi, 2010; Franco et al., 2016; Molina et al., 2013; Sperotto et al., 2017). Bayesian Networks (BNs), in fact, thanks to their probabilistic nature, can be used to summarize large amount of information coming from different knowledge domains and to display effects of different scenarios in an effective way. Consequently, they can be used to translate results of deterministic predictions into a probabilistic form. This makes the uncertainty in model results more explicit and interpretable, enhancing their value in decision making.

In this study, we apply a risk assessment procedure based on Bayesian Network modelling to link future scenarios of climate change (i.e. changes in precipitation and temperature, irregularities in water regime) with water quality alteration (i.e. changes in nutrients loadings). Specifically, Bayesian Networks were used as integrative tool for building a Decision Support System (DSS) that structures and combines the information available in existing hydrological models (i.e. SWAT), climate change projections, current land use and agronomic practices, historical observations and expert opinion. The model was implemented and applied to the case study of the Zero river basin in Northern Italy, one of the main tributaries of the Venice Lagoon. The DSS is able to produce alternative risk scenarios to communicate the probability of changes in nutrients (i.e. NO_3, NH_4, PO_4) delivered from the basin into the lagoon over future scenarios and to support the identification and prioritization of most effective management and adaptation strategies to maintain good water quality status (e.g. Water Framework Directive) under climate change conditions.

After a brief introduction to the case study area (Section1) the paper describes the methodological steps and input data used to implement the risk assessment procedure (Section 2) and finally, discusses the scenarios developed for the Zero river basin case study (Section 3).

1. Case study area

The Zero river basin (ZRB) (latitudes 45°28'N-45°48'N, longitudes 11°54'E-12°25'E) (Figure 1) covers an area of 140 km^2, it is located within the Venetian floodplain (Northern Italy) and it is a sub-basin of the Venice Lagoon Watershed (Figure 1a). The Zero river (Figure 1b), which is 47 km long, originates near "San Marco di Resana", and along its way, it collects the waters of numerous tributaries (e.g. Brenton del Maglio, Scolo Vernise, Rio Zermason). Then it merges with the Dese river about 2 kilometres upstream the discharge into the Venice Lagoon. Overall, the Dese and Zero rivers together provide the greatest contribution of freshwater (21% of the total) to the lagoon of Venice (Zuliani et al., 2005). Thanks to its transitional position the basin features a Mediterranean climate but with typical traits of more Continental climates (Guerzoni and Tagliapietra, 2006). Thus, this climate is characterized by cold winters and generally well distributed precipitation throughout the year, with peaks in spring-autumn and minimums during the winter-summer periods. Summers are frequently characterized by intense storms of short duration (Guerzoni and Tagliapietra 2006). Specifically, the region features an average annual precipitation of around 1000 mm (period 2007-2012) and an average annual temperature of 14 °C (period 2004-2013) but it is characterized by a marked inter-annual climate variability, which can originate years climatologically very different from each other.

The environmental and the hydrological characteristics of the ZRB are heavily influenced by natural phenomena and human activities that together had shaped a complex hydrologic network. The basin, in fact, is characterised by several hydraulic infrastructures and artificial channels developed to reclaim land for agricultural purposes and to regulate the flow discharging into the lagoon of Venice (CVN, 2006). Furthermore, spring waters originated and risen in the surrounding areas influence the hydrology of the Zero river with the main contribution coming from an unconfined aquifer system located on the high plain (Servizio Acque Interne, 2008).

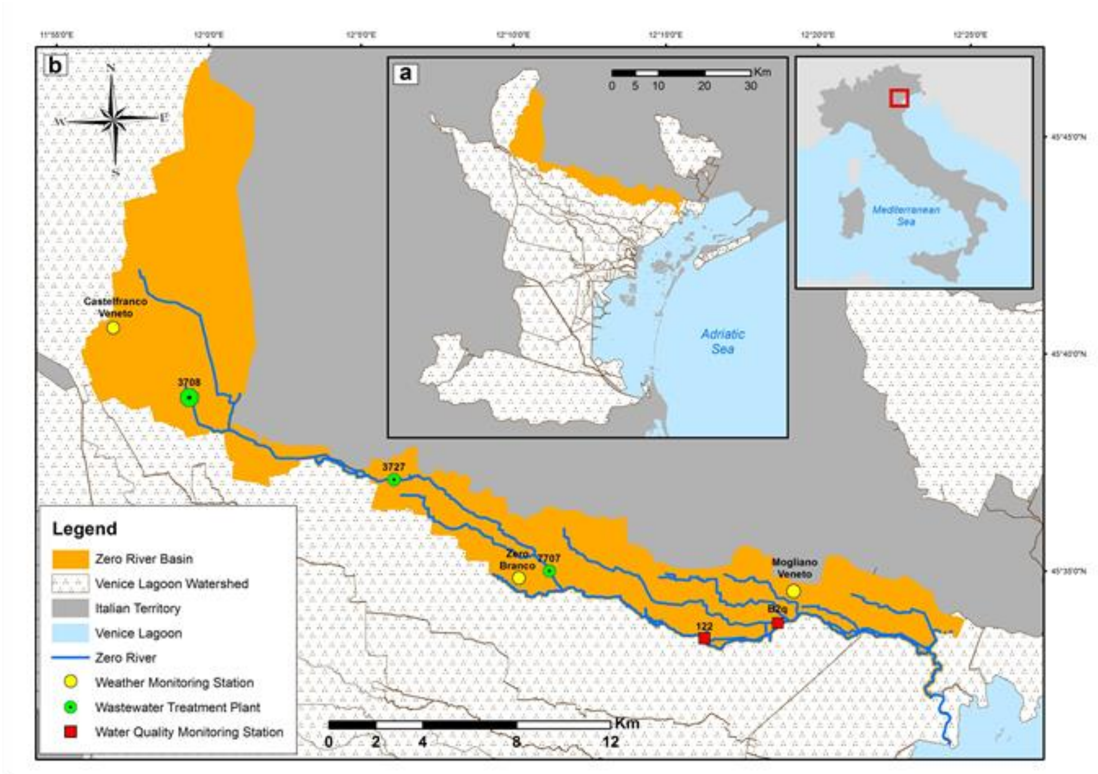

Figure 1 The Zero river basin case study

The land use of the ZRB is mainly characterized by agricultural areas, representing the 73% of the total surface, while the remaining surface of the basin is covered by artificial (24%), semi-natural and forested areas (4 %).

Agricultural areas are dominated by industrial crops typologies, including corn (45%) (i.e. Zea mays L.), soy (9%) (i.e. Glycine max L.), and autumn-winter cereals (13%) such as winter wheat (i.e. Triticum aestivum L.) and barley (i.e. Hordeum vulgare L.). A negligible percentage of the agricultural land is also used for the cultivation of beets and other permanent horticultural crops. Furthermore, the north-western part is characterized by an intensive rearing activity and a significant presence of livestock farms, with a density of 5 to 10 farms per km^2 (ARPAV, 2009).

Artificial surfaces are mainly represented by housing areas (54%), industrial businesses (32%) and transportation and services (14%). Accordingly, several industrial and residential activities exist on the basin. Three waste water treatment plans (i.e. Morgano, Zero-Branco and Castelfranco Veneto) (Figure 1b) with capacities ranging from 2500 to 32000 of Population Equivalents (P.E.) directly discharge into the Zero river.

The intensive agriculture, characterized by an elevated level of fertilization, and the dense urbanization are considered significant pollution sources for the area; especially for what concern nutrients (i.e. phosphorous, nitrogen) loadings. Diffuse and point nutrients pollution has become a major concern in the area since late 1980s when eutrophication reached its peak in the Venice Lagoon. This process brought toxic algae blooms and consequent implications for environmental, human health and water quality (Facca et al., 2014). Since then several national and regional policies, legislation and measures have been implemented to support investments for pollution control. Furthermore, good agricultural practice in concert with the Common Agricultural Policy (CAP) and other European regulations and directives has been implemented. In fact, the area has been identified as a Nitrate Vulnerable Zone (NVZ) according to the Nitrate European Directive (1991/676/CEE), with the aim of regulating and controlling the input of fertilizers from agricultural activities. At the same time, limits for the Maximum Admissible Load of nutrients discharged into the lagoon from the drainage basin were fixed at 3000 t/year for nitrogen and 300 t/years for phosphorous by the national competent law (DM 09/02/1999).

2. Material and methods

The risk assessment framework proposed in this work aims to assess the interactive effect of climate and anthropogenic changes on nutrients loadings in transitional waters. To do so, we adopt a multi-disciplinary approach to which different knowledge domains (i.e. environmental and social science, agronomy, hydrology, climate change) contribute. Also, quantitative and qualitative data, coming from multiple information sources, are integrated in a harmonic manner trough BNs. Accordingly, the proposed risk assessment approach is made upon different integrated components in communication through a dynamic exchange of information (Figure 2).

The core is the Bayesian Network, which is used as meta-modelling tool for structuring and combining, into a probabilistic form, information provided by hydrological models, climate change projections, historical observations and expert judgment. Different information types populate the Bayesian Network at different level of implementation. Qualitative information elicited from experts is used to develop the conceptual model of the network and to train socio-economic and agronomic variables of the model for which quantitative data are not available.

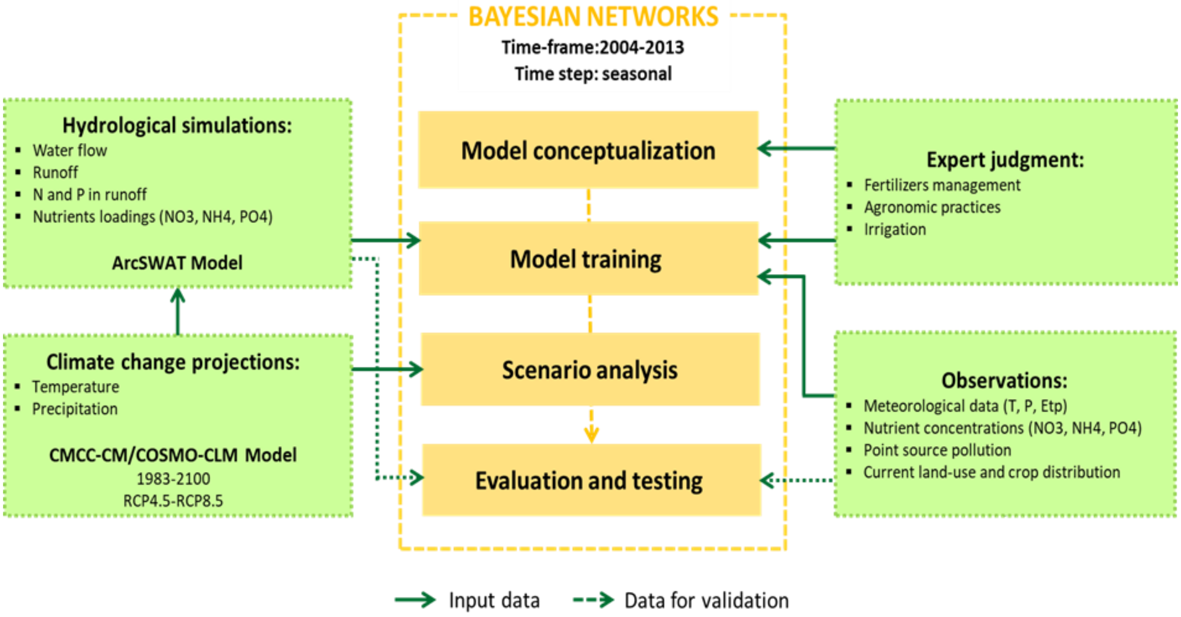

Figure 2 General risk assessment framework applied to evaluate the interactive effect of climate and anthropogenic changes on nutrients loadings in transitional waters

Historical observations are used as input for the training of the network together with some hydrology and nutrient loadings variables provided by the hydrological simulation with the Soil and Water Assessment Tool *(*SWAT) (Arnold et al., 2012) for current conditions (i.e. 2004-2013). In addition, an independent set of observations is used for validation. After the training, climate change projections are employed as input for scenarios analysis to simulate the effect of future climate change on nutrients loadings. At the same time, SWAT simulations forced with the same climate change projections are used to evaluate the performance of the network over future condition.

Main outputs of the risk assessment approach are the values of key state and management variables for alternative risk scenarios, communicating the probability of water quality alterations. This is achieved taking into account both projected climatic and not climatic conditions to support the identification of appropriate adaptation strategies at the local scale.

2.1 Input data

The capacity of the Bayesian Network to correctly represent hydrological and water quality processes of the case study area strongly depends on the quality and completeness of input data. Accordingly, Table 1 summarized the data collected for the implementation and evaluation of the network in the Zero river basin case study, highlighting the typology of data used, the time scale, spatial resolution and source.

Table 1 List of input data used for the application of the risk assessment model in the Zero river basin

Data type	Description	Time scale	Resolution	Source
Observations				
Land cover map	▪ Land use map of the Veneto region	2006	1:10.000	Regione del Veneto – Infrastruttura dati territoriali (http://idt.regione.veneto.it/app/metacatalog/)
Climatic Data	▪ Daily precipitation ▪ Max/min daily temperature ▪ Daily evapotranspiration	2004-2013	3 stations (i.e. Castelfranco, Veneto, Zero Branco, Mogliano Veneto)	ARPAV – Servizio Meteorologico
HWater quantity and quality data	▪ Observed daily? river discharge ▪ Observed nutrients' (NO3, NH4, PO4) concentrations in the lagoon?	2007-2012	2 stations (i.e. Manual station (Code 122), Automatic station (Code: B2q)	ARPAV – Servizio Acque Interne MAV – Magistrato Acque Venezia
Point-source pollution	▪ Monthly N and P loadings from WWTP and Industrial discharges	2004-2013	3 stations (i.e. Morgano, Zero-Branco, Castelfranco Veneto)	ARPAV – Servizio Acque Interne
Hydrological simulations				
Water quantity and quality data	▪ Simulated runoff ▪ Simulated N and P load in the runoff	2004-2013	River basin	SWAT simulations (Pesce et al., 2017)
	▪ Simulated river discharge or flow rate ▪ Simulated nutrient loadings (NO3, NH4, PO4) in the lagoon	2004-2013	1 station (i.e. Manual station (Code 122)	
	▪ Simulated nutrients loadings in the lagoon under future climate change scenarios	1983-2100		
Climate change projections				
Climatic data	▪ Temperature ▪ Precipitation	1976–2100	8 km	CMCC-CM/COSMO-CLM simulations (Cattaneo et al., 2012; Scoccimarro et al., 2011)

2.1.1 Observations

Observations regarding the main climatic parameters (i.e. precipitation, temperature and evapotranspiration) were provided by the ARPAV meteorological service and obtained from three weather monitoring stations (Figure 1b) representative of the climatic condition of the case study area for the period 2004-2013. Quantitative information regarding point-source pollution for the period 2004-2013 were obtained from the measures of ARPAV-Internal Waters Services which monitor the loadings of N and P originating from wastewater treatment plants (WWTP) and industrial discharges located along the Zero river. Observed hydrologic data (i.e. river discharge (Q), nutrient concentrations (i.e. NO_3, NH_4, PO_4) used to evaluate the performance of the model under current conditions were provided by ARPAV – Internal Water Services and the former MAV (Magistrato alle Acque Venezia) for the period 2007-2012.

2.1.2 SWAT model simulations

Due to the lack of a consistent record of observations for the training period, all the information used to characterize the hydrological aspects of the model under current condition were extrapolate from the output of SWAT model simulation runs for the period 2004-2013 in the case study (Pesce et al., 2017) (Table 1). Specifically, water flow and nutrients loadings were simulated trough SWAT at the closure of the river basins (Figure 1b) while for the runoff and N and P in the runoff simulations at the river basin scale were used. At the same time, SWAT model simulations of nutrient loadings at the basin mouth for the period 1983-2100 according to two RCPs (Representative Concentration Pathways) (i.e. RCP8.5-4.5) (Table 1) were used to evaluate the performance of the model under future conditions.

2.1.3 Climate change projections

Future daily precipitation and temperature projections, used as input for the development of alternative climate change scenarios, were obtained from simulations of the CMCC-CM/COSMO-CLM model developed by the CMCC (Centro Euro-Mediterraneo sui Cambiamenti Climatici) which produces climate scenarios at a spatial resolution of 8 km for the selected region covering the period 1976–2100. According with the purpose of the study, simulations developed using the two more extreme Representative Concentration Pathways (RCPs) (IPCC, 2013), RCP4.5 and RCP8.5 were selected.

2.2 Bayesian Network development

The BN for the Zero river basin was implemented and run using the software HUGIN Expert, version 8 (Bromley et al., 2005; Madsen et al., 2005). The development of a BN is an iterative and adaptive process which consist in four major steps: i) the development of the conceptual model of the system; ii) the training of the model with data; iii) scenario analysis; and finally, iv) the evaluation of model performances (Kragt, 2009) (Figure 2). Accordingly, the following Sections describe how the different BNs development phases have been implemented in the Zero river basin case study.

2.2.1 Development of the conceptual model of the system

The phase of model conceptualization aims at developing an influence (i.e. "box and arrow") diagram providing a graphical representation of the system under consideration. The network conceptualization, therefore, includes the identification of the main system variables (i.e. nodes) as well as the links between them (i.e. directed arcs). The identification of relevant variables and links can be typically based on a literature review, expert knowledge and consultation with local stakeholders. For each variable, appropriate indicators as much as possible measurable, observable and predictable have to be identified. Once the variables and relative indicators are defined, the links between them are identified and represented as unidirectional arrows as BNs do not permit feedback loops.

Figure 3 provides a representation of the influence diagram developed for the Zero river case study which was developed based on expert consultation following the DPSIR (Driving forces, Pressures, States, Impacts and Responses) framework (EEA, 1999; Kristensen, 2004). The DPSIR here was adopted to conceptualize the system identifying the main cause-effect relationships and interactions between climatic changes, actual land use and the quality of water resources.

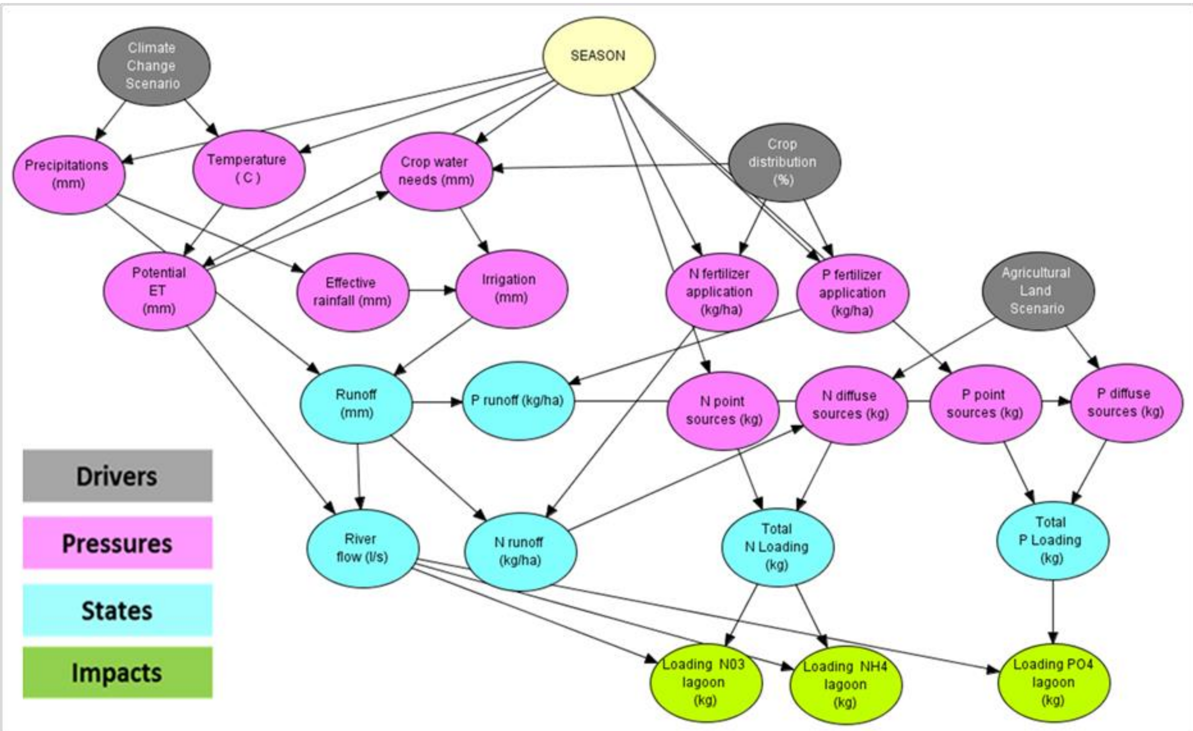

Figure 3 Conceptual model of the system developed for the Zero river basin

Accordingly, different kind of nodes representing the different nature of variables involved have been included in the BN (Figure 3):

- **Driver nodes**, consist in the input or parent nodes of the network and include environmental and socio-economic factors representing the main drivers of water quality alterations. Accordingly, in this study, driver nodes include climate change scenarios, agricultural land scenario (i.e. alternative agricultural land extension) and crop distributions (i.e. alternative combination of different percentage of crop typologies).

- **Pressures nodes**, represent the variables which are influenced by the identified drivers. Precipitation, temperature and potential evapotranspiration's will depend on the climate change scenario, inducing certain pressures on the system, including alternations in water needs for the different crops which, together with a reduced effective rainfall, will mostly lead to an increased water demand for irrigation. On the other hand, regarding anthropogenic drivers, both agricultural land scenarios and crop typology distributions will drive irrigation demand but also the quantity and timing of fertilizer application (i.e. N and P fertilizer application), affecting the loading of nitrogen and phosphorous entering in the system through diffuse (i.e. N and P diffuse sources) and non-diffuse sources (i.e. N and P point sources).

- **States nodes**, representing the characteristics (i.e. states) of water resources that can be altered by the aforementioned pressures both in quantitative and qualitative terms. Quantitative alterations include, in this study, the alteration of river flow and runoff as results of changes in precipitation and temperature under different climate change scenarios. Qualitative alterations are instead represented by the change of N and P loadings in the runoff and in the increase of the total loading of N and P into the river resulting from the interaction between multiple climatic and anthropogenic pressures.

- **Impact nodes,** consist in the output or child nodes of the network and are represented by the increase of nutrients loadings (i.e. NO_3, NH_4, PO_4) discharged by the Zero river basin into the Venice Lagoon which can have severe impacts on the environment and human activities.

2.2.2 Model training

The second step regards models training and involves assigning states, prior and conditional probabilities to all nodes of the networks, thus translating the conceptual model developed in Section 2.2.1 (Figure 3) into probabilistic results. For each node a certain number of states must be identified. States represent potential values or conditions that the variable can assume in the analysed system (Kragt, 2009) and can be featured in different way, representing Boolean functions (e.g. true, false), categorical definitions (e.g. low, medium, high), continuous or discrete numeric intervals (de Santa Olalla et al., 2005).

Once the type and number of states have been defined, the prior probability associated to each state of the node have to be calculated based on available information and knowledge (Pollino et al., 2007). The prior probability distribution represents the starting point for each node in the network and thus the expectation of the node being in a certain condition.

Finally, to operationalize the network, Conditional Probabilities (CPs) of nodes have to be specified for all combinations of states of its parent nodes. CPs, represented in the Conditional Probabilities Table (CPTs) of every node, describe the strength of relationships between the systems' variables and thus the probability of the node of being within a state, given the combination of values of parent states. If a node has no parents (i.e. input nodes), it can be described probabilistically by a marginal probability distribution. CPTs can be defined using a range and combination of methods including observed data, probabilistic or empirical equation, results from model simulation or elicitation from expert knowledge (Pollino and Henderson, 2010). Within this study, states, prior probability distribution of nodes as well as the conditional probability distributions have been defined combining different quantitative and qualitative information available for a training period of 10 years (i.e. 2004-2013) at a seasonal time-step. Table 2 describes the states of the different nodes of the network and the type of information and data, which have been used for the definition of prior and conditional probability distributions. Most nodes present numerical interval type states, which have been identified starting from existing observed dataset, model simulation or expert judgement. Specifically, for each numeric interval nodes, continuous numerical dataset (i.e. series of observation or model simulations) have been discretized into states dividing the range between the maximum and the minimum values of the series into four intervals of equal amplitude (Table 2).

Table 2 Overview of nodes and states in the Bayesian Network model for the Zero river basin

Node	Description	Type	States	Parametrization method
Season	Alternative seasons	Labelled	Winter Spring Summer Autumn	Expert judgement
Climate change scenario	Alternative climate change scenarios	Labelled	Baseline 1983-2012 RCP 4.5 2041-2070 RCP 4.5 2071-2100 RCP 8.5 2041-2070 RCP 8.5 2071-2100	CMCC-CM/COSMO-CLM simulations
Agricultural land scenario	Extension of land (ha) occupied by agricultural activities under different scenarios	Labelled	Actual 2004-2013; Future 2050	Observations-LUISA simulations
Temperature	Seasonal average temperature (°C)	Numeric interval	0-8.37 8.37-13.79 13.79-19.21 >19.21	Observations
Precipitation	Seasonal cumulative precipitation (mm)	Numeric interval	0-201.50; 201.50-328.73 328.73-455.96 > 455.96	Observations
Potential ET	Seasonal cumulative potential evapotranspiration (mm)	Numeric interval	0-133.85 133.85-228.3 228.3-322.75 >322.75	Observations
Effective rainfall	Seasonal cumulative effective rainfall reaching the soil (mm)	Numeric interval	0-64.13 64.13-122.95 122.95-181.77 >181.77	SWAT simulations
Crop water needs	Seasonal water demand for different crop typology (mm)	Numeric interval	0-109.77 109.77-213.64 213.64-317.50 >317.50	Equation
Irrigation	Seasonal amount of water applied as irrigation	Numeric interval	<-55.29 -55.29-101.28 101.28-257.86 >257.86	Equation
N fertilizer application	Nitrogen fertilizer applied for each season according to different crop typology (kg/ha)	Numeric interval	0-45.74 45.74-87.52 87.52-129.30 >129.30	Expert judgment
P fertilizer application	Phosphorous fertilizer applied for each season according to different crop typology (kg/ha)	Numeric interval	0-25.41 25.41-50.83 50.83-76.25 >76.25	Expert judgment
N diffuse sources	Seasonal amount of nitrogen coming from agricultural practices (kg)	Numeric interval	0-7388.86 7388.86-13959.99 13959.99-20531.11 >20531.11	Equation
P diffuse sources	Seasonal amount of phosphorous coming from agricultural practices (kg)	Numeric interval	0-5169.28 5169.28-10221.75 10221.75-15274.21 >15274.21	Equation
N point sources	Seasonal amount of nitrogen coming from point sources (i.e. Waste Water Treatment Plans and Industrial discharges) (kg)	Numeric interval	0-9382.64 9382.64-10389.82 10389.82-11396.99 >11396.99	Observations
P Point sources	Seasonal amount of phosphorous coming from point sources (i.e. WWTPs and Industrial discharges) (kg)	Numeric interval	0-1143.64 1143.64-1478.99 1478.99-1814.35 >1814.35	Observations
River discharge	Seasonal average river discharge (l/s)	Numeric interval	0-1458.96 1458.96-2360.53	SWAT simulations

Node	Description	Type	States	Parametrization method
			2360.535-3262.102	
			> 3262.10	
Runoff	Seasonal cumulative runoff (mm)	Numeric interval	0-49.90	SWAT simulations
			49.90-90.15	
			90.15-130.40	
			>130.40	
N in runoff	Seasonal amount of nitrogen loaded in the runoff (kg/ha)	Numeric interval	0-0.63	SWAT simulations
			0.63-1.19	
			1.19-1.75	
			>1.75	
P in runoff	Seasonal amount of phosphorous loaded in the runoff (kg/ha)	Numeric interval	0-0.44	SWAT simulations
			0.44-0.87	
			0.87-1.30	
			>1.30	
Total N loading	Seasonal nitrogen load in the river (kg)	Numeric interval	0-17031.20	Equation
			17031.20-24401.92	
			24401.92-31772.64	
			> 31772.64	
Total P loading	Seasonal phosphorous load in the river (kg)	Numeric interval	0-5405.76	Equation
			5405.76-9710.91	
			9710.91-14016.07	
			>14016.07	
Loading NO_3 lagoon	Seasonal loading of NO_3 reaching the lagoon (kg)	Numeric interval	0-28047.50	SWAT simulations
			28047.50-48615.00	
			48615.00-69182.50	
			>69182.50	
Loading NH_4 lagoon	Seasonal loading of NH_4 reaching the lagoon (kg)	Numeric interval	0-3224.52	SWAT simulations
			3224.52-5009.3	
			5009.3-6794.17	
			>6794.17	
Loading PO_4 lagoon (kg)	Seasonal loading of PO_4 reaching the lagoon (kg)	Numeric interval	0-1978.90	SWAT simulations
			1978.90-2954.00	
			2954.00-3929.10	
			>3929.10	

For the labelled node types, instead, states have been defined based on the alternative conditions the node can assume (i.e. alternative seasons, alternative climate change scenarios) (Table 2). As described in Table 2 for most nodes prior probability and conditional probability distributions have been extrapolated directly from the observed frequencies of the corresponding variable. For nodes associated with climatic variables (i.e. temperature, precipitation, evapotranspiration), probabilities have been learned from the frequencies of observations of weather monitoring stations available in the case study (Section 2.1.1). Probabilities distribution of hydrological variables (i.e. runoff, river flow, nutrients loadings, N and P in the runoff), instead, have been calculated based on the frequency analysis of the results of hydrological simulations performed with the SWAT model (Section 2.1.2). Finally, for nodes describing agronomic practices (i.e. water needs, irrigation, P and N fertilizer application), due to the lack of quantitative information in the case study, the CPs were calculated through expert elicitation and applying empirical equations. An exhaustive description of assumption and information used to parametrize CPs of such nodes can be found in Annex I (SP). Figure II1 Annex II (SP) show the configuration of the BN for the Zero river basin once states, prior and conditional probabilities of each node have been parametrized.

2.2.4 Scenario analysis

Once the BN was trained, the resulting model can be used to analyse the performance of the system under different scenarios. This allows to assess the relative changes in the outcome probabilities of output nodes (e.g. nutrient loadings) when altering the probability distribution of one or more input nodes (e.g. climate change scenarios). A common manner to develop scenarios using BNs is to “set evidence” for one or more nodes (e.g. assigning 100% probability for one state) and thereby, let the information propagating through the nodes that are linked by CPTs in the network (Kragt, 2009).

In this study, we were interested in assessing the effect of future climate change scenarios on nutrient loadings and therefore, five 30-year scenarios were developed as representative of a control period (1983-2012), a mid-term (2041-2070) and long-term (2071-2100) scenarios under two different representative concentration pathways (i.e. RCP4.5-RCP8.5).

Accordingly, for each climate change scenario the probability distribution of temperature and precipitation was calculated based on the respective CMCC-CM/COSMO-CLM model simulations (Section 2.1.2) and set as evidence in the input nodes.

Figure II2 Annex II (SP) provide an example of scenario analysis using the BN while a quantitative discussion of the results of BN simulations with other climate change scenarios is provided in Section 3.1.

2.2.3 Model evaluation

A fundamental aspect in BNs developed to support risk assessment and decision making is model evaluation. This steps is crucial as it allows to quantify the performance of the model and to assess the achievement of the objectives for which it was designed (Kragt, 2009). According to Pollino and Henderson (2010), two main types of validation methods can been used, the data-based validation (i.e. comparing the frequency of the predicted node state with a set of observed data) and the qualitative evaluation (i.e. using an independent domain of experts or comparing results with peer reviewed literature)

Within this study, in order to evaluate the predictive performance a data-based validation was performed both for current and future conditions. Specifically, for the current condition, BN predictions were compared with observations from water quality monitoring stations. For future conditions, instead, considering that observations and experiences are not available an alternative validation was performed using outputs of SWAT models simulation, forced with the same climate change scenarios, as comparative dataset as suggested by Uusitalo et al., 2016).

Another form of evaluating the developed model consist in the sensitivity analysis which allow to test the sensitivity of model outcomes to variations of model parameters (Kragt, 2009). In the context of BN sensitivity analysis help in exploring the behaviour of the system and ranking on the model sensitivity to different variables. Through sensitivity analysis, in fact, it is possible to detect how the variation in the output of a model can be apportioned to different variations in the inputs and thus track relevant causal pathways between variables. Accordingly, sensitivity to parameters was analysed to identify the most influential set of variables (i.e. those have the greatest influence on the model endpoints), as well as to rank the relevance and strength of inputs nodes on model output (i.e. nutrients loadings).
The analysis was performed adopting an empirical approach in which the input parameters were modified one by one and the related changes in the output parameters were observed (Coupé et al., 1999; Pollino et al., 2007; Stelzenmüller et al., 2010).
Results of data-based evaluation and sensitivity analysis for the developed BN are described and discussed in Sections 3.2 and 3.3.

3. Results

3.1 Quantitative assessment of seasonal nutrient loadings under climate change scenarios

Once the DSS was trained, the BN was used to perform scenario analysis to assess the effect of future climate change on nutrients loadings and hydrological variables. This was done by forcing the model with the 30-year seasonal distribution of temperature and precipitation for mid-term (2041-2070) and long-term (2071-2100) projections under two different representative concentration pathways (i.e. RCP4.5-RCP8.5) according with the projections provided by the CMCC-CM/COSMO-CLM (Section 2.1.2) and

Future projections of the CMCC-CM/COSMO-CLM show a general increase of temperatures in every season with the probability of medium (i.e. 8.36-13.76 °C), high (13.76-19.21 °C) and very high (>19.21 °C) temperature states that increase in all seasons and scenarios respect to the baseline 1983-2012 (Figure 4a). Maximum increases are reached by the RC8.5 2071-2100 scenario with a 76% probability of very high temperature state in spring and 50% probability of medium temperature state in autumn.

Differently, for precipitations, projections show a general decrease in spring and summer (Figure 4a). The probability of lower precipitation states (0-201 mm), in fact, increases across scenarios reaching the 90 % in the RCP8.5 2071-2100 in summer with an increase of 50% respect to the baseline 1983 (i.e. 43%). Despite the decrease, for scenario RCP8.5 2041-2070 in spring the probability of very high (i.e. >455 mm) and high (i.e. 328-455) precipitation states is remarkable (i.e. 8% and 10% respectively), denoting an increase in the probability of occurrence of extreme precipitation events during this season. In winter, future scenarios project a decrease in precipitation in the mid-term period follow by an increase over long-term and by the end of the century for both RCPs.

The highest increase however will be registered in autumn with the probability of higher precipitation states (i.e. 328-455, >455 mm) that increase in all the scenarios and up to 30% in the long-term period for both RCPs.

Changes in precipitation and temperature associated with different climate change scenarios induce changes in the main hydrological variables of the systems (e.g. river flow, runoff, N and P in the runoff). Figure 5 show the changes in the probability distribution of river flow respect to the baseline (1983-2012) considering multiple climate change projections. In order to make the outcome of each simulated scenarios more understandable, the probabilistic results (Figure 5, left) have been also translated into deterministic form (i.e. numerical value) (Figure 5, right) and expressed using the Expected Value of the Probability distribution (Annex III). Deterministic results (Figure 5a, right) for different climate change scenarios show just slight changes of river flows from the baseline 1983-2012. However, looking at the probabilistic results an increase in autumn and a clear decrease in summer for both RCP 4.5 and RCP 8.5 scenarios can be observed (Figure 5a, left).

Specifically, maximum increase is projected for the RCP8.5 2041-2070 in autumn (Figure 5a) with the probability of the highest river discharge state (i.e. >3263 l/s)) that increase from the

27% of the baseline (i.e. 1983-2012) to the 50% according with the maximum increase of precipitation in the same scenario (Figure 4a).

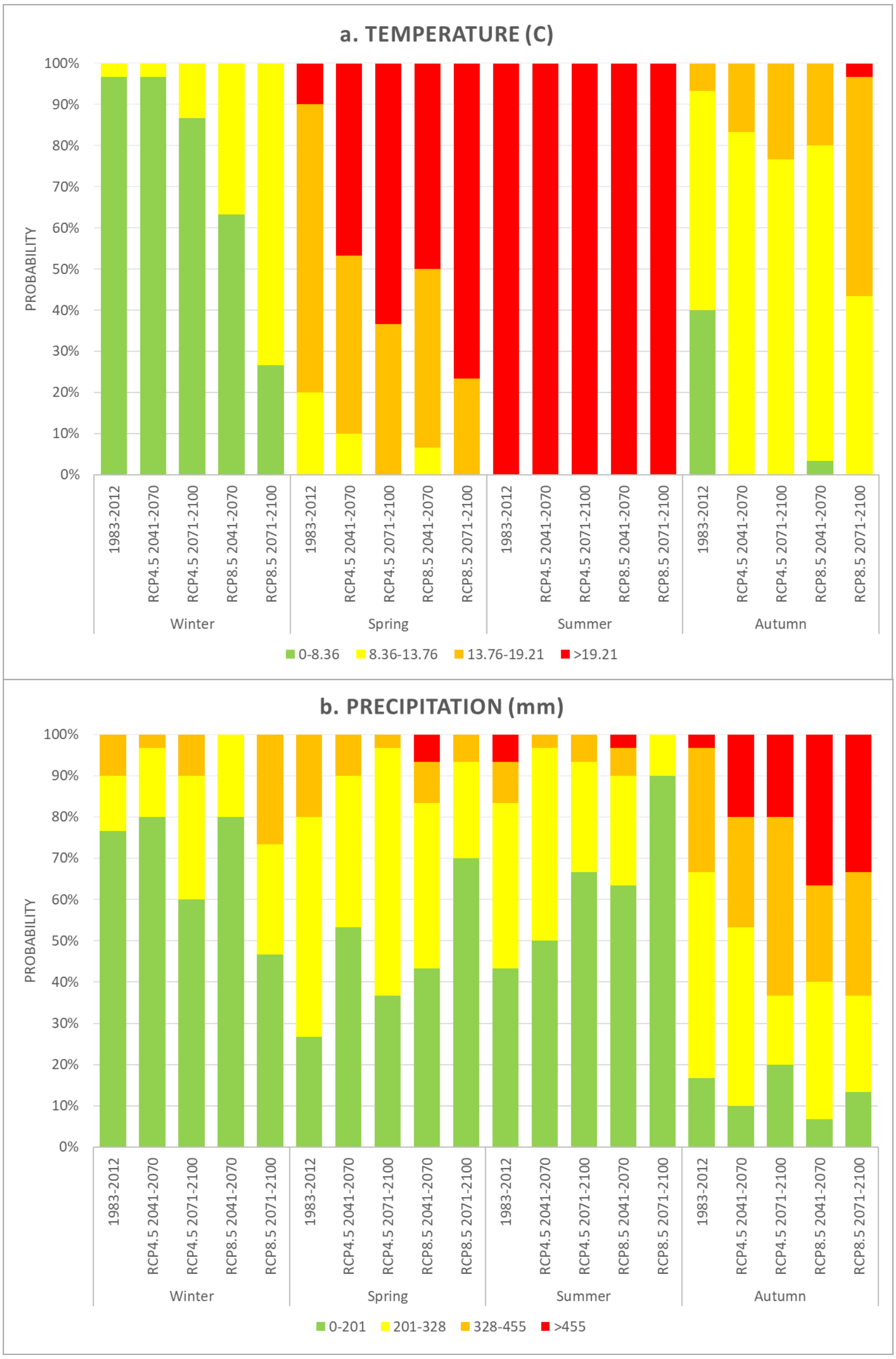

Figure 4 Probability distribution of temperature (a) and precipitation (b) for different seasons across climate change scenarios

Figure 5 Probabilistic (left) and deterministic (right) results for river discharge (a) and runoff (b) for different seasons across climate change scenarios

In winter, the BN predicts a general decrease in river flows in the mid-term period follow by an increase over long-term and by the end of the century for both RCPs. Despite the projected decrease in precipitation and the strong increase in temperature (Figure 4), and thus in evapotranspiration, just a slight decrease in river flow is projected for spring.

The runoff (Figure 5b) shows a marked decrease in spring-summer and an increase in autumn. Specifically, in spring the probability of the lowest states (i.e. 0-49.90 mm) increase from the 10% of the baseline to the almost 50% in the in the baseline RCP8.5 long-term period (i.e. 2071-2100) while in summer from 64% to 92%. Despite, the great reduction of runoff in spring, for scenario RCP8.5 2041-2070 a small probability of high runoff states exists probably due to the occurrence of extreme precipitation events in this scenario (Figure 5b). In autumn, greater increase in the runoff is predicted for the RCP8.5 2041-2070 scenario (Figure 5b, left) with a probability of 50% of being in the higher runoff states against the 20% of the baseline. In winter, the model predicts a general decrease in runoff in the mid-term period follow by an increase over long-term and by the end of the century for both RCPs (Figure 5), which strongly reflect the changes in precipitation distribution (Figure 4a).

The climate, runoff and river discharge control the capability of the river basin to export nutrients and therefore their changes affect the amount of nutrients seasonally loaded in the lagoon. The BN predicts changes in the seasonal distribution of NO_3 loadings respect to the current condition (i.e. 1983-2012) (Figure 6). Specifically, for future scenario it can be notice a shift in high NO_3 loadings with greater loadings occurring in autumn rather than in winter (Figure 6a). Both RCP4.5 and RCP 8.5 scenarios show a clear increase in autumn loads and a small decrease in both spring and summer loads. In autumn, in fact, the probability of high (i.e. 90.15-130.40 kg/season) and very high (i.e. >130.40 kg/season) loadings states increase across scenarios reaching respectively the 62% and 11% in the RCP4.5 2071-2100 scenario and the 67% and 10% in the RCP8.5 2041-2100 scenario (Figure 6a). Accordingly, in autumn, the greatest increase in NO_3 loadings is predicted under the long-term scenarios RCP4.5 2071-2100 and the medium-term scenarios RCP8.5 2041-2070 (Figure 6a) in correspondence with the greater increase in river flow (Figure5a). In spring and summer greater reduction in NO_3 loading are predicted for scenario RCP8.5 2071-2100, the one also characterized by the greatest decrease in river flow (Figure 5a).

Regarding ammonium (i.e. NH_4), the projections show a slight decrease of loadings in spring and summer and an increase in autumn (Figure6b). Specifically, in autumn the probability of low loading state decreases gradually across scenarios followed by an increase in the probability of very high loadings (i.e.>6794 kg/season), which reaches a 22% under the RCP8.5 2041-2070 (Figure 6b). High loadings occur in correspondence with the highest projected runoff (Figure 5b), suggesting that this variable could play a major role in controlling the transport of NH_4.

Finally, seasonal changes in the phosphorous (i.e. PO_4) loading have been also observed (Figure 6c). Results indicate a marked increase in autumn loads and a general decrease in spring and summer loads across scenarios. An exception is for the scenario RCP8.5 2041-2070, for which a slight increase in spring is predicted. In autumn, in fact, the probability of low loadings state decreases gradually followed by an increase in the probability of high loadings which reach the 28% under the RCP8.5 2041-2070 (Figure 6c). These changes can be attribute to the predicted increase in runoff (Figure 5b) caused by increasing in precipitations in the autumn-winter period.

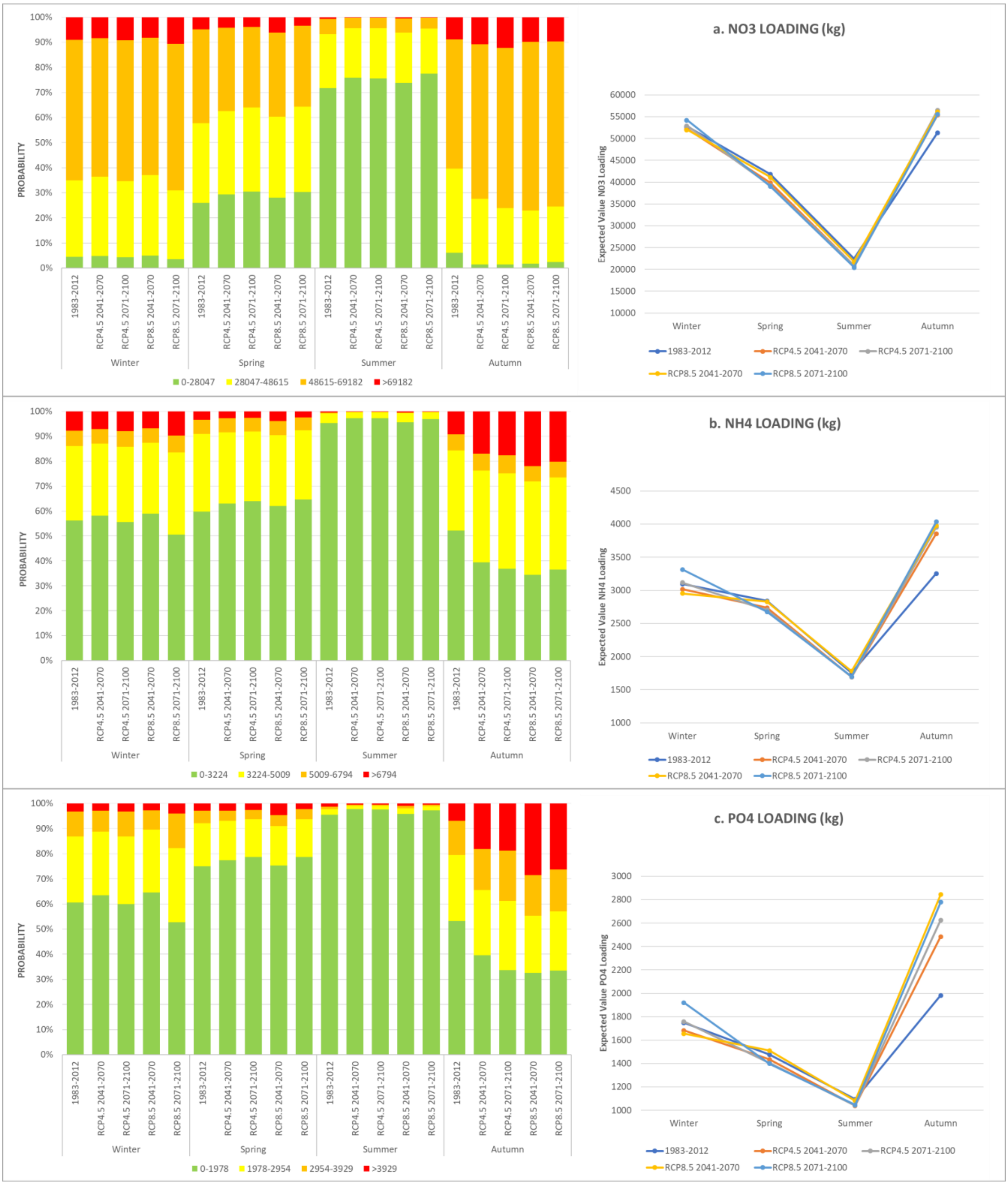

Figure 6 Probabilistic (left) and deterministic (right) results for NO3 (a), NH4 (b) and PO4 (c) loadings for different seasons across climate change scenarios

3.2 Model evaluation

3.2.1 Data-based evaluation

As described in Section 2.2.3 a data-based evaluation was performed to validate the predictive performance of the developed BN model and the consistence of the produced scenarios both for current and future conditions. Specifically, for the current condition the nutrients loadings predicted by the BN were compared with observations from water quality monitoring stations available in the case study (Table 1, Section 2.1). Unfortunately, observations were available only for 2007-2012 and therefore the evaluation was conducted only for this period. Figure 7 compares the Expected Value of the probability distributions of nutrient loadings (i.e. NO_3, NH_4, PO_4) of observed data for the period 2007-2012 (red) and of the Bayesian Network outputs (blue).

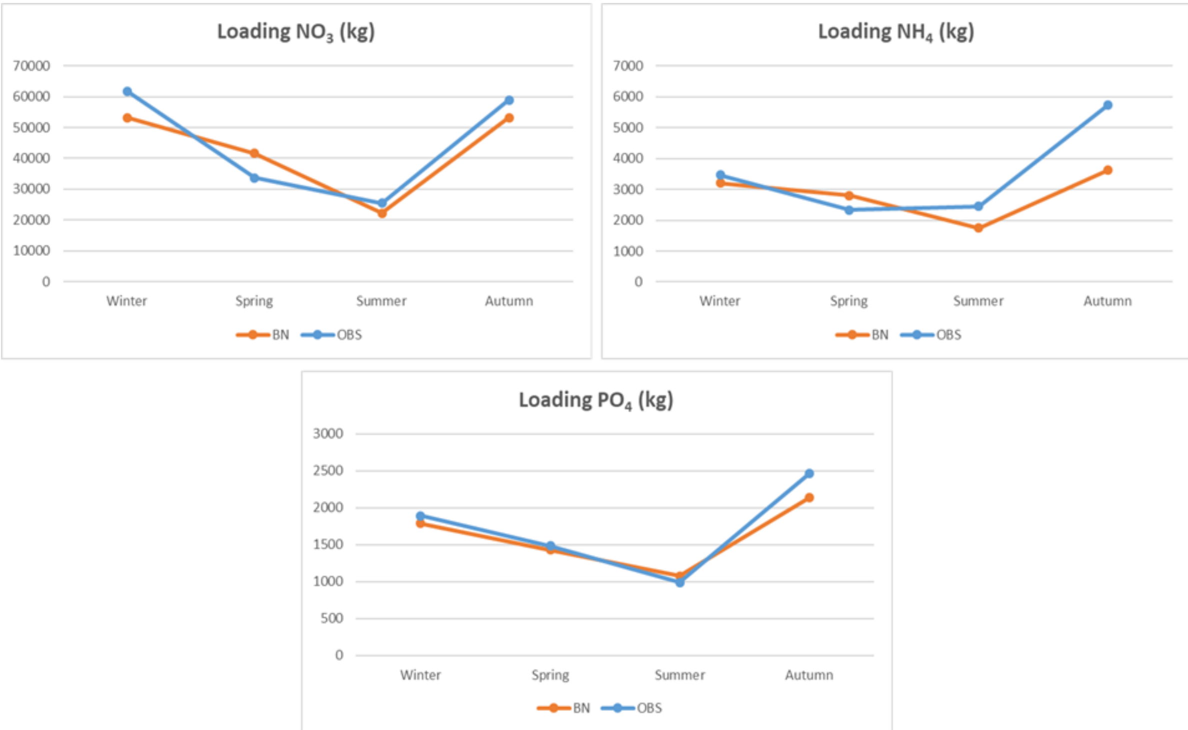

Figure 7 Expected Value of the probability distributions of nutrient loadings (NO3, NH4, P04) of observed data for the period 2007-2012 (red) and of Bayesian Network outputs (blue), obtained by fixing the states of precipitation and temperature according with the same period 2007-2012.

Overall, the BN was able to reproduce the observed nutrients dynamics with loadings closely replicated for most seasons. The evaluation produced satisfactory results for nitrate (NO_3) and phosphorous (PO_4) while for ammonium (NH_4) the correlation between observed and predicted nutrient loadings was slightly worse. BN overpredicts the decrease of ammonium loading between spring and summer and underestimates the autumn loading (Figure 7).

Difficulties in reproducing the observed loads may be attributed to a number of factors including uncertainties with model structure, missing or low-quality data and process algorithms used to train the BN. A major source of input uncertainty could be related with assumptions underlying agronomic practices. Fertilizers application and irrigation have been considered uniform across the whole catchment while they could vary considerably, both spatially and temporally, inside the same season. Potential uncertainties associated with input data also include inaccuracies in point pollution sources (i.e. Waste Water Treatment Plans and Industrial discharges) measurements and their temporal sparsity. For some years of the training period 2004-2013, in fact, this information was lacking.

For future conditions, instead, nutrient loadings scenarios developed through the BN, were compared with outputs of SWAT model simulations for the case study (Table 1, Section 2.1), forced with the same climate change scenarios (i.e. 1983-2012, 2041-2070, 2070-2100). BN loadings of nutrients show a general agreement with the one predicted by SWAT. Figures 8 compares the Expected Value of the probability distributions of PO_4 of SWAT simulation across different scenarios (blue) with Bayesian Network outputs (red) showing a good correlation especially for medium-term periods (Figure 8).

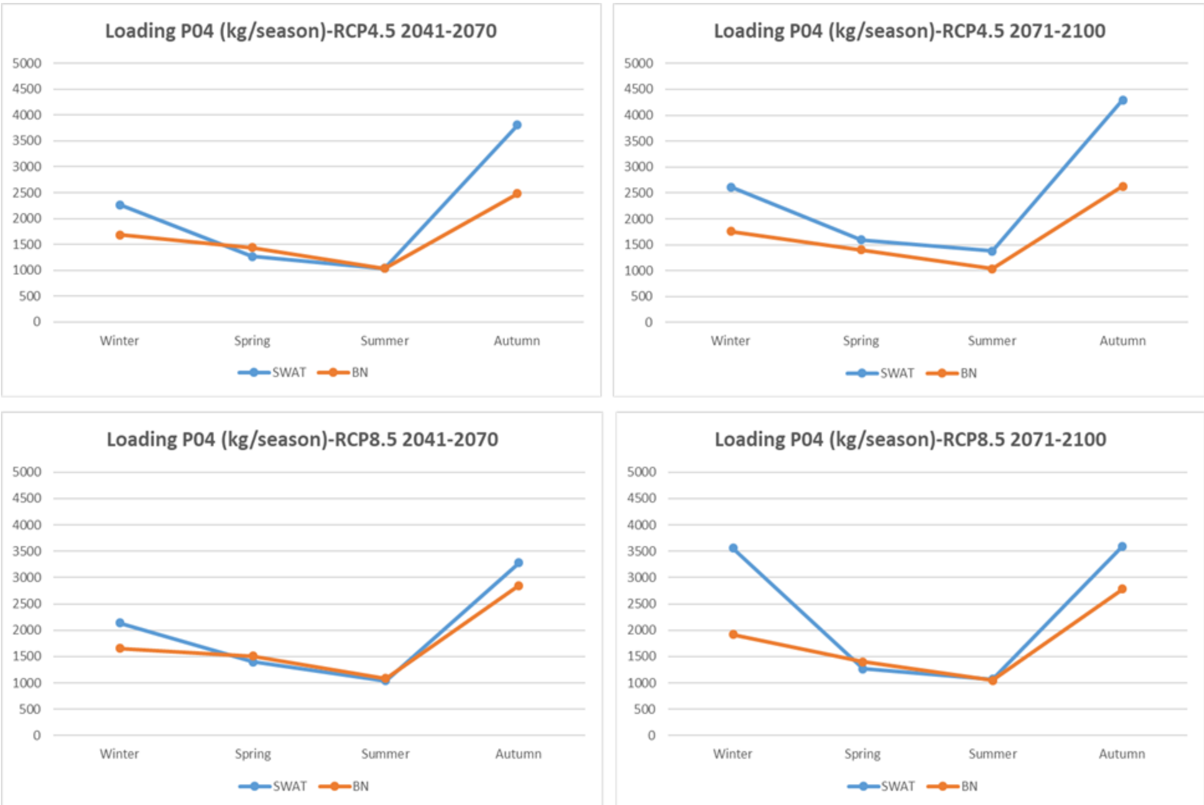

Figure 8 Expected Value of the probability distributions of PO_4 loading of SWAT model simulation across different scenarios (blue) and of Bayesian Network outputs (red), obtained by fixing the states of precipitation and temperature according with the same climate change projection.

Also, NO_3 loadings predicted by the BN shows a quite good correlation with SWAT results for all the developed scenarios (Figure IV1, Annex IV (SP)). The best agreement is predicted for RCP 4.5 scenarios for which, however, BN predicts lower loadings respect to SWAT especially in winter and spring. Also for ammonium ((Figure IV2, Annex IV (SP)).) results are quite satisfactory especially for RCP8.5 2041-2070.

Such discrepancies between BN and SWAT results can be attributed mainly to the different representation of systems components and processes under the two approaches and to different assumptions regarding the simulation of agricultural and irrigation practices. SWAT, as physically based model, is able to represent complex nutrients dynamics (i.e. feedback effects) that are not well captured by BN due to their impossibility to include feedback loops. Despite the above issues, the BN model produced quite satisfactory results at a seasonal time step and therefore, was considered suitable for projecting future climate change scenarios.

3.2.2 Sensitivity analysis-Identification of most influencing variables

Sensitivity analysis considering the sensitivity to parameters was performed to identify and prioritize variables that have the greatest influence on model outputs (i.e. nutrients loadings). Based on the empirical approach proposed by Pollino et al. (2007), each node was alternatively maximized by setting the probability of its higher state equal to 100% and, consequently the relative change in each of the other nodes was analysed. Magnitude of change was measured calculating the Percent Change of the Expected Value of the probability distribution of output nodes (i.e. NO3, NH4, PO4 loadings) according with the Equation V.I (Annex V (SP)) (Molina et al., 2016). Results (Table V1, Annex V (SP)) have been normalized into a 0-1 interval based on the minimum and maximum values obtained in order to make outcomes immediately understandable and comparable. Results, summarized in the Figure 9, allowed to develop a ranking of input variables according with their relevance in the BN and consequently in the system. A higher Percent Change value denotes that the analysed variable has a high influence on the output variables (i.e. nutrient loadings), by contrary a lower value suggests a negligible effect.

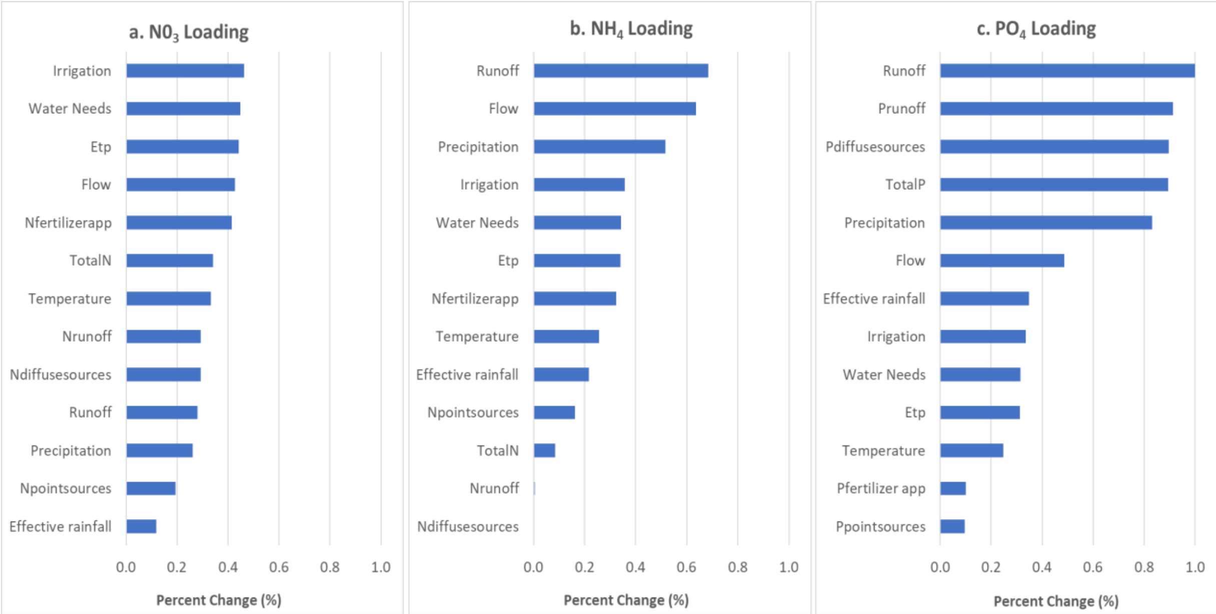

Figure 4 Graphical representation of the results of the sensitivity analysis, represented as the normalized (0-1) percentage change (%) of output variables (i.e. NO_3, NH_4, PO_4 loadings).

According to sensitivity analysis outcomes, NO_3 loadings are mainly driven by agronomic practices including irrigation, fertilizers application and water needs of crops which, in turn, is strictly related to crop potential evapotranspiration. All these variables, in fact, induced the higher percent change in the NO_3 loading node ranging from the 0.46 (51% change, Table III1, Annex III) for irrigation to the 0.41 (46% change, Table V1, Annex V (SP)) for N fertilizer application. Also, the river flow moderately influences the loading with 0.46 of percent change correspondent to 47% (Table III1, Annex III). Despite not being directly linked through the network, irrigation is the variable that mostly influence the $N0_3$ loading. NO_3 is highly soluble in water and therefore is likely to be rapidly washed out by the water applied trough irrigation and to be transported in dissolved form through the river when the river flow is regular. Irrigation is usually higher during summer, when higher are also the application of nitrogen fertilizers and water needs for summer crops (i.e. maize). Consequently, it could explain the concomitant influence of these agronomic variables in increasing NO_3 loadings.

The runoff is the variable that more strongly influence the NH_4 loading, inducing a 0.68 % change with a change of 76% of the Expected Value in the output node. Ammonium (NH_4) is not very soluble, however, the portion adsorbed to soil colloids can be transported into surface water during water erosion process induced by extreme runoff. River flow, being directly linked with the NH_4 loading in the network, have a moderate influence (i.e. 0.64 correspondent to 71% change (Table V1, Annex V (SP))

PO4 loading, instead, is strongly affected by the runoff, the loading of phosphorous into the runoff and consequently, by the intensity of diffuse pollution sources. In particular, the runoff causes the maximum variation (i.e. 1) corresponding with a percent change of 111% while the phosphorous in the runoff and phosphorous diffuse sources contribute respectively for the 102% and 101% percent of change (Table V1, Annex V, (SP)). High runoff intensity, mainly related to intense precipitation are recognized as one of the main factor influencing the transport of phosphorous from agricultural areas to water bodies (Lundekvam et al., 2003).

For all nutrient species (i.e. NO_3, NH_4, PO_4) diffuse pollution represent more important sources of loading respect to point ones which are always classified as variables with negligible influence in the last position of the ranking.

4. Discussion

Scenarios obtained through BN simulations confirms that climate change will drive changes in both the hydrology and nutrient loadings as suggested by previous studies (Dunn et al., 2012; El-Khoury et al., 2015; Huttunen et al., 2015; Shrestha et al., 2017; Whitehead et al., 2009). Specifically, results indicate a high probability of an increase of freshwater discharge and nutrient loadings in autumn, and a slightly decrease in spring and summer with respect to the current condition (Panagopoulos et al., 2011) and (Bouraoui et al., 2002) reached similar conclusions analysing climate change and diffuse pollution effects at catchment level respectively in Greece and United Kingdom.

Climate change scenarios for the Zero river basin indicate that increase in temperatures combined with decreasing precipitation will increase evapotranspiration and consequently induce dry and low flow conditions in summer. These effects could be significantly greater than those experiences at the current conditions and could impact on the autumn hydrological responses of the basin.

Processes responsible for the reduced load in the summer season are mainly related with the increase of temperature which enhance the mineralization of organic matter during dry period followed then by the washing out of the accumulated nutrients during subsequent extreme precipitation events. This, combined with reduced summer flow rates, could explain the increase loads in autumn months as suggested by Whitehead et al.(2006) and (Wilby et al.)(2006).

Results also highlight that the processes governing nutrients losses from the basin to surface water under climate change scenarios are different depending on nutrients species. In fact, while NO_3 loadings resulted strongly dependent on river flow and temperature, runoff resulted the factors playing the greatest role in driving NH_4 loadings. In spring and summer, in fact, NO_3 and NH_4 are commonly applied as fertilizers amendments. In dry and warm conditions NH_4, however, is readily adsorbed to clay mineral and therefore is scarcely prone to movements. Its load, is decreasing in summer and spring under projected climate change while increase, in autumn, drive up by runoff and extreme precipitation events. $N0_3$, on the other side, is highly soluble and thus suitable to be transported by hydrological flow (Lapp et al., 1998). In autumn, the elevated temperature and wet conditions projected will enhance nitrification process making NO_3 highly available. This, combined with the seasonal increase in the river flow, could explain the great increase of NO_3 load during autumn season respect to current scenarios. In the soil, soluble form of phosphorous (PO_4) are mobile, and can be transported by diffusion or by surface water flow. At elevated temperature and in dry condition, however, PO4 is easily adsorbed to clay particles or immobilized by organic matter accumulating in the upper soil layers (Lapp et al., 1998). This characteristic makes phosphorous available for transport to surface water, primarily by surface runoff (Weldehawaria, 2013). Accordingly, decrease of summer load can be attributed to the increase temperature and decrease precipitation enhancing PO_4 immobilization and the reduction of sediment transport due to low flow conditions. In autumn, an increase in runoff, following the enrichment of the topsoil of phosphorous occurred during the summer, increase PO_4 transport and thus its loads in the river. In addition, the projected increase of dry prolonged conditions in summer might speed up soil erosion phenomena and, consequently, enhance the runoff of adsorbed mineral forms of phosphorus trough the basin leading to peak of PO_4 load in autumn as soon as the drought breaks. Strong relationships between phosphorous and the runoff magnitude have been reported by (Molina-Navarro et al., 2014; Shrestha et al., 2017) in Mediterranean catchments.

Conclusions

A risk assessment procedure based on BNs modelling was implemented in the Zero river basin (Northern Italy) to link future scenarios of climate change with water quality alterations. This produces alternative risk scenarios to communicate the probability of changes in the amount nutrients (i.e. NO_3, NH_4, PO_4) delivered from the basin under different climate change projections (i.e. RCP 4.5 and 8.5). The developed BN has been shown to be an effective tool to support the assessment of the state of water resources under changing conditions, allowing to test multiple scenarios and to inform managers on a range of plausible future impacts. Thanks to their probabilistic nature, in fact, BNs resulted quite effective in translating the information provided by climatic and physical models improving the incorporation and communication of uncertainties of future climate change scenarios and impacts. Moreover, by identifying key components and processes affecting flow and water quality BNs could help in identifying variables of the system that should be targeted by adaptation and management and to select the opportune typology of responses to implement. Finally, being highly flexible, as new data and projections become available the developed BN can be easily revised updating evidences and uncertainty, thus increasing the robustness of the risk assessment outcomes (Failing et al., 2004) and contributing to the adaptive management process (Pollino and Henderson, 2010).

Simulated scenarios show that seasonal changes in precipitation and temperature are likely to modify both the hydrology and nutrient loadings of the Zero River and that diffuse pollution sources play a key role in determining the amount of nutrients loaded while point source have only a marginal effect. Both NH_4 and PO_4 loadings are mainly influenced by changes in hydrological variables (i.e. runoff) while NO_3 loadings, despite being highly dependent on flow conditions, are also influenced by agronomic practices and land use (i.e. irrigation, fertilization). These findings confirm that climate change, will play a significant role in exacerbating the risk of water quality degradation especially considering that most dramatic changes (e.g. increase in precipitation and runoff) will happen during periods characterised by intensive agricultural activities (e.g. manure application in the fields during the autumn).

Both the developed BN and the future scenarios produced have been evaluated through a cross comparison with existing observed data and hydrological models' simulation (i.e. SWAT) available for the case study providing acceptable results. In summary, the BN approach was able to represent the effect of climate change and land use on water quality attributes in a policy-relevant manner, demonstrating the suitability of this method to supplement traditional process-based models commonly applied in water resources management, characterized by high complexity and data needs not always directly applicable to decision-making.

However, it is important also to acknowledge some limitations. Some uncertainty exists mainly due to the availability and quality of input data including fertilizer applications, irrigation and wastewater discharges. Obtaining more detailed information throughout the catchment and involving a higher number of experts in the model development would improve its calibration, validation and, as results, future projections.

Furthermore, extreme events, which are recognized to play a significant role in driving nutrient loadings, are usually not well represented by climate change models especially at seasonal time step. Accordingly, the use of climate change projections as input of the BN could, to some extent, underestimate extreme events related processes such as extreme runoff and erosion and, consequently, the loading of nutrients.

Finally, land use (i.e. agricultural land extension, crop typologies distribution) and agricultural management practices (i.e. amount of fertilizer application) changes, that in this BN version have been kept constant over future scenarios, should be accounted in the model to provide a realist picture of future risks and allow their prioritization (Mantyka-Pringle et al., 2014). As this BN will keep continuously updated, upcoming advances will overtake these current technical limitations. Further improvements of the proposed approach could consider the implementation of a dynamic version of the BN (Molina et al., 2013) to better handle temporal dynamics and the development of new scenarios, considering land use changes projections or assuming that specific management measures have been put in place.

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Annex I-Information and assumptions used to calculate node's states and probabilities in the BN

Annex I provides an extensive description of the information and assumptions used to characterize states, prior and conditional probabilities of nodes in the BN developed for the Zero river basin (Figure 3). As described in Section 2.2.2, for most nodes, prior probability and conditional probability distributions have been extrapolated directly from the frequencies of observations or simulations available for the corresponding variables. For other nodes, they have been calculated as follows.

N and P fertilizer application

Nodes related with the nitrogen and phosphorous fertilizer application, describe respectively the amount (kg/ha) of P and N fertilizers applied for each season according to different crop typology.

Accordingly, their parametrization was based on the seasonal needs of N and P for the three main crops of the case study (i.e. Corn, Soy, Winter Wheat) (Table 1I). This information was obtained from both literature (Carpani and Giupponi, 2010) and interviews with experts of Veneto Agricoltura (Bonetto, 2012; Regione Veneto, 2014).

Table I3 Seasonal amount of N and P fertilizers (kg/ha) applied to different crop typologies in the case study

Fertilizer application (kg/ha)		Winter	Spring	Summer	Autumn
Corn	N	0	50	230	0
	P	0	120	0	0
Winter Wheat	N	50	100	0	30
	P	0	0	0	100
Soy	N	0	30	0	0
	P	0	100	0	0

Water needs

The node "Water needs" represent the depth (mm) of water needed from different crop s to meet the water loss through evapotranspiration and thus the amount of water needed to grow optimally. Accordingly, node states and probabilities have been calculated based on the empirical Equation I.I proposed by FAO ((Brouwer and Heibloem, 1986) :

Water Needs$_{crop}$ = Et$_p$ × K$_c$ *Equation I.I*

where:

Water Needs $_{crop}$ is the crop water needs (mm/season);
K$_c$ is the crop factor;
Et$_p$ is the reference evapotranspiration (mm/season).

The Kc for the three types of crops, incorporating crop characteristics and effects of evaporation from the soil, have been selected according with FAO (Allen et al., 1998) (Table I2).

Table I4 Kc for different crop typologies in the case study

Kc	Winter	Spring	Summer	Autumn
Corn	0	0.3	1.2	0.6
Winter Wheat	1.15	0.25	0	0.7
Soy	0	0.4	1	0.5

Irrigation

The node "Irrigation" represents the amount of water applied as artificial irrigation (mm) for each season and, in the BN, it is directly dependent on the water needs and the effective rainfall (i.e. the amount of precipitation that is stored in the soil and thus available for the plant). Accordingly, its probability distribution has been calculated based on Equation I.II (Brouwer and Heibloem, 1986):

Irrigation = Water needs $_{crop}$-ER *Equation I.II*

where:

Irrigation is the amount of water applied as irrigation (mm/season);
Water Needs $_{crop}$ is the crop water needs (mm/season);
ER is the effective rainfall (mm/season).

Total N and P loadings

The nodes "Total N loadings" and "Total P loadings represent the total amount of N and P that are discharged from the river basin into the river seasonally. They are the results of the sum of the loadings apportioned to point and non-point sources and, accordingly, their probability distributions were calculated based on Equation I.III (here presented for N):

N total loading= N point sources+ N diffuse sources *Equation I.III*

where:

N total loading is the loading of nitrogen in the river (kg/season);
N point sources is the amount of nitrogen coming from point sources (i.e. WWTPs and Industrial discharges) (kg/season);
N diffuse sources is the amount of nitrogen coming from agricultural practices (kg/seasons)

Annex II-Bayesian Network Configurations

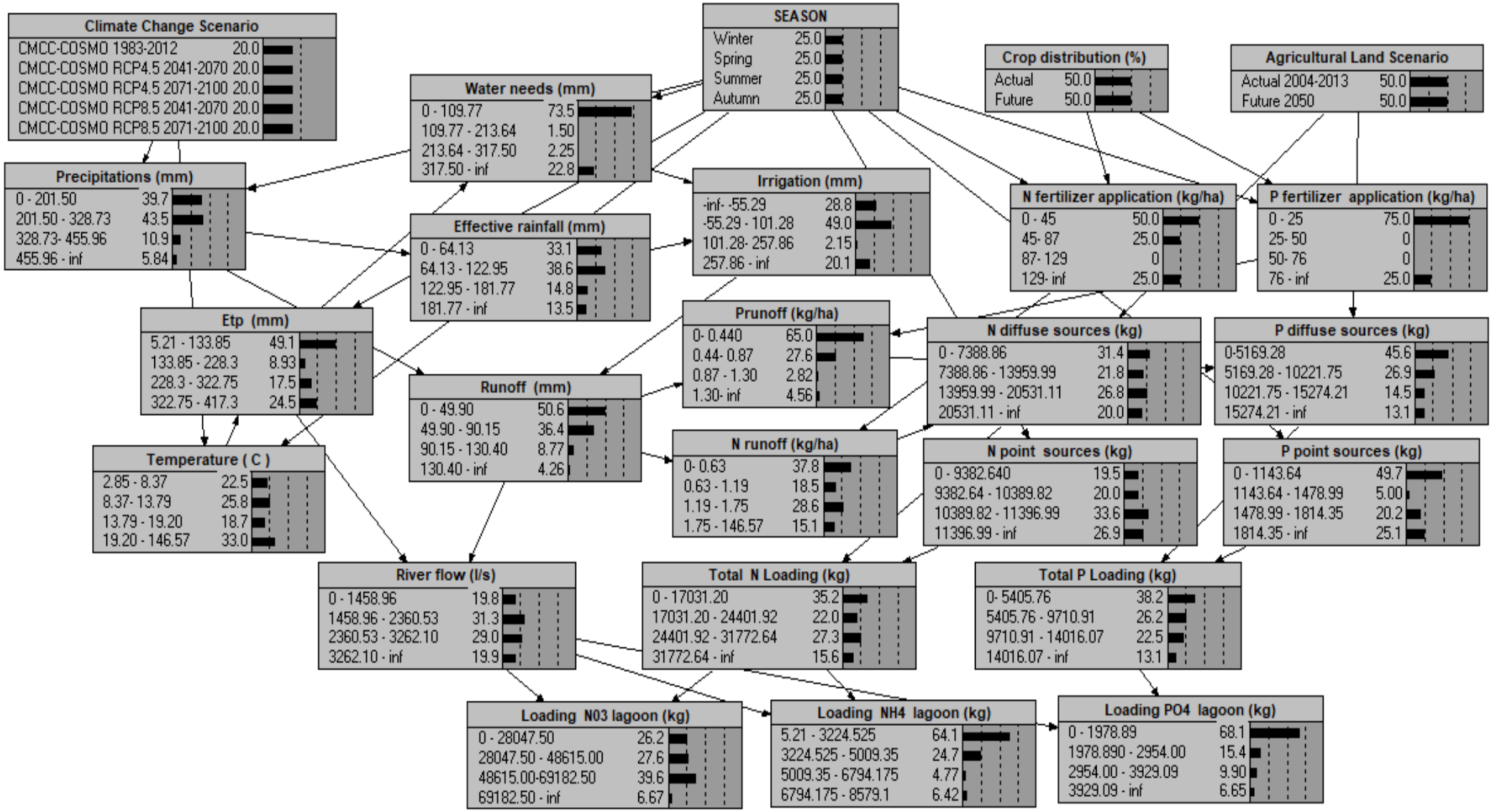

Figure II1 Configuration of the Bayesian Network for the Zero river basin trained with the information for the period 2004-2013

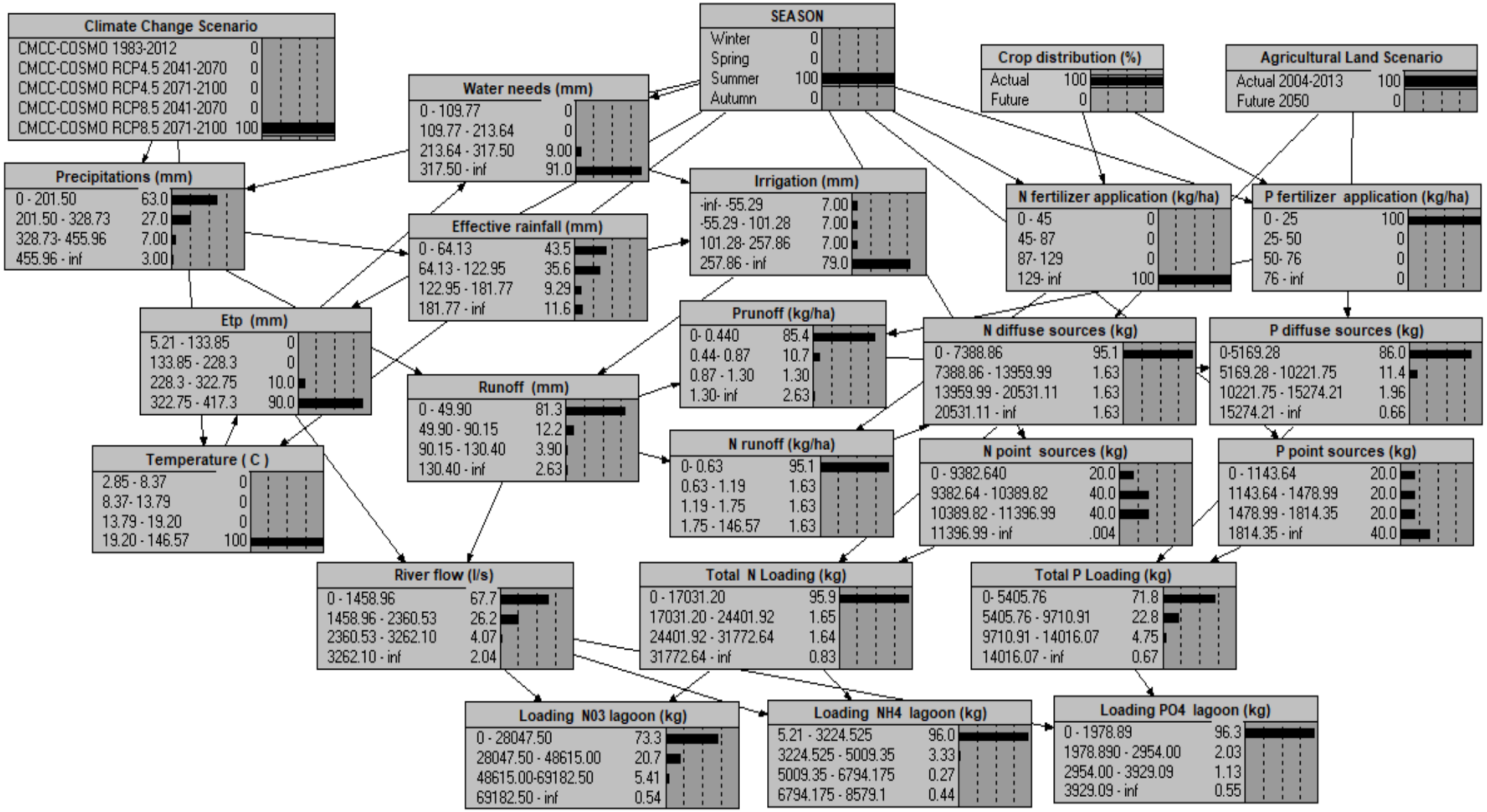

Figure II2 Configuration of the BN for the Zero river basin used for scenario analiysis simulating the nutrients loadings (kg/season) under the COSMO-CLM RCP8.5 2071-2100 climate change scenarios and current land use in summer season

Annex III- Expected Value of the Probability distribution

The Expected Value of the probability distribution of a discrete random variable represents the probability-weighted average of all possible values the variable can assume. In other words, each possible value of random is multiplied by its probability of occurring, and the resulting products are summed to produce the expected value. For a finite discrete random variable *X* the Expected Value E(X) is defined as (Equation III.I):

E(X)= x1**p1* **+ x2****p2* **+ ----- + xk****pk* ***Equation III.I***

where:

E(X) is the expected value of X;

x1,x2,…,xk are the finite number of outcomes of X;

p1, p2,…,pk are the probabilities associated to each outcome of X.

Within the BN developed for the case of study, however each variable is characterized by multiple states (i.e. intervals) and therefore the Expected Value has been calculated as the sum of the products of the intermediate value of each interval/state of the variable for its associated probability (Equation III.II):

E(X)= I1**p1* **+ I2****p2* **+ ----- + Ik****pk* ***Equation III.II***

where:

E(X) is the expected value of X;

I1,I2,…,Ik are the intermediate value of each interval/state of X;

p1, p2,…,pk are the probabilities associated to each intermediate value of each interval of X.

Table III1 provide an example of the application of Equation II.II for the calculus of the Expected Value for the variable “Loading NO3 in the lagoon” of the BN for one of the scenarios (RCP4.5 2041-2070, winter).

E (Loading NO3) = 14023.67**0.05* + 38331.25**0.32*+ 58898.75*0.55 + 83206.25*0.08 **=** 52284.6

Table III1 Example of the computation on the Expected Value for the variable “Loading NO_3 in the lagoon”

Variable (X)	Interval/State	Probabilities (p)	Intermediate value (I)
Loading NO3 in the lagoon	0-28047	0.05	14023.75
	28047-48615	0.32	38331.25
	48615-69182	0.55	58898.75
	69182-97230	0.08	83206.25

Annex IV-Evaluation results

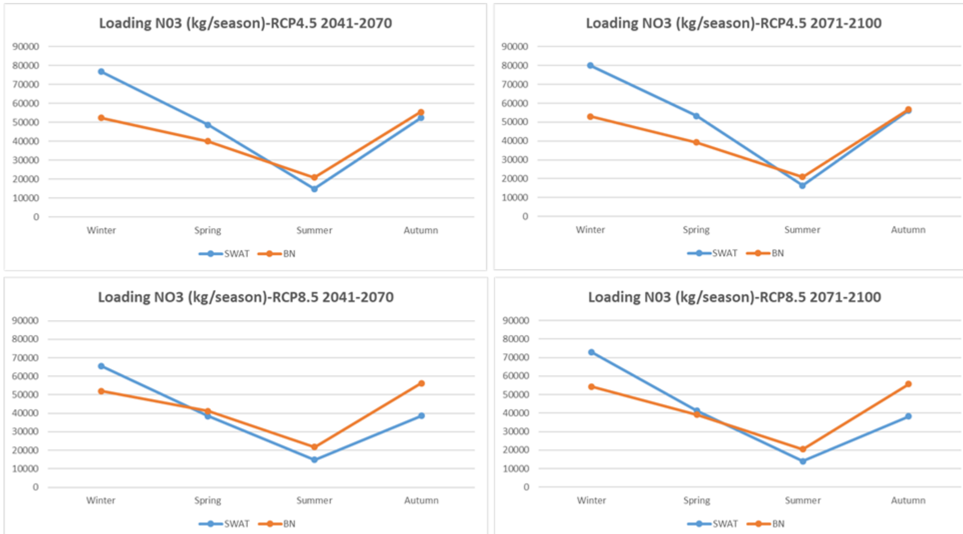

Figure IV1 Expected Value of the probability distributions of NO_3 loading of SWAT model simulation across different scenarios (blue) and of Bayesian Network outputs (red), obtained by fixing the states of precipitation and temperature according with the same climate change projection

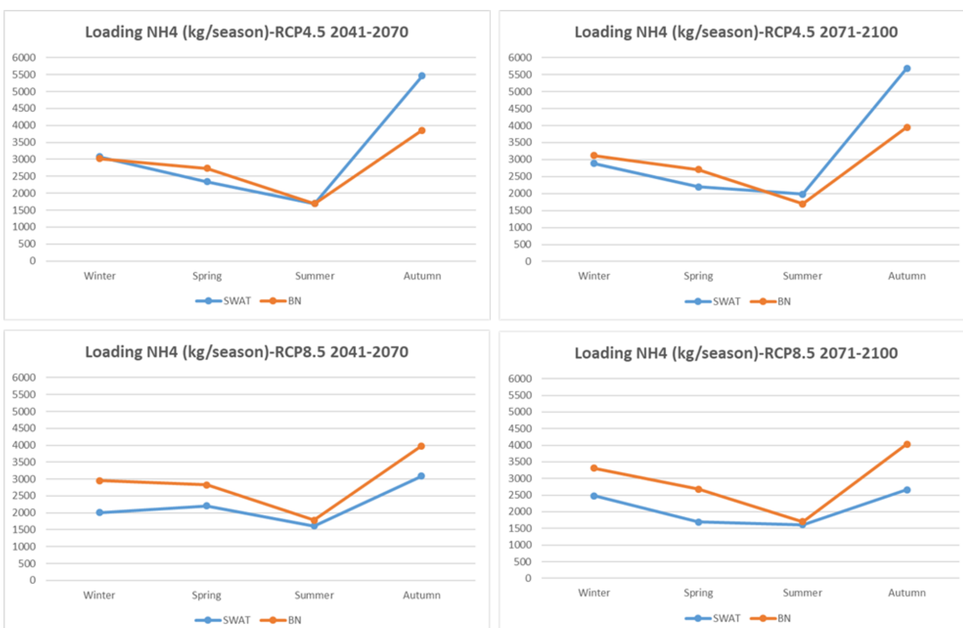

Figure IV2 Expected Value of the probability distributions of NH_4 loading of SWAT model simulation across different scenarios (blue) and of Bayesian Network outputs (red), obtained by fixing the states of precipitation and temperature according with the same climate change projection.

Annex V Percent change

The Percent change is a measure of the change of a variable intensity, magnitude or extent over time. In this case, it is used to measure the increase or decrease of the Expected value of output nodes as consequence of the maximization of input nodes according with Equation V.I

Percent change= $$\left(\left(\frac{New\ Expected\ Value}{Expect\ Value}\right) - 100\right) * 100 \qquad \textit{Equation V.I}$$

where:

New Expected Value is the Expected Value of the output node after the maximization of input nodes;

Expected Value is the initial Expected Value of the output node.

Results of the application of Equation V.I to all the nodes of the BN are provided in Table V1.

Table V1 Percentage change (%) of output variables (i.e. NO_3, NH_4, PO_4 loadings)

	Temperature	Precipitation	Etp	Water Needs	Irrigation	Effective rainfall	Runoff	Flow	Nrunoff	Prunoff	Nfertilizerapp	Pfertilizer app	Ndiffuse sources	Pdiffuse sources	Npoint sources	Ppoint sources	TotalN	TotalP
NO3	37.0	29.1	49.2	50.0	51.7	13.2	31.2	47.6	32.6	0.0	46.3	0.0	32.6	0.0	21.7	0.0	38.1	0.0
NH4	28.6	57.6	38.1	38.3	39.8	24.2	76.4	71.1	0.5	0.0	36.1	0.0	0.1	0.0	18.1	0.0	9.5	0.0
PO4	27.6	92.9	35.0	35.0	37.4	38.9	111.6	54.5	0.0	102.0	0.0	11.2	0.0	100.1	0.0	10.8	0.0	100.0

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Paper 3-Water quality scenarios under uncertainty: applying Bayesian Networks to compare multiple models and scenarios

Introduction

Uncertainty is a pervasive component of climate change studies (Beck and Krueger, 2016; Carter and Kenkyū, 1994). It can be attributed to a number of reasons including the uncertainty about the path of greenhouse gases emissions, the limited understanding of the climate system, processes and related impacts, the way such processes can be represented in climate and impacts models (Parker, 2013). In water resources management, this uncertainty is hampered by the inherent complexity and randomness of water systems and their interaction with socio-economic factors including the land use and population growth.

Understanding the uncertainty in projected climate variations and related impacts on water resources is of paramount importance to support informed decisions based on robust quantitative estimates (Burgman, 2005; Power and McCarty, 2006). Proper uncertainty quantification is vital to facilitate a risk-based approach to decision making, where the range of possible futures are considered (Burgman, 2005; Power and McCarty, 2006) and costs-benefits of adaptation are estimate accordingly. For this reason, uncertainties should be communicated as an inevitable component of each impact assessment study in a form which is understandable also by a no-scientific community to avoid misjudged information and to prevent overconfidence in impact projections (Uusitalo, 2007).

A promising way to evaluate and deal with uncertainty is represented by taking an “ensemble modelling approach” (Wallach et al., 2016) where simulations of future conditions are produced with multiple climate models (i.e. multi-model ensemble) or model versions (i.e. perturbed physics ensemble). Multi-model ensembles are commonly used to investigate structural uncertainty, and thus employ more than one climate model to perform multiple simulations and analyse how climate change projections differ. Perturbed-physics ensembles, instead, are produced by running multiple versions of a single climate model incorporating, in turn, different values of the same parameter and accordingly, are used to parametric uncertainty (Parker, 2013). The development of ensembles in both climate and impact studies is strongly encouraged also by the IPCC since the Fourth Assessment Report (AR4, 2007) which suggests the use of multiple climate models and scenarios to cover different sources of uncertainty (IPCC, 2007). The variability among ensemble components, in fact, can be used as measure the state of our knowledge but also to describe out confidence about the impact of climate change on the system modelled: if most ensemble members give comparable results, we have a high confidence in projected climate change impacts while by contrary, if a large spread between components exist, we are less confident of the projected impacts. Furthermore, has been shown that ensemble often gives a more accurate prediction of future climate impacts than even the best individual model (Krishnamurti et al., 2000; Martre et al., 2015; Tebaldi and Knutti, 2007).

Relying on the extensive experience acquired in climate modelling, the use of ensemble has been transfer also to the water resources field where attempts to build ensemble of impact models and scenarios (i.e. hydrological, water quality) are becoming increasingly common (Luo et al., 2017; Schellekens et al., 2017) to support water resources management and adaptation.

In this context, the paper proposes a Bayesian Network (BN) approach to develop an ensemble of impact scenarios assessing the effect of different climate change projections on the quality of waters of transitional systems (i.e. estuaries). Ensembles of future temperature and precipitation downscaled from available Global and Regional Climate models (i.e. GCMs-RCMs) are directly used to inform a BN and thus to drive simulations of nutrient loadings (i.e. NO_3, NH_4, PO_4) projected under future climate change scenario. Accordingly, BN are use as modelling framework to track and propagate uncertainties across a range of climate change projection helping in determining and communicating the level of confidence of projected water quality alterations between baseline and future climate regimes.

The approach was implemented and applied to the case study of the Zero river basin in Northern Italy, one of the main tributaries of the Venice Lagoon, building on a BN model previously validated in the case study (Paper 2, Sperotto et al., In preparation) which was here extended to allow the incorporation of multiple GCM-RCM's inputs.

BNs outcomes (i.e. multiple impact scenarios) can be used to inform about the spectrum of plausible effects of expected climate change on the Zero river basin and thus to support the choice o of effective adaptation strategies for a sustainable management of the water resources quality at the local scale.

After a brief introduction to the modelling approach chosen for the treatment of uncertainty (Section1) the paper describes the methodology and input data employed (Section 2) and finally, discusses the scenarios developed for the Zero river basin case study (Section 3).

1. Bayesian networks and uncertainty representation

BNs have been chosen, in this study, as a flexible and effective operational approach for exploring and incorporating uncertainty into climate change scenarios and river basin responses. Several authors (Catenacci and Giupponi, 2010; Mann et al., 2017; Richards et al., 2013) suggested BNs to deal with the uncertainty affecting climate change decision making processes thanks to their flexibility in characterizing the uncertainty affecting complex systems, incorporating it into impact assessment analysis and communicating the outcome to decision makers (Catenacci and Giupponi, 2010).

Bayesian Networks use probability as quantitative measure of uncertainty. Probability is recognized as one of the most common way to formalize and characterize uncertainty (Morgan et al., 1992). The commonly adopted frequentist statistic, defines probability of an event as the relative frequency based on a large number of identical and independent trials. (Mann et al., 2017). Accordingly, the probability is an objective and fixed property of the event itself.

Bayesian Networks, by contrary, applied an epistemic or subjective interpretation of probability which represents the degree of belief assigned to events by an individual assessing the state of the world, and thus is function of the state of information rather than of the event (Cuzzolin, 2012). In the Bayesian view data are fixed while the probability of a certain event can change as soon as new information become available and are incorporated in the model.

Exploiting the probabilistic nature of BN, uncertainty in the input data (i.e. climatic variables) can be incorporated in the analysis by applying sequential learning, sensitivity analysis and scenario reasoning. When developing scenarios through BN, a certain level uncertainty in the inputs is recognized and propagates through the system determining uncertainty in the outputs. Users can test how uncertainty in input variables (i.e. climatic variables) affect the uncertainty in the outputs/response (i.e. river flow, nutrient loadings) and identify whether it can be reduced (Sperotto et al., 2017). At the same way, main sources (e.g. lack of knowledge, natural variability, model structure), types of uncertainty (i.e. epistemic or aleatory) but also the pathways through which it propagates, can be easily track and accounted.

Finally, thanks to their graphical structure and the transparency in input information, the assumptions and uncertainties lying behind the assessment can be communicated into a relatively simple, yet evidence-based, graphical way increasing the likelihood that the outputs will be accepted and, consequently adopted, in decision making (Pollino et al., 2007).

2. Material and methods

2.1 Input data

To assess the effect of climate change on the nutrients loadings (i.e. NO_3, NH_4, PO_4) changes in temperature and precipitations over future scenarios were selected as climate change indicators and used as input for the development of alternative climate change impact scenarios using the BN model. The aim of the study, however, was to capture uncertainties across a range of available climate change models and projections thus, in order to represent the widest range of temperature and precipitations change projected for the case study area, a set of different climate change model's outputs were considered (Table 1). This allowed to consider both "worst" and "best" cases in the BN, thus giving the users a big flexibility in exploring and understanding the possible implications of climate change in the future. Climate change models were selected, among those available considering: i) their representativeness for the case study area and for the selected time periods (i.e. 2041-2070 and 2071-2100); ii) their ability to perform at high spatial resolution; iii) the possibility to be available in an open-source format. Accordingly, an ensemble of ten climate change scenarios were selected (Table 1) including the CMCC-CM/COSMO-CLM GCM-RCM and 9 GCM-RCM model combinations from the EURO-CORDEX project (Jacob et al., 2014).

The CMCC-CM global model (Scoccimarro et al., 2011) is a coupled atmosphere-ocean general circulation model while the COSMO-CLM (CCLM) (Cattaneo et al., 2012) is an high resolution (between 1 and 50 km) climate regional model both developed by the Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) that, when coupled, allow a spatial resolution of 8 km for the selected region.

EURO-CORDEX is the European branch of the CORDEX initiative sponsored by the World Climate Research Program (WRCP) with the aim of organizing an internationally coordinated framework to produce improved regional climate change projections for all land regions world-wide based on dynamical statistical downscaling models forced by multiple GCMs. CORDEX-results are commonly used as input for climate change impact and adaptation studies within the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC). In this study, 9 climate change scenarios resulting from different combination of GCM and RCM at 12 km of spatial resolutions, were selected (Table 1). Different GCMs and RCMs have been developed by different research groups including the Danish Meteorological Institute (DMI), the Swedish Meteorological and Hydrological Institute (SMHI), the Met Office Hadley Centre (MOHC).

Table 5 Future climate scenarios selected and implemented in the BN

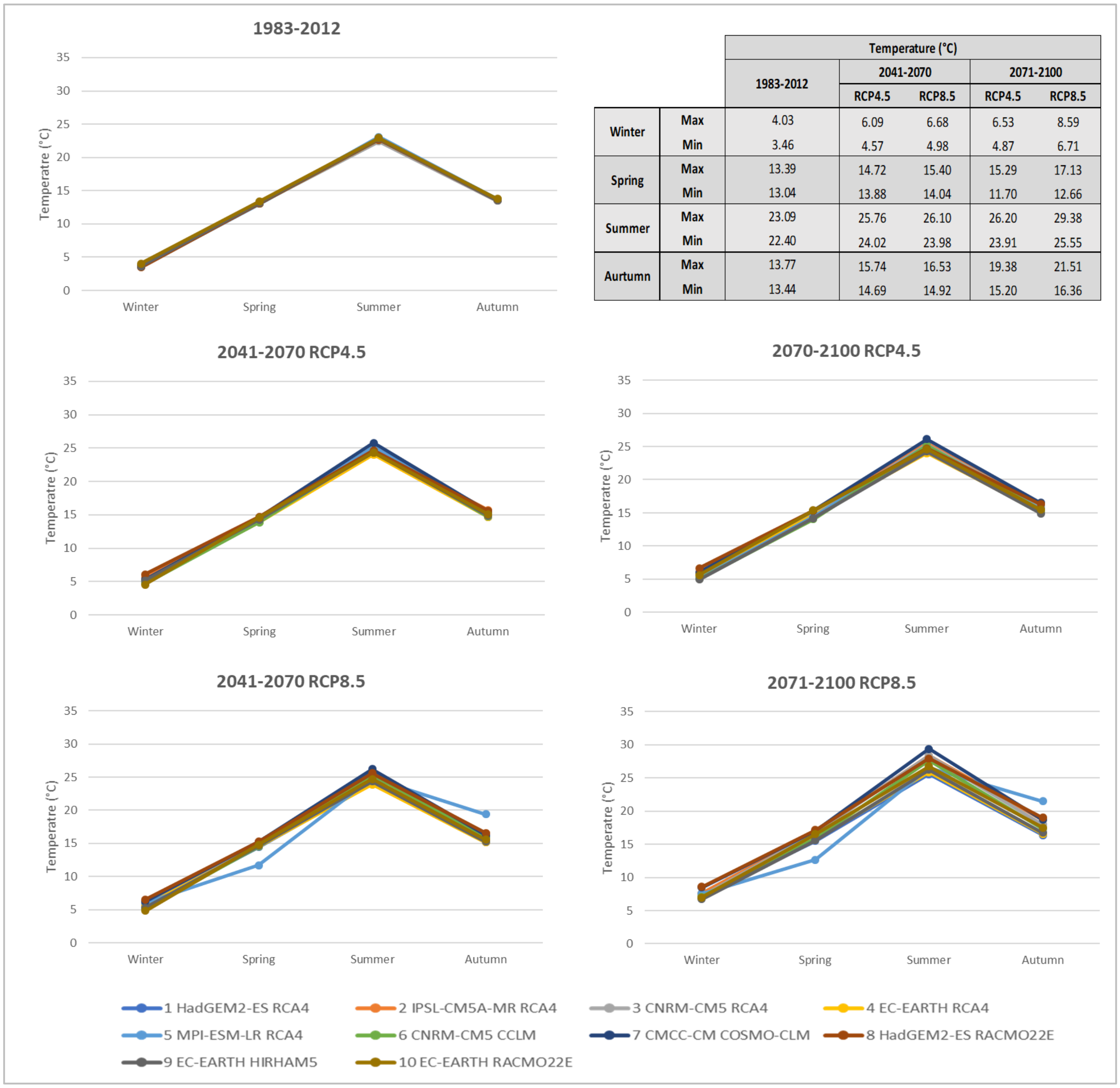
No.	Global Climate Model (GCM)	Regional Climate Models (RCM)	Representative Concentrations Pathway (RCP)	Resolution	Time range	Institute
1	HadGEM2-ES	RCA4	4.5, 8.5	12 km	1970-2099	SMHI
2	IPSL-CM5A-MR	RCA4	4.5, 8.5	12 km	1970-2100	SMHI
3	CNRM-CM5	RCA4	4.5, 8.5	12 km	1970-2100	SMHI
4	EC-EARTH	RCA4	4.5, 8.5	12 km	1970-2100	SMHI
5	MPI-ESM-LR	RCA4	4.5, 8.5	12 km	1970-2100	SMHI
6	CNRM-CM5	CCLM	4.5, 8.6	12 km	1950-2100	CLMcom
7	CMCC-CM	COSMO-CLM	4.5, 8.5	8 km	1976-2100	CMCC
8	HadGEM2-ES	RACMO22E	4.5, 8.5	12 km	1950-2099	KNMI
9	EC-EARTH	HIRHAM5	4,5, 8,5	12 km	1951-2100	DMI
10	EC-EARTH	RACMO22E	4,5, 8,5	12 km	1950-2100	KNMI

To make the outputs of GCM-RCMs suitable to be implemented at the spatial scale of impact assessment models a bias correction was applied (Pesce, 2017). GCMs, in fact, have a spatial resolution too coarse for local-scale assessments and for this reason they are generally coupled with RCMs to consider the effects of orography, land-sea surface contrast and land surface characteristics. However, also RCMs often show significant biases due to an imperfect conceptualization, discretization and spatial averaging within grid cells (Christensen and Christensen 2007) and, therefore, a bias correction is required (Teutschbein and Seibert, 2012). For the data used in this study, the linear scaling (LS) method, was applied to correct the biases in the monthly values of temperature and precipitation based on observed ones. The LS method was applied using the software CLIME, a GIS software for climate data analysis developed by the Regional Models and geo-Hydrogeological Impacts division (REMHI) of CMCC (Cattaneo et al., 2015), as extensively described in (Pesce, 2017). Specifically, the method was implemented to all the ten climate scenarios for every weather station of the case study (Figure 1, Paper 2) using the rainfall and temperature observations for the period 1993-2012 as correction factor. Once corrected, outputs of the GCM-RCMs for each of the ten climate scenarios and for each of the three weather stations of the case study (i.e. Castelfranco Veneto, Zero Branco, Mogliano Veneto) were elaborated to obtain suitable input for the BN model.

2.1.2 Climate change scenarios for the Zero river basin

Based on the outputs of the selected GCM-RCMs different climate change scenarios were developed for the Zero river basin case study (Figure 1, Paper 2) by extrapolating the mean temperature (°C) and the cumulative precipitation (mm) calculated on a monthly base. Specifically, for each GCM-RCMs five different 30-year scenarios were developed for a control period (i.e. 1983-2012), a mid-term (i.e. 2041-2070) and long-term (i.e. 2071-2100) period under two different representative concentration pathways (i.e. RCP4.5-RCP8.5). The RCP4.5, represent the moderate emission scenario which predicts an increase in radiative forcing up to 4.5 W m-2 by 2100 and a stabilization of the emissions (i.e. 650 ppm) shortly after 2100 (Thomson et al., 2011) while RCP8.5, was chosen as representative of the extreme emission scenario, in which the GHGs emissions and concentrations increase considerably over the 21st century, leading to a radiative forcing of 8.5 W m-2 by 2100 (Riahi et al., 2011) thus describing a future without any specific climate mitigation target.

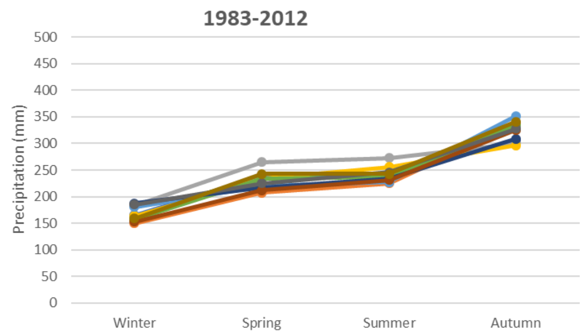
Figure 1 show the variability of temperature for different time periods and RCPs across different climate change models used to inform the BN. It is possible to observe that temperature variability across future projection is quite narrow. All climate scenarios agree on projected temperature during the control period (i.e. 1983-2012). Greater variability, instead, is depicted for RCP8.5 where, especially one model (i.e. MPI-ESM-LR/RCA4, Model 5) of the ENSEMBLE, projects lower temperatures in spring and higher temperatures in autumn. In general, all models predicted an increase of mean seasonal temperature respect to the baseline across the different considered scenarios (Table I1, Annex I). The MPI-ESM-LR/RCA4 (Model 5), represents the only exception predicting a decrease in temperature in spring for both RCP8.5 (Table I1, Annex I). The greater increase in temperature respect to the baseline are predicted by RCP8.5 2071-2100.



		Temperature (°C)				
		1983-2012	2041-2070		2071-2100	
			RCP4.5	RCP8.5	RCP4.5	RCP8.5
Winter	Max	4.03	6.09	6.68	6.53	8.59
	Min	3.46	4.57	4.98	4.87	6.71
Spring	Max	13.39	14.72	15.40	15.29	17.13
	Min	13.04	13.88	14.04	11.70	12.66
Summer	Max	23.09	25.76	26.10	26.20	29.38
	Min	22.40	24.02	23.98	23.91	25.55
Aurtumn	Max	13.77	15.74	16.53	19.38	21.51
	Min	13.44	14.69	14.92	15.20	16.36

Figure 1 Variability of mean seasonal temperature within the GCM/RCM ensemble adopted in the case study

Differently, precipitation features a marked variability in all scenarios shown in Figure 2. All 10 GCMs/RCMs of the ENSEMBLE generate quite similar statistics for the control period (i.e. 1983-2012) with a narrow range between max-min values for all seasons (Figure 4). By contrary, the variability increases consistently along the century especially for RCPs8.5. Greater variability can be depicted in summer, autumn and winter where the range between max-min values projected by different GCMs/RCMs become quite wide (Figure 4). However, while for winter and autumn most models agree on an increase in the cumulative precipitation (Table I2, Annex I), for spring and summer models give opposite results making impossible an agreement about the direction of change (i.e. decrease-increase) (Table I2, Annex I).



		Precipitation (mm)				
		1983-2012	2041-2070		2071-2100	
			RCP4.5	RCP8.5	RCP4.5	RCP8.5
Winter	Max	186.97	247.44	239.54	252.47	335.58
	Min	149.90	166.72	141.87	158.20	153.04
Spring	Max	265.15	257.97	270.20	297.02	257.97
	Min	207.42	229.25	213.17	203.83	181.17
Summer	Max	272.42	247.23	296.41	312.29	301.49
	Min	224.63	206.16	129.10	154.37	93.79
Aurtumn	Max	351.59	402.74	461.10	405.62	420.09
	Min	296.13	293.00	259.53	292.63	293.00

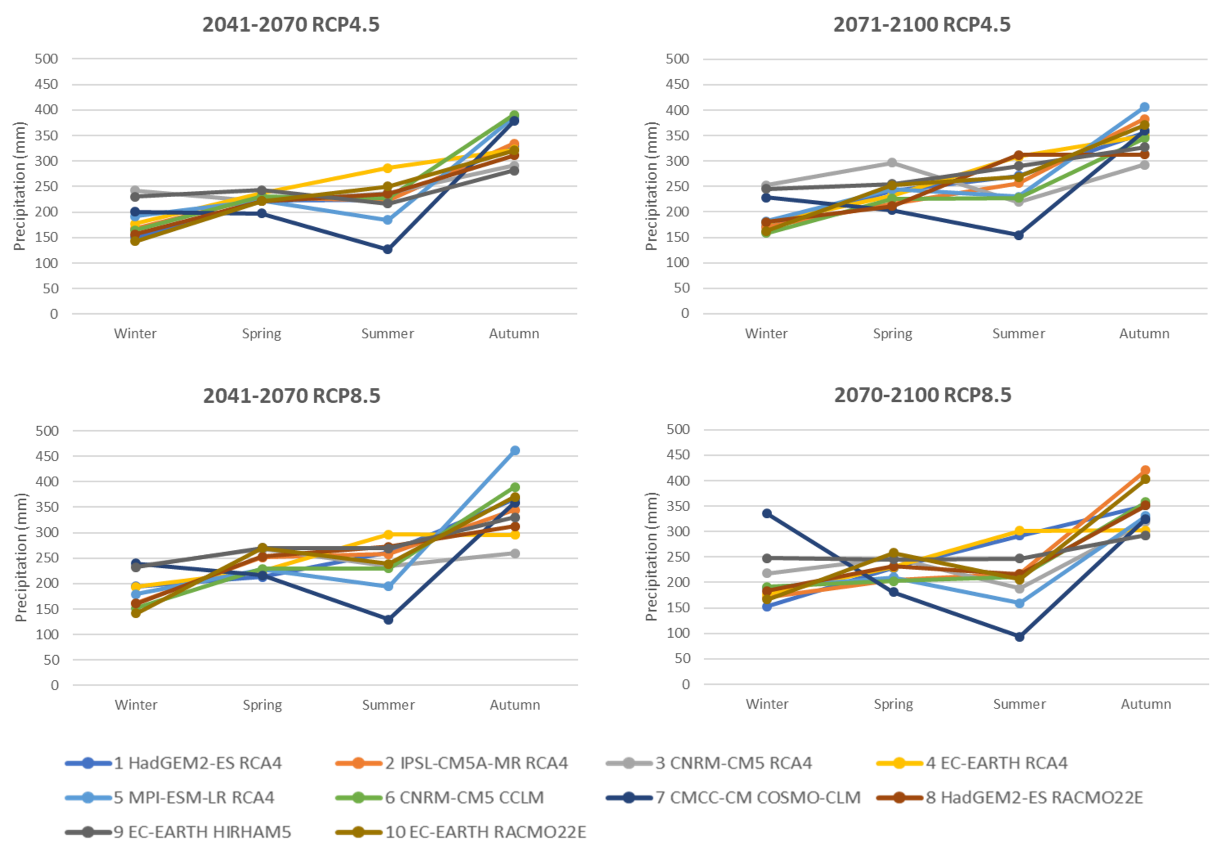


Figure 2 Variability of cumulative seasonal precipitation within the GCM/RCM ensemble adopted in the case study

2.2 Methodology

A BN has been employed to assess and compare the impacts of different climate change scenarios on nutrients loadings (i.e. NO_3, NH_4, PO_4) in the transitional waters of the Zero river basin and thus to generate an ensemble of impacts scenarios supporting the identification of climate change effect on water quality. The BN was implemented building on a BN model previously developed and validated in the case study (Paper 2, Sperotto et al., In preparation) which was extended to allow the incorporation of multiple GCM-RCM's inputs. The BN for the Zero river basin was run using the software HUGIN Expert, version 8 (Bromley et al., 2005; Madsen et al., 2005) and following the methodology described in Paper 2 (Sperotto et al., In preparation). The BN relies on multiple information source including both qualitative and quantitative data and consequently integrating different knowledge domains (i.e. environmental and social science, agronomy, hydrology, climate change). As described in Paper 2 (Sperotto et al., In preparation), the BN for the Zero river basin has been designed following the DPSIR framework starting from the conceptual models in Figure 3, (Paper 2, Sperotto et al., In preparation). An influence (i.e. "box and arrow") diagram was then developed including the most relevant systems variables (i.e. nodes) as well as the links between them (i.e. directed arcs) allowing the identification of the main cause-effect pathways and interactions between input variables, represented by climatic changes and land use, and output variables represented by the increase of nutrients loadings (i.e. NO_3, NH_4, PO_4) discharged by the Zero river basin.

Successively, the BN has been trained assigning states, prior and conditional probabilities to all nodes of the networks, thus translating the conceptual model into an operative probabilistic form. The training has been performed using a heterogeneous set of information for the period 2004-2013 at seasonal time steps including historical observations, hydrological model simulations (i.e. SWAT) and expert opinion. Specifically, for nodes associated with climatic variables (i.e. temperature, precipitation, evapotranspiration) probabilities have been learned directly from the frequencies of observations of weather monitoring stations available in the case study. Probabilities distribution of hydrological variables (i.e. runoff, river flow, nutrients loadings, N and P in the runoff), instead, have been calculated based on the frequencies of results of hydrological simulations performed with the Soil and Water Assessment Tool (SWAT)(Arnold et al., 2012). Finally, nodes describing agronomic practices (i.e. water needs, irrigation, P and N fertilizer application), were trained through expert elicitation or by applying empirical equations due to the lack of quantitative information and experiences in the case study.

The predictive performance of the BN in the case study has been evaluated performing a data-based comparison for both current and future conditions. Specifically, for the current condition the nutrients loadings predicted by the BN were compared with observations from water quality monitoring stations while for future conditions with outputs of SWAT model simulations forced with the same climate change scenarios (i.e. 1983-2012, 2041-2070, 2070-2100). For further details about the development and validation of the BN in the Zero river basin please refer to Paper 2 (Sperotto et al., In preparation).

The model developed as above was used in this study to perform scenarios analysis allowing the assessment of the relative changes in outcome probabilities of output nodes (e.g. nutrient loadings) when altering the probability distribution of one or more input nodes (e.g. climate change scenarios). For each GCM-RCM combination (Table 1) and climate change scenario (i.e. 2041-2070 and 2071-2100 under two different representative concentration pathways RCP4.5-RCP8.5) the probability distribution of temperature and precipitation was calculated based on the frequency in the respective model simulations (Section 1.2.1). The BN was then run fixing alternatively the evidence of being in a particular scenario assigning 100% probability to the related state in the “Climate change scenario node”, letting the information propagating through nodes that are linked by Conditional Probability Tables (Figure 5) and calculating the change in the posteriori probabilities of output variables (i.e. NO3, NH4, PO4 loadings).

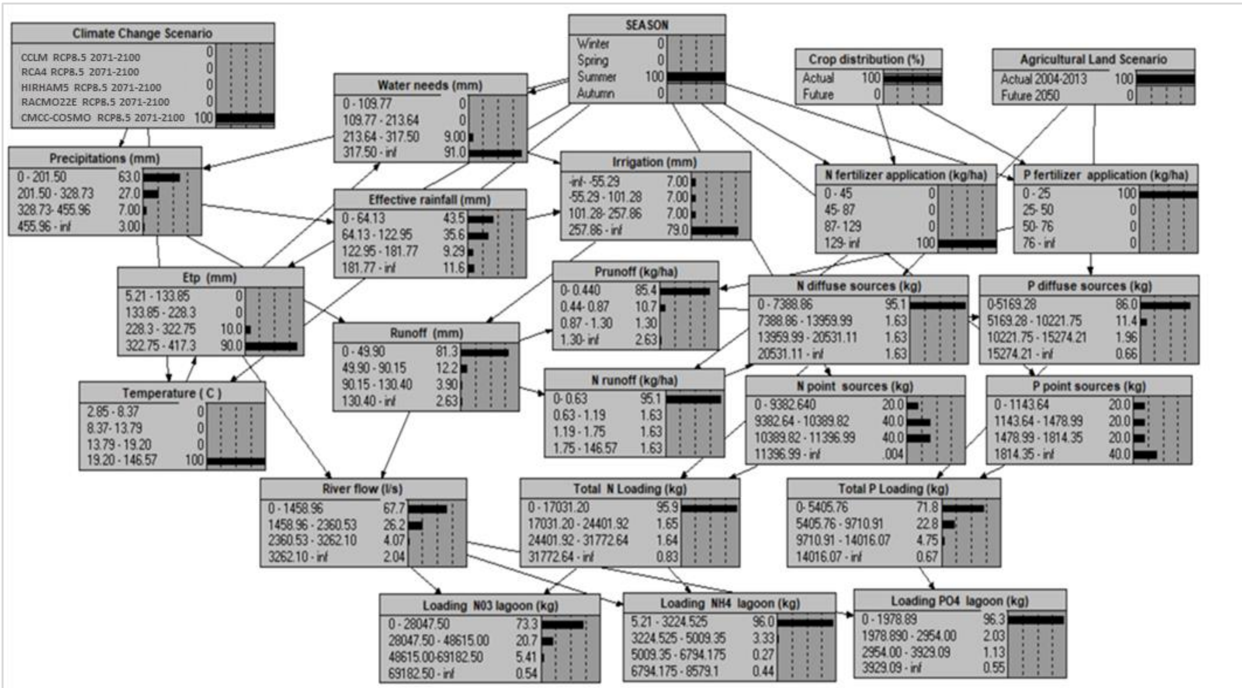


Figure 5 Example of scenarios simulation for the COSMO-CLM RCP8.5 2071-2100 climate change scenarios in summer season

3. Results

3.1 Nutrient loadings scenarios

The BN model was run fixing alternatively the probability distribution of precipitation and temperature according with the medium and long-term projections (i.e.2041-2070, 2071-2100) provided by the different available combinations of GCM-RCMs (Section 1.2.1) under two different representative concentration pathways (i.e. RCP4.5-RCP8.5). Accordingly, the network was used to develop multiple impacts scenarios linking the effect of future climate change projections on nutrients loadings. The develop scenarios represents the probability of different classes of nutrients loadings (i.e. low, medium, high, very high) calculated by the BN model as results of changes in the probability distribution of input variables (i.e. temperature and precipitation).

Figure 6-7-8 give a concise overview of the probabilistic results obtained through the BN for each season and scenario across the different GCM-RCM models considered (Table 1). Specifically, each triangular portion of the graph represent one of the different climate change scenarios considered (i.e. RCP4.5 2041-2070, RCP8.5 2041-2070, RCP4.5 2071-2100, RCP8.5 2071-2100) while, inside them, each slice represents the results of different GCM-RCM arranged clockwise direction (i.e. from 1 to 10, in Tab 1). Each slice, in turn, is divided into the four different classes of loadings with an amplitude correspondent to the value of the associate probability (i.e. from 0 to 100).

For what concern NO_3 (Figure 6) impact scenarios report that higher loadings will take place in autumn and winter while lowest loadings are predicted for summer. Across different models, in fact, in autumn higher probabilities are associated with high (i.e. 48615-69182 kg/season, orange) and very high loading classes (i.e. >69182 kg/season, red). The highest loading is predicted by the MPI-ESM-LR/RCA4 (Model 5) under the RCP8.5 2071-2100 scenario with 70% probability associated with the high loading class (Table 1II, Annex II).

In summer, by contrary, higher probability are associated with low (i.e. 0-28047 kg/season green) loading classes, with the CMCC-CM/COSMO-CLM (Model 7) predicting the highest probability (77%) under the long term RCP8.5 scenario (Table 1II, Annex II).

For ammonium (i.e. NH_4) results across different models predict high probabilities of low loading during summer and spring (Figure 7). The lowest loading is predicted by CMCC-CM/COSMO-CLM (Model 7) under the RCP8.5 2041-2070 with a 97% of probability associated to low class (i.e. 0-3224 kg/season, green) (Table 2II, Annex II). In autumn, the probability of low loadings states decreases gradually across scenarios follow by an increase in the probability of medium (i.e. 3224-5009 kg/season, yellow) and very high loadings (i.e.>6794 kg/season, red) which reach respectively the 38% and the 24 % under the RCP8.5 2071-2100 in the simulation with the IPSL-CM5A-MR/RCA4 (Model 2) (Table 2II, Annex II). Results for PO_4 show a marked seasonality with high autumn loads and low loads in spring and summer across different scenarios (Figure 8). In summer, in fact, higher probabilities are those associated with low loadings state (i.e. 0-1978 kg/season, green). Specifically, lowest loadings are predicted by the CMCC-CM/COSMO-CLM (Model 7) under the medium and long term RCP8.5 scenarios with a probability of 98% (Table 3II, Annex II). High loadings are instead predicted for autumn with the probabilities of high (i.e. 2954-3929 kg/season, orange) and very high classes (i.e. >3929 kg/season, red) that increase across scenarios. The IPSL-CM5A-MR/RCA4 (Model 2), the one describing the more extreme loadings for the season, predict a probability of 34% and 16% of being in very high and high classes under the long term RCP8.5 scenario (Table 3II, Annex II).

Figure 6 Probability of different classes of NO_3 loadings associated to different seasons and scenarios across the GCM-RCM combinations consider

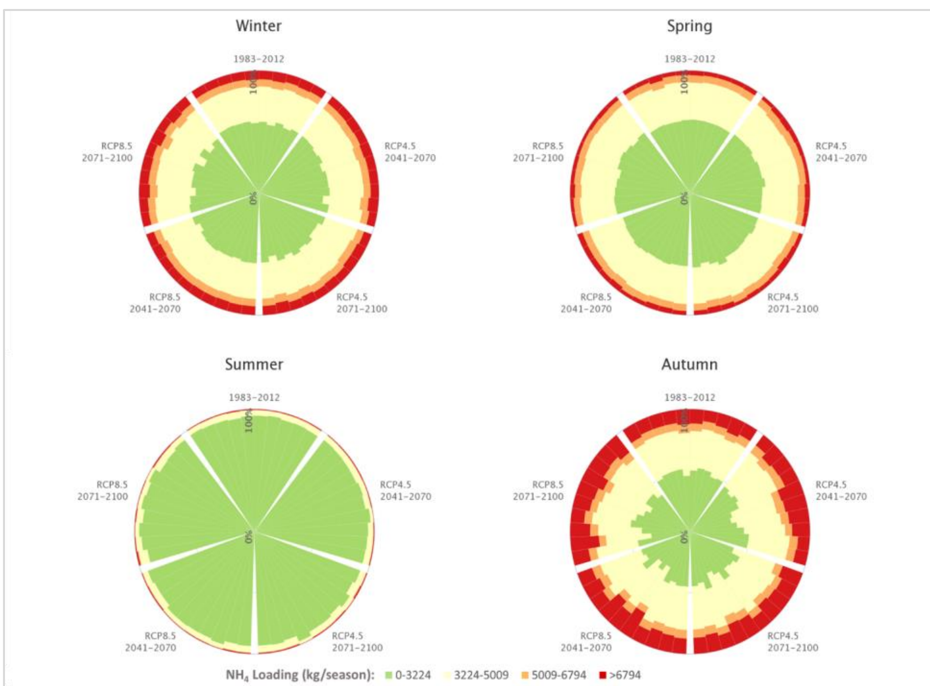


Figure 7 Probability of different classes of NH_4 loadings associated to different seasons and scenarios across the GCM-RCM combinations considered

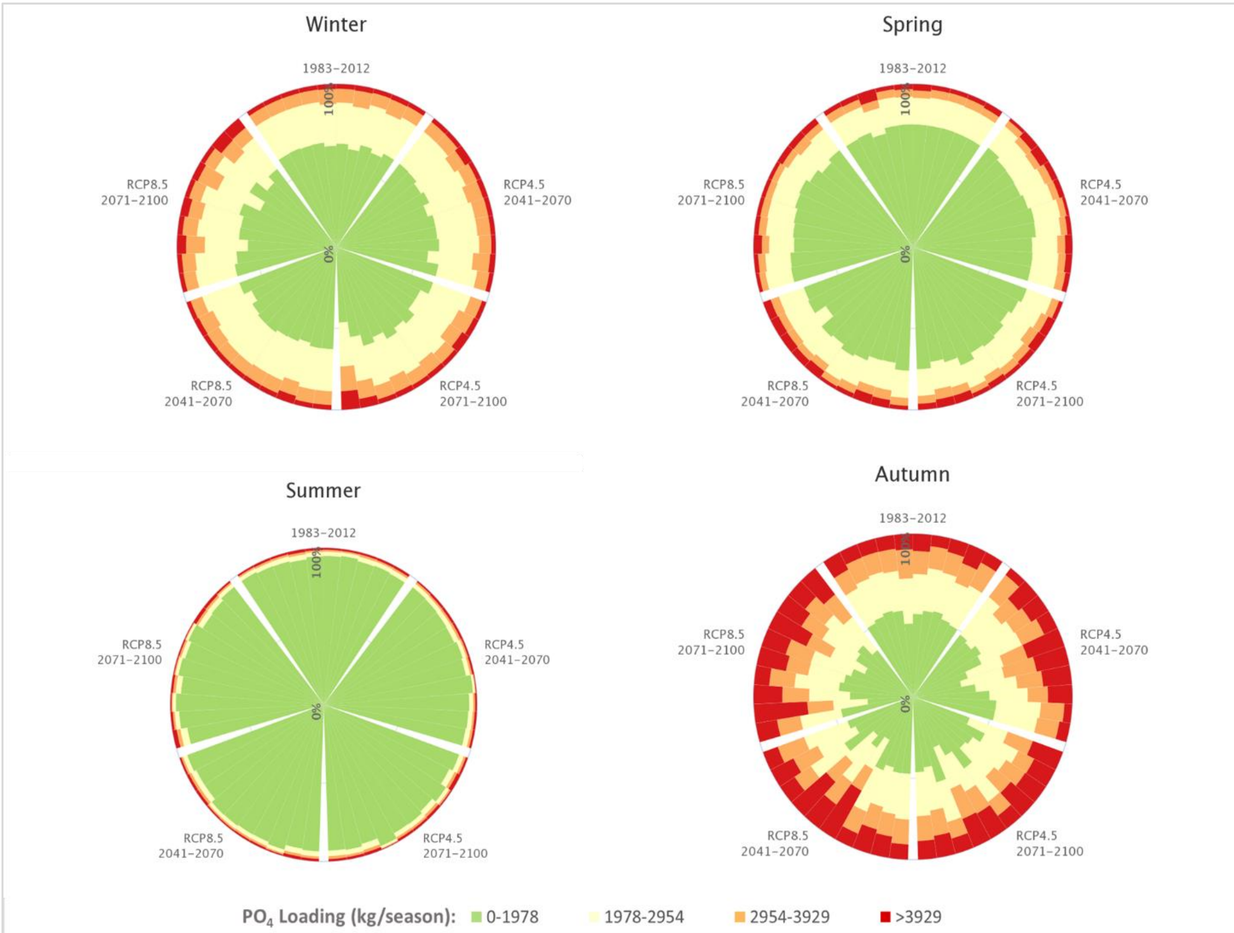


Figure 8 Probability of different classes of PO_4 loadings associated to different seasons and scenarios across the GCM-RCM combinations considered

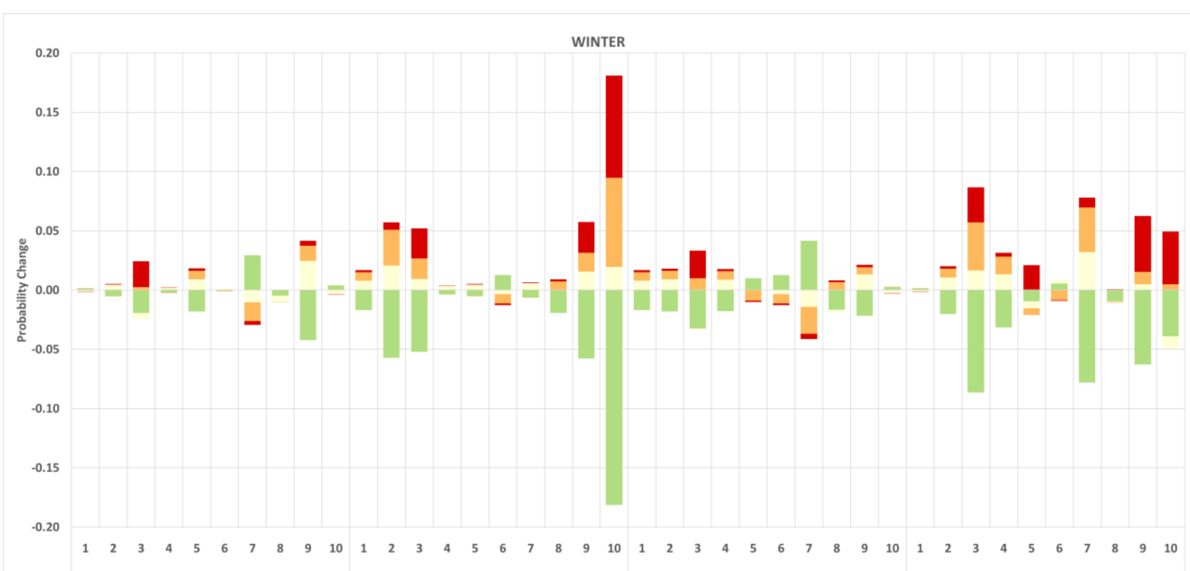
3.2 Analysis of confidence of projected changes/Variability of the results

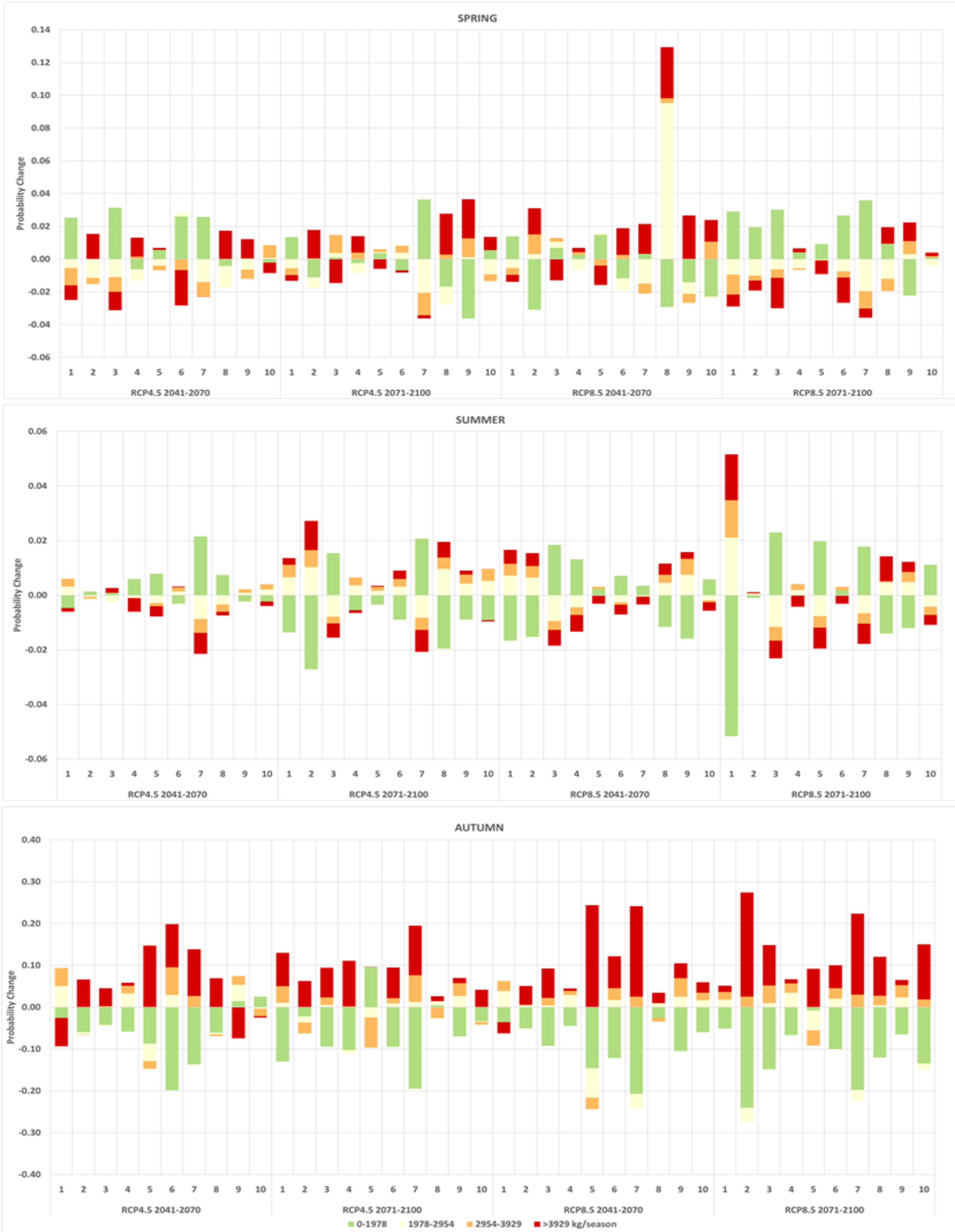
The variability of results was also analysed comparing outputs obtained with each of the ten GCM-RCM combinations across scenarios and seasons. To make results comparable, the change in the probability of each loading class respect to the respective baseline scenario (i.e. 1983-2012) was calculated for each combination of GCM-RCM. Accordingly, in Figure 9, which provide an example for PO_4 loadings, negative values describe a decrease of the probability of specific loading classes (i.e. coloured bars) respect to the baseline, while positive value indicate an increase.

Orthophosphate (i.e. PO4) loadings show a clear variability during spring and summer (Figure 9). During these periods, in fact half of considered models predict an increase of loading while other predicted a strong decrease. Less marked variability, however, is depicted in the RCP8.5 2071-2100 where most models agree on a reduction of loadings in summer-spring period and an increase of the probabilities associated with the low class. A good agreement among models, instead, can be depicted in autumn and especially in RCP8.5 2071-2100 where most models predict an increase of the probabilities of very high and high loadings. Despite the good agreement on the increase of loading, a moderate variability in the magnitude of the change respect to the baseline remain. For the RCP8.5 2041-2070, for instance, the maximum variation is related with the MPI-ESM-LR/RCA4 (Model 5) (i.e.+20 %) while EC-EARTH/RCA4 (Model 4) just predicted a of increase of +1.5%. In RCP8.5 2071-2100 the increase of probability ranges from +28% of the IPSL-CM5A-MR/RCA4 (Model 2) to the 2% of the EC-EARTH/RCA4 and the EC-EARTH/HIRHAM5 (Model 4 and 9).

Also in winter, a general increase of loading is predicted with an increase of the probabilities associated with higher classes and a consequent decrease of probabilities of lower classes. Maximum increase (i.e. +10%) are depicted with the EC-EARTH/RACMO22E (Model 10) for the RCP4.5 2071-2100. Results for NO_3 and NH_4 loadings present a similar tendency (Figure 1III-2III, Annex III).

The best agreement among models resulted for the autumn season where an increase in the loading is predicted across all scenarios and for all the GCM-RCM combinations. Specifically, for NO3 an increase in the probability of high loading class is depicted, while for NH4 the increase is associated with the highest loading class (i.e. very high).





Note GCM-RCM combinations: 1. HadGEM2-ES/RCA4; **2.** IPSL-CM5A-MR/RCA4; **3.** CNRM-CM5/RCA4; **4.** EC-EARTH/RCA4; **5.** MPI-ESM-LR/RCA4; **6.** CNRM-CM5/CCLM; **7.** CMCC-CM/COSMO-CLM; **8.** HadGEM2-ES/RACMO22E; **9.** EC-EARTH/HIRHAM5; **10.**EC-EARTH/RACMO22E.

Figure 9 Variations in the probability of each PO4 loading classes respect to the baseline (i.e. 1983-2012) under different scenarios and GCM-RCM combinations

Also for winter, the variability of results is quite low with most of models that agree on an increase of probability of high and very high classes across different scenarios. By contrary, two models (i.e. CNRM-CM5/CCLM and CMCC-CM/COSMO-CLM (Model 6 and 7)) predict a decrease of loadings for both NO3 and NH4. A large variability resulted for both summer and spring seasons so that is not possible to identify a clear direction of change.

Overall, the results for different nutrients species highlight that, in general, the best agreement between models resulted for autumn and winter and, especially for RCP8.5 scenarios. In summer and spring, instead, variability is high and thus there is a less confidence in the changes projected. This seasonal pattern of variability, to some extent reflect those of precipitation (Section 1.2.1, Figure 3-4) suggesting that this variable could play a major role in the model in determining both the direction and the magnitude of changes in nutrient loadings.

Comparing the results (Figure 9, 1III,2III, Annex III) with the changes in precipitation across the different models (Figure 2II, Annex II) a strong correlation between the increase in precipitations and increase in the probability of high loading can be found. In summer and spring (Figure 9, 1III,2III, Annex III), in fact, those models which predict the highest increase of probability of high loadings are also those showing a positive variation (i.e. increase) in precipitation respect to the baseline (Figure 2II, Annex II).

In this context, it is interesting to notice how, in spring (Figure 1III,2III, Annex III) some models (e.g. model 8-9-10) contemporarily predict an increase of the probability of the two most extreme classes (i.e. low and very high). The same models are also those predicting the highest increase of precipitation respect to the baseline (Figure 2II, Annex II) suggesting that the unexpected high probabilities of very high loading classes could be related with the projections of extreme precipitation events in the considered scenarios.

Discussion and conclusion

A BN was used to develop an ensemble of impact scenarios assessing the effect of different climate change projections on the quality of waters of transitional systems (i.e. estuaries) in the Zero river basin in Northern Italy, one of the main tributaries of the Venice Lagoon.

The BN used was implemented building on a model previously developed and tested in the case study (Paper 2, Sperotto et al., In preparation) integrating a heterogeneous set of data coming from multiple information sources (i.e. observations, hydrological model simulations, climate change projections). The BN was evaluated through a cross comparison between predicted and observed loadings providing satisfactory results at the seasonal time step and therefore, was considered suitable for projecting future climate change scenarios.

Accordingly, the BN was informed with an ensemble of projections downscaled from multiple GCMs-RCMs and employed to track and propagate uncertainties across a range of climate change projections and river basin responses supporting the identification of the level of confidence of projected water quality alterations.

Overall, impact scenario developed shows that seasonal changes in precipitation and temperature are likely to affect nutrient loadings and thus the water quality of the Zero River. Results suggest a good confidence that, across considered scenario, nutrients loadings will increase especially during autumn and winter seasons. Most models, in fact, agree in projecting a high probability of an increase nutrient loadings respect to current conditions. In summer and spring, instead the large variability between different GCM-RCM results make impossible to identify a clear direction of change.

This big variability, seems to be strongly correlated with that of precipitation suggesting that this variable could play a major role in the model in determining both the direction and the magnitude of changes in nutrient loadings.

A general conclusion that can be drawn is that the selection of climate change information to fed impact studies should be considered carefully as it strongly affects the outcome and the conclusion of the assessment: the selection of a more extreme climate scenario rather than other will produce more extreme results, and vice versa. Adaptation decisions are taken based on this information with the consequence that societies may underprepare for real risks, increasing the likelihood of severe impacts or, by contrary, overreact wasting resources and efforts targeting irrelevant threats.

The use of multiple GCM-RCM outputs and the consideration of multiple scenarios can help reducing this risk and communicating the confidence in models results. Through the identification of worst or best-case scenario it permits to bound the spectrum of plausible climate change impacts into an uncertainty space inside which define and test a set of optimal adaptation and management strategies.

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Annex I-Variability of input data

Table 1I Variation in cumulative seasonal temperature respect to the baseline (i.e. 1983-2012) within GCM-RCM ensemble

Season	RCP4.5 2041-2070									
	1 HadGEM2-ES RCA4	2 IPSL-CM5A-MR RCA4	3 CNRM-CM5 RCA4	4 EC-EARTH RCA4	5 MPI-ESM-LR RCA4	6 CNRM-CM5 CCLM	7 CMCC-CM COSMO-CLM	8 HadGEM2-ES RACMO22E	9 EC-EARTH HIRHAM5	10 EC-EARTH RACMO22E
Winter	1.02	2.06	1.16	1.20	1.28	0.99	1.69	2.63	1.54	0.54
Spring	0.74	1.55	1.58	0.74	1.17	0.79	1.47	1.63	1.09	1.23
Summer	1.61	2.06	2.30	1.34	2.07	1.92	2.91	1.96	1.49	1.41
Autumn	0.98	2.06	1.44	0.99	1.59	1.01	1.99	2.09	1.34	1.35

Season	RCP4.5 2071-2100									
	1 HadGEM2-ES RCA4	2 IPSL-CM5A-MR RCA4	3 CNRM-CM5 RCA4	4 EC-EARTH RCA4	5 MPI-ESM-LR RCA4	6 CNRM-CM5 CCLM	7 CMCC-CM COSMO-CLM	8 HadGEM2-ES RACMO22E	9 EC-EARTH HIRHAM5	10 EC-EARTH RACMO22E
Winter	1.89	2.43	1.94	1.83	1.59	1.36	2.44	3.22	1.37	1.62
Spring	1.31	2.19	1.70	1.40	1.43	0.95	2.16	2.23	1.01	2.02
Summer	1.46	2.72	2.88	1.30	2.07	2.43	3.25	2.03	1.41	1.67
Autumn	1.45	2.56	2.56	1.47	1.86	1.71	2.99	2.76	1.34	1.70

Season	RCP8.5 2041-2070									
	1 HadGEM2-ES RCA4	2 IPSL-CM5A-MR RCA4	3 CNRM-CM5 RCA4	4 EC-EARTH RCA4	5 MPI-ESM-LR RCA4	6 CNRM-CM5 CCLM	7 CMCC-CM COSMO-CLM	8 HadGEM2-ES RACMO22E	9 EC-EARTH HIRHAM5	10 EC-EARTH RACMO22E
Winter	1.81	2.17	1.97	1.80	2.48	1.45	2.65	3.07	1.73	0.83
Spring	1.21	2.13	2.02	1.37	-1.33	1.46	2.10	2.21	1.47	1.43
Summer	1.35	2.80	3.42	1.23	1.76	2.62	3.35	2.93	1.55	1.81
Autumn	1.51	2.83	2.78	1.49	5.67	2.21	2.73	3.02	1.67	1.82

Season	RCP8.5 2071-2100									
	1 HadGEM2-ES RCA4	2 IPSL-CM5A-MR RCA4	3 CNRM-CM5 RCA4	4 EC-EARTH RCA4	5 MPI-ESM-LR RCA4	6 CNRM-CM5 CCLM	7 CMCC-CM COSMO-CLM	8 HadGEM2-ES RACMO22E	9 EC-EARTH HIRHAM5	10 EC-EARTH RACMO22E
Winter	3.31	4.00	3.41	3.21	3.97	3.35	4.86	5.12	3.09	2.97
Spring	2.25	3.73	3.68	2.58	-0.37	2.81	3.87	4.04	2.41	3.16
Summer	2.81	5.60	5.94	3.20	3.42	4.93	6.54	5.27	3.39	3.80
Autumn	2.63	5.02	4.54	2.88	7.80	3.64	5.14	5.47	3.15	3.75

Table 2I Variation in cumulative seasonal precipitation respect to the baseline (i.e. 1983-2012) within GCM-RCM ensemble

Season	RCP4.5 2041-2070									
	1 HadGEM2-ES RCA4	2 IPSL-CM5A-MR RCA4	3 CNRM-CM5 RCA4	4 EC-EARTH RCA4	5 MPI-ESM-LR RCA4	6 CNRM-CM5 CCLM	7 CMCC-CM COSMO-CLM	8 HadGEM2-ES RACMO22E	9 EC-EARTH HIRHAM5	10 EC-EARTH RACMO22E
Winter	-14.07	17.83	59.87	13.30	11.76	7.73	13.42	4.34	44.78	-16.16
Spring	-15.77	21.13	-43.52	4.08	3.20	-2.22	-19.95	9.58	18.00	-21.32
Summer	-17.69	-2.35	-35.25	30.18	-43.19	-10.00	-106.05	4.01	-28.97	7.56
Autumn	24.20	-2.67	-9.31	26.26	34.31	56.90	69.32	-14.42	-46.75	-20.44

Season	RCP4.5 2071-2100									
	1 HadGEM2-ES RCA4	2 IPSL-CM5A-MR RCA4	3 CNRM-CM5 RCA4	4 EC-EARTH RCA4	5 MPI-ESM-LR RCA4	6 CNRM-CM5 CCLM	7 CMCC-CM COSMO-CLM	8 HadGEM2-ES RACMO22E	9 EC-EARTH HIRHAM5	10 EC-EARTH RACMO22E
Winter	6.00	20.48	69.77	15.60	2.03	1.39	41.65	27.77	60.34	3.61
Spring	2.59	8.39	31.87	-1.20	24.41	-7.73	-13.09	-0.42	29.90	10.32
Summer	28.65	31.93	-53.24	52.86	2.41	-9.47	-78.80	80.84	44.51	25.57
Autumn	50.91	45.40	-7.46	53.85	54.03	10.85	50.80	-12.56	-1.08	29.17

Season	RCP8.5 2041-2070									
	1 HadGEM2-ES RCA4	2 IPSL-CM5A-MR RCA4	3 CNRM-CM5 RCA4	4 EC-EARTH RCA4	5 MPI-ESM-LR RCA4	6 CNRM-CM5 CCLM	7 CMCC-CM COSMO-CLM	8 HadGEM2-ES RACMO22E	9 EC-EARTH HIRHAM5	10 EC-EARTH RACMO22E
Winter	29.04	11.61	51.32	30.23	-1.24	-4.56	52.57	8.42	46.99	-16.95
Spring	-25.92	44.28	2.61	-9.45	7.13	-4.80	-1.12	41.46	45.36	27.64
Summer	19.06	33.65	-37.51	40.32	-32.79	-6.85	-104.07	41.10	23.26	-4.43
Autumn	60.83	7.90	-40.56	-0.45	109.50	55.55	50.35	-13.13	2.48	28.75

Season	RCP8.5 2071-2100									
	1 HadGEM2-ES RCA4	2 IPSL-CM5A-MR RCA4	3 CNRM-CM5 RCA4	4 EC-EARTH RCA4	5 MPI-ESM-LR RCA4	6 CNRM-CM5 CCLM	7 CMCC-CM COSMO-CLM	8 HadGEM2-ES RACMO22E	9 EC-EARTH HIRHAM5	10 EC-EARTH RACMO22E
Winter	-12.24	20.87	35.42	13.45	9.43	34.49	148.61	31.06	62.16	7.90
Spring	-10.40	-2.52	-17.16	-3.72	-9.90	-30.93	-35.75	19.41	20.65	15.50
Summer	49.25	-7.07	-84.18	45.40	-67.79	-26.06	-139.39	-14.79	1.71	-36.75
Autumn	45.43	83.05	19.28	5.85	-21.26	23.80	15.97	25.87	-34.98	61.53

Annex II-Probabilistic results across GCM-RCM combinations

Table 1II Probability of different classes of NO3 loadings associated to different seasons and scenarios across the GCM-RCM combinations considered

Winter

Classes	1983-2012										RCP4.5 2041-2070										RCP4.5 2071-2100										RCP8.5 2041-2070										RCP8.5 2071-2100									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
0-28047	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.04	0.04	0.05	0.05	0.05	0.04	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.04	0.05
28047-48615	0.33	0.32	0.32	0.32	0.31	0.32	0.30	0.32	0.31	0.32	0.32	0.32	0.31	0.32	0.30	0.32	0.32	0.32	0.29	0.32	0.32	0.30	0.30	0.32	0.31	0.32	0.30	0.32	0.29	0.31	0.31	0.31	0.31	0.31	0.32	0.32	0.32	0.32	0.30	0.32	0.32	0.31	0.28	0.31	0.31	0.32	0.27	0.32	0.28	0.30
48615-69182	0.55	0.55	0.55	0.55	0.56	0.55	0.56	0.55	0.56	0.55	0.55	0.55	0.56	0.55	0.56	0.55	0.55	0.55	0.57	0.55	0.55	0.57	0.57	0.55	0.56	0.55	0.56	0.55	0.57	0.56	0.55	0.55	0.56	0.55	0.55	0.55	0.55	0.55	0.56	0.55	0.55	0.55	0.58	0.56	0.56	0.55	0.58	0.55	0.58	0.56
>69182	0.08	0.08	0.08	0.08	0.09	0.08	0.09	0.08	0.09	0.08	0.08	0.08	0.09	0.08	0.09	0.08	0.08	0.08	0.10	0.08	0.08	0.09	0.09	0.08	0.09	0.08	0.09	0.09	0.10	0.09	0.09	0.09	0.09	0.09	0.09	0.08	0.08	0.08	0.09	0.08	0.08	0.09	0.10	0.09	0.09	0.08	0.11	0.08	0.10	0.09

Spring

Classes	1983-2012										RCP4.5 2041-2070										RCP4.5 2071-2100										RCP8.5 2041-2070										RCP8.5 2071-2100									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
0-28047	0.26	0.26	0.26	0.25	0.26	0.27	0.26	0.26	0.26	0.26	0.27	0.28	0.28	0.26	0.27	0.28	0.29	0.27	0.27	0.27	0.27	0.27	0.26	0.27	0.27	0.27	0.31	0.27	0.25	0.27	0.27	0.26	0.27	0.27	0.26	0.27	0.28	0.26	0.27	0.26	0.29	0.29	0.28	0.27	0.26	0.30	0.30	0.29	0.26	0.28
28047-48615	0.31	0.32	0.30	0.32	0.32	0.32	0.32	0.32	0.31	0.32	0.33	0.32	0.32	0.31	0.33	0.33	0.33	0.31	0.32	0.31	0.32	0.31	0.29	0.31	0.32	0.32	0.34	0.31	0.29	0.32	0.32	0.30	0.31	0.32	0.33	0.31	0.32	0.31	0.31	0.30	0.33	0.33	0.32	0.32	0.33	0.33	0.34	0.33	0.31	0.32
48615-69182	0.38	0.37	0.35	0.38	0.37	0.36	0.38	0.38	0.38	0.36	0.36	0.34	0.32	0.37	0.35	0.35	0.33	0.35	0.35	0.37	0.37	0.35	0.37	0.37	0.37	0.36	0.32	0.36	0.39	0.35	0.37	0.38	0.36	0.37	0.36	0.34	0.34	0.36	0.35	0.37	0.34	0.34	0.33	0.36	0.37	0.33	0.32	0.34	0.38	0.34
>69182	0.05	0.05	0.09	0.05	0.05	0.06	0.05	0.05	0.05	0.06	0.04	0.07	0.08	0.06	0.05	0.04	0.04	0.07	0.06	0.05	0.05	0.07	0.07	0.05	0.05	0.05	0.04	0.07	0.07	0.05	0.05	0.06	0.07	0.05	0.04	0.07	0.06	0.07	0.07	0.07	0.04	0.04	0.06	0.04	0.04	0.04	0.03	0.05	0.05	0.05

Summer

Classes	1983-2012										RCP4.5 2041-2070										RCP4.5 2071-2100										RCP8.5 2041-2070										RCP8.5 2071-2100									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
0-28047	0.72	0.70	0.69	0.68	0.71	0.70	0.72	0.68	0.71	0.69	0.68	0.71	0.70	0.67	0.72	0.69	0.76	0.70	0.70	0.66	0.67	0.65	0.71	0.64	0.70	0.69	0.76	0.64	0.68	0.64	0.67	0.66	0.73	0.70	0.70	0.71	0.74	0.65	0.65	0.69	0.60	0.70	0.74	0.64	0.75	0.69	0.77	0.69	0.68	0.71
28047-48615	0.21	0.22	0.22	0.23	0.21	0.22	0.22	0.24	0.21	0.23	0.24	0.21	0.22	0.25	0.21	0.23	0.20	0.23	0.22	0.25	0.25	0.24	0.22	0.26	0.22	0.23	0.20	0.25	0.24	0.27	0.24	0.24	0.21	0.23	0.23	0.22	0.20	0.26	0.26	0.23	0.28	0.22	0.20	0.27	0.20	0.24	0.18	0.21	0.23	0.22
48615-69182	0.06	0.07	0.08	0.08	0.07	0.07	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.07	0.04	0.07	0.07	0.08	0.07	0.10	0.06	0.08	0.07	0.07	0.04	0.09	0.08	0.08	0.08	0.08	0.06	0.07	0.07	0.06	0.06	0.08	0.08	0.07	0.11	0.07	0.05	0.08	0.05	0.06	0.04	0.09	0.08	0.06
>69182	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.01

Autumn

Classes	1983-2012										RCP4.5 2041-2070										RCP4.5 2071-2100										RCP8.5 2041-2070										RCP8.5 2071-2100									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
0-28047	0.06	0.06	0.05	0.06	0.04	0.07	0.06	0.06	0.04	0.05	0.02	0.02	0.03	0.02	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.06	0.02	0.02	0.03	0.02	0.02
28047-48615	0.31	0.32	0.33	0.32	0.28	0.31	0.34	0.33	0.32	0.31	0.32	0.30	0.32	0.31	0.24	0.21	0.26	0.31	0.34	0.34	0.25	0.33	0.30	0.28	0.36	0.27	0.23	0.36	0.29	0.30	0.31	0.31	0.30	0.32	0.20	0.26	0.21	0.34	0.27	0.29	0.30	0.19	0.26	0.31	0.28	0.27	0.22	0.28	0.29	0.24
48615-69182	0.54	0.53	0.52	0.52	0.56	0.54	0.52	0.52	0.55	0.54	0.55	0.58	0.56	0.56	0.65	0.65	0.62	0.58	0.53	0.54	0.63	0.57	0.59	0.61	0.54	0.61	0.64	0.54	0.59	0.57	0.56	0.57	0.59	0.56	0.69	0.62	0.67	0.55	0.60	0.58	0.58	0.70	0.62	0.56	0.58	0.61	0.66	0.60	0.59	0.63
>69182	0.09	0.09	0.09	0.09	0.11	0.09	0.09	0.09	0.09	0.11	0.12	0.09	0.09	0.11	0.10	0.12	0.11	0.09	0.10	0.10	0.11	0.08	0.10	0.09	0.08	0.10	0.12	0.08	0.11	0.10	0.11	0.10	0.10	0.10	0.09	0.11	0.10	0.09	0.11	0.12	0.10	0.09	0.11	0.11	0.08	0.11	0.10	0.09	0.10	0.11

Note GCM-RCM combinations: 1. HadGEM2-ES/RCA4; **2.** IPSL-CM5A-MR/RCA4; **3.** CNRM-CM5/RCA4; **4.** EC-EARTH/RCA4; **5.** MPI-ESM-LR/RCA4; **6.** CNRM-CM5/CCLM; **7.** CMCC-CM/COSMO-CLM; **8.** HadGEM2-ES/RACMO22E; **9.** EC-EARTH/HIRHAM5; **10.**EC-EARTH/RACMO22E.

Table 2II Probability of different classes of NH4 loadings associated to different seasons and scenarios across the GCM-RCM combinations considered

	Winter																																																	
Classes	**1983-2012**										**RCP4.5 2041-2070**										**RCP4.5 2071-2100**										**RCP8.5 2041-2070**										**RCP8.5 2071-2100**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0-3224	0.59	0.59	0.59	0.59	0.57	0.58	0.56	0.59	0.57	0.59	0.59	0.59	0.57	0.59	0.56	0.58	0.58	0.59	0.54	0.59	0.59	0.55	0.55	0.59	0.57	0.59	0.56	0.58	0.53	0.57	0.58	0.58	0.56	0.57	0.58	0.59	0.59	0.58	0.55	0.59	0.59	0.58	0.53	0.57	0.56	0.58	0.51	0.58	0.52	0.56
3224-5009	0.28	0.28	0.29	0.28	0.29	0.29	0.30	0.28	0.29	0.28	0.28	0.29	0.29	0.29	0.30	0.29	0.29	0.28	0.31	0.28	0.28	0.30	0.31	0.29	0.30	0.28	0.30	0.29	0.32	0.29	0.29	0.29	0.30	0.29	0.29	0.28	0.28	0.29	0.30	0.28	0.28	0.29	0.32	0.30	0.30	0.29	0.33	0.29	0.32	0.30
5009-6794	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.06	0.07	0.06
>6794	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.07	0.07	0.07	0.08	0.07	0.07	0.08	0.08	0.07	0.08	0.07	0.08	0.07	0.09	0.07	0.07	0.07	0.08	0.07	0.07	0.07	0.07	0.07	0.08	0.07	0.07	0.07	0.09	0.08	0.08	0.07	0.10	0.07	0.09	0.08

	Spring																																																	
Classes	**1983-2012**										**RCP4.5 2041-2070**										**RCP4.5 2071-2100**										**RCP8.5 2041-2070**										**RCP8.5 2071-2100**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0-3224	0.59	0.60	0.59	0.59	0.60	0.60	0.60	0.60	0.60	0.59	0.61	0.61	0.61	0.60	0.61	0.61	0.63	0.60	0.60	0.61	0.60	0.61	0.59	0.60	0.61	0.60	0.64	0.61	0.58	0.61	0.60	0.60	0.61	0.60	0.60	0.61	0.62	0.61	0.60	0.60	0.63	0.63	0.63	0.62	0.60	0.64	0.65	0.63	0.61	0.62
3224-5009	0.31	0.31	0.29	0.32	0.31	0.30	0.31	0.31	0.31	0.31	0.31	0.29	0.28	0.31	0.30	0.30	0.29	0.30	0.30	0.30	0.31	0.29	0.30	0.31	0.31	0.30	0.28	0.29	0.31	0.30	0.31	0.30	0.29	0.31	0.31	0.29	0.29	0.29	0.29	0.30	0.29	0.28	0.28	0.30	0.31	0.28	0.28	0.28	0.30	0.29
5009-6794	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.06	0.06	0.05	0.06	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.06	0.05	0.05	0.05	0.05	0.05
>6794	0.04	0.04	0.05	0.03	0.04	0.04	0.03	0.03	0.04	0.04	0.03	0.04	0.05	0.04	0.03	0.03	0.03	0.04	0.04	0.03	0.03	0.04	0.05	0.04	0.03	0.04	0.03	0.04	0.05	0.04	0.03	0.04	0.04	0.03	0.03	0.05	0.04	0.04	0.04	0.05	0.02	0.03	0.04	0.03	0.03	0.03	0.02	0.03	0.04	0.03

	Summer																																																	
Classes	**1983-2012**										**RCP4.5 2041-2070**										**RCP4.5 2071-2100**										**RCP8.5 2041-2070**										**RCP8.5 2071-2100**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0-3224	0.95	0.94	0.94	0.93	0.94	0.95	0.95	0.94	0.94	0.94	0.95	0.94	0.94	0.94	0.95	0.94	0.97	0.95	0.94	0.94	0.94	0.92	0.95	0.93	0.94	0.94	0.97	0.92	0.94	0.93	0.94	0.93	0.96	0.95	0.95	0.95	0.96	0.93	0.93	0.95	0.90	0.94	0.96	0.93	0.96	0.95	0.97	0.93	0.93	0.95
3224-5009	0.04	0.05	0.05	0.05	0.05	0.04	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.02	0.04	0.05	0.05	0.05	0.06	0.04	0.06	0.05	0.05	0.02	0.06	0.05	0.06	0.05	0.06	0.04	0.05	0.04	0.04	0.04	0.06	0.06	0.05	0.08	0.05	0.03	0.05	0.03	0.04	0.03	0.06	0.05	0.04
5009-6794	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00
>6794	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.01

	Autumn																																																	
Classes	**1983-2012**										**RCP4.5 2041-2070**										**RCP4.5 2071-2100**										**RCP8.5 2041-2070**										**RCP8.5 2071-2100**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0-3224	0.49	0.51	0.51	0.51	0.46	0.50	0.52	0.52	0.48	0.49	0.47	0.44	0.47	0.45	0.37	0.35	0.39	0.45	0.49	0.49	0.39	0.46	0.43	0.42	0.49	0.41	0.37	0.49	0.43	0.45	0.45	0.45	0.43	0.46	0.34	0.39	0.34	0.47	0.41	0.43	0.44	0.32	0.40	0.54	0.46	0.40	0.36	0.43	0.43	0.38
3224-5009	0.32	0.32	0.32	0.32	0.35	0.32	0.32	0.32	0.33	0.34	0.35	0.35	0.33	0.35	0.37	0.39	0.37	0.34	0.34	0.34	0.37	0.34	0.35	0.35	0.33	0.36	0.38	0.33	0.36	0.35	0.35	0.35	0.35	0.35	0.37	0.37	0.38	0.34	0.36	0.36	0.35	0.38	0.36	0.35	0.33	0.36	0.37	0.35	0.36	0.37
5009-6794	0.06	0.06	0.06	0.06	0.07	0.06	0.07	0.06	0.06	0.07	0.07	0.06	0.06	0.07	0.06	0.07	0.07	0.06	0.07	0.07	0.07	0.06	0.06	0.06	0.06	0.07	0.07	0.06	0.07	0.07	0.07	0.06	0.06	0.07	0.06	0.07	0.06	0.06	0.07	0.07	0.07	0.06	0.07	0.07	0.06	0.07	0.06	0.06	0.07	0.07
>6794	0.13	0.11	0.11	0.11	0.12	0.12	0.09	0.11	0.13	0.11	0.11	0.15	0.13	0.13	0.20	0.19	0.17	0.15	0.10	0.11	0.18	0.14	0.15	0.17	0.12	0.17	0.18	0.12	0.15	0.13	0.13	0.14	0.15	0.12	0.24	0.17	0.22	0.13	0.16	0.13	0.14	0.24	0.17	0.12	0.15	0.16	0.20	0.15	0.14	0.18

Note GCM-RCM combinations: 1. HadGEM2-ES/RCA4; **2.** IPSL-CM5A-MR/RCA4; **3.** CNRM-CM5/RCA4; **4.** EC-EARTH/RCA4; **5.** MPI-ESM-LR/RCA4; **6.** CNRM-CM5/CCLM; **7.** CMCC-CM/COSMO-CLM; **8.** HadGEM2-ES/RACMO22E; **9.** EC-EARTH/HIRHAM5; **10.**EC-EARTH/RACMO22E.

Table 3II Probability of different classes of PO_4 loadings associated to different seasons and scenarios across the GCM-RCM combinations considered

Winter

Classes	1983-2012										RCP4.5 2041-2070										RCP4.5 2071-2100										RCP8.5 2041-2070										RCP8.5 2071-2100									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
0-1978	0.65	0.65	0.64	0.65	0.62	0.64	0.61	0.65	0.62	0.65	0.65	0.64	0.62	0.64	0.60	0.63	0.63	0.65	0.58	0.65	0.63	0.59	0.59	0.64	0.62	0.65	0.60	0.63	0.56	0.46	0.63	0.63	0.61	0.63	0.63	0.65	0.65	0.63	0.60	0.65	0.65	0.63	0.56	0.61	0.61	0.64	0.53	0.64	0.56	0.61
1978-2954	0.25	0.25	0.25	0.25	0.26	0.25	0.26	0.26	0.26	0.25	0.25	0.25	0.25	0.25	0.27	0.25	0.25	0.25	0.28	0.25	0.26	0.27	0.26	0.25	0.26	0.25	0.27	0.26	0.27	0.27	0.26	0.26	0.25	0.26	0.26	0.25	0.25	0.25	0.27	0.25	0.25	0.26	0.27	0.26	0.25	0.26	0.30	0.26	0.26	0.24
2954-3929	0.08	0.08	0.08	0.08	0.09	0.08	0.10	0.08	0.09	0.08	0.08	0.08	0.08	0.08	0.10	0.08	0.08	0.08	0.11	0.08	0.08	0.11	0.09	0.08	0.09	0.08	0.10	0.08	0.11	0.15	0.08	0.08	0.09	0.08	0.08	0.08	0.08	0.08	0.10	0.08	0.08	0.08	0.12	0.09	0.09	0.08	0.14	0.08	0.10	0.08
>3929	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.05	0.03	0.03	0.03	0.03	0.03	0.06	0.11	0.03	0.03	0.05	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.06	0.03	0.05	0.03	0.04	0.03	0.08	0.07

Spring

Classes	1983-2012										RCP4.5 2041-2070										RCP4.5 2071-2100										RCP8.5 2041-2070										RCP8.5 2071-2100									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
0-1978	0.75	0.75	0.72	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.77	0.75	0.75	0.74	0.76	0.78	0.78	0.75	0.75	0.75	0.76	0.74	0.72	0.75	0.76	0.74	0.79	0.73	0.71	0.75	0.76	0.72	0.72	0.75	0.77	0.74	0.75	0.72	0.74	0.73	0.78	0.77	0.75	0.76	0.76	0.78	0.79	0.76	0.73	0.75
1978-2954	0.17	0.17	0.16	0.18	0.17	0.16	0.17	0.17	0.17	0.17	0.17	0.16	0.15	0.17	0.16	0.17	0.16	0.16	0.16	0.17	0.17	0.16	0.16	0.17	0.17	0.17	0.15	0.16	0.17	0.16	0.17	0.17	0.17	0.17	0.17	0.16	0.16	0.27	0.16	0.17	0.16	0.16	0.16	0.17	0.17	0.16	0.15	0.16	0.17	0.16
2954-3929	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.06	0.05	0.05	0.05	0.04	0.05	0.06	0.05	0.05	0.06	0.05	0.05	0.04	0.05	0.04	0.05	0.05	0.06	0.04	0.04	0.05	0.05	0.05	0.04	0.04	0.04	0.06	0.05
>3929	0.03	0.03	0.07	0.03	0.03	0.04	0.03	0.03	0.03	0.04	0.02	0.05	0.06	0.04	0.03	0.02	0.03	0.04	0.04	0.03	0.03	0.05	0.06	0.04	0.03	0.04	0.03	0.05	0.05	0.04	0.02	0.05	0.06	0.03	0.02	0.06	0.05	0.06	0.06	0.05	0.02	0.03	0.05	0.03	0.02	0.02	0.02	0.04	0.04	0.04

Summer

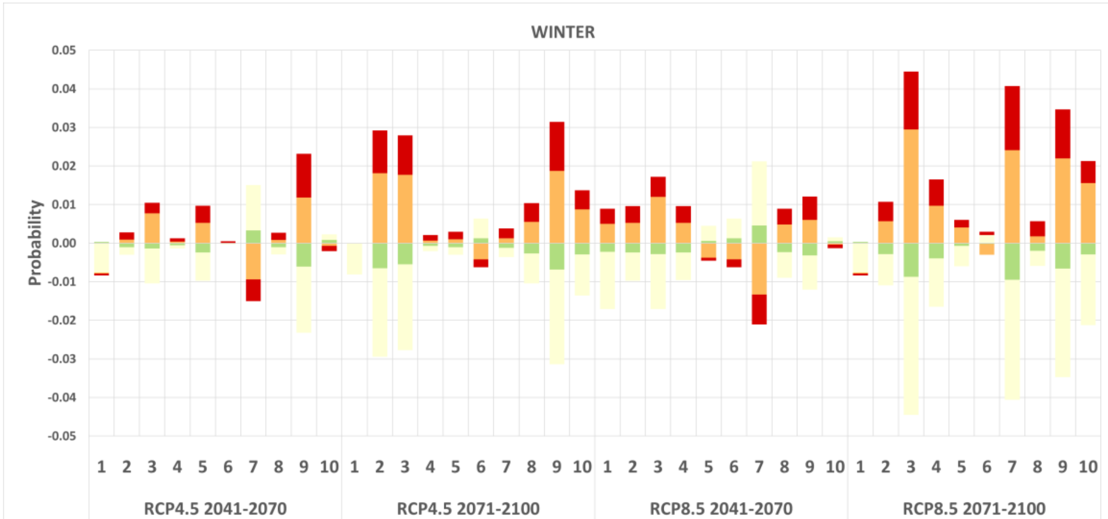
Classes	1983-2012										RCP4.5 2041-2070										RCP4.5 2071-2100										RCP8.5 2041-2070										RCP8.5 2071-2100									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
0-1978	0.95	0.94	0.94	0.93	0.95	0.95	0.96	0.94	0.95	0.94	0.95	0.95	0.94	0.94	0.95	0.95	0.98	0.95	0.94	0.94	0.94	0.92	0.96	0.93	0.94	0.94	0.98	0.92	0.94	0.93	0.94	0.93	0.96	0.95	0.95	0.96	0.96	0.93	0.93	0.95	0.90	0.94	0.96	0.93	0.97	0.95	0.97	0.93	0.93	0.95
1978-2954	0.02	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.01	0.03	0.03	0.03	0.03	0.04	0.02	0.04	0.03	0.03	0.01	0.04	0.03	0.04	0.03	0.03	0.02	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.05	0.03	0.02	0.03	0.02	0.03	0.02	0.03	0.03	0.03
2954-3929	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.00	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.02	0.01
>3929	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.03	0.01	0.02	0.01	0.02	0.00	0.02	0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01

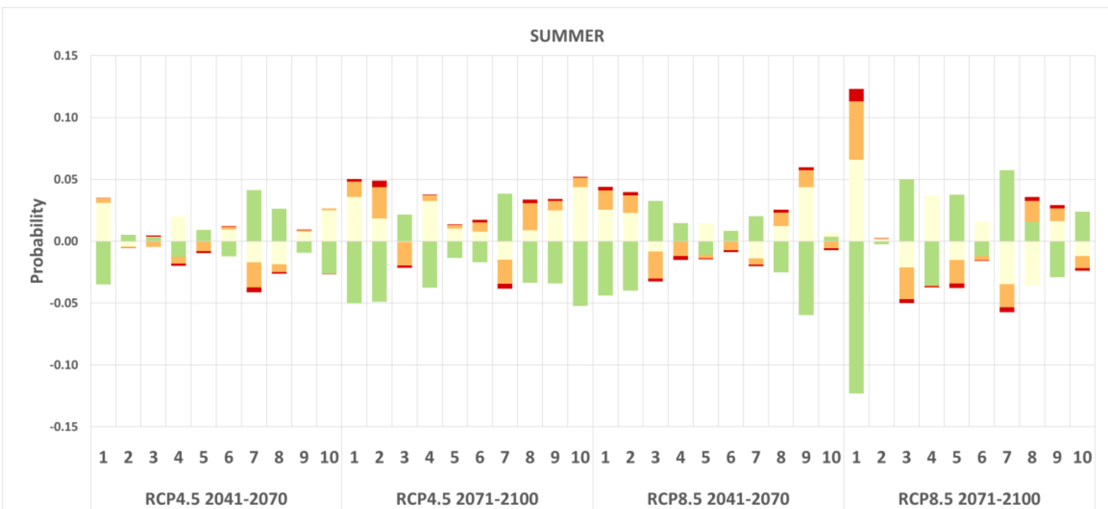
Autumn

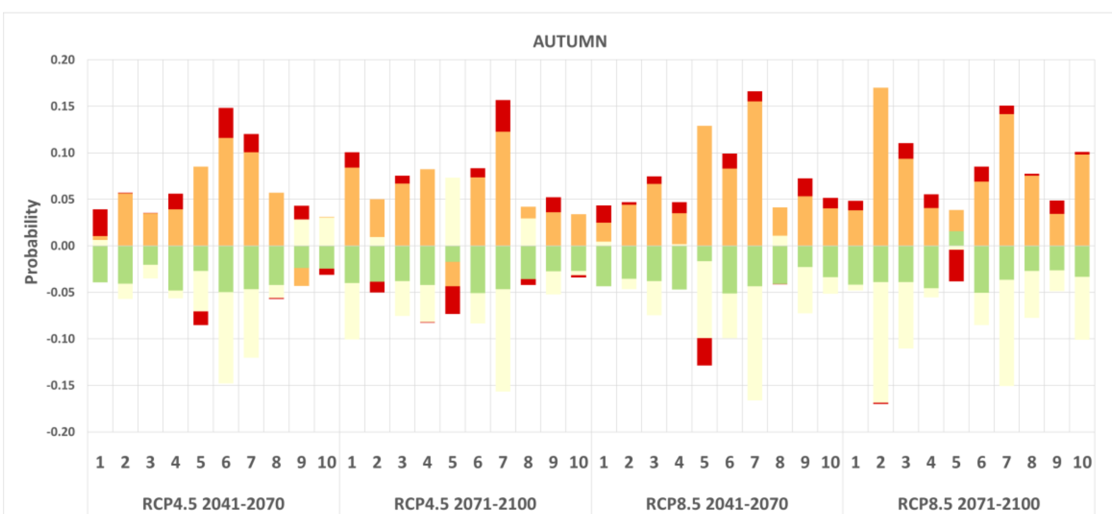
Classes	1983-2012										RCP4.5 2041-2070										RCP4.5 2071-2100										RCP8.5 2041-2070										RCP8.5 2071-2100									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
0-1978	0.51	0.53	0.54	0.53	0.45	0.51	0.53	0.54	0.51	0.50	0.48	0.47	0.50	0.48	0.36	0.31	0.40	0.48	0.52	0.52	0.38	0.50	0.45	0.43	0.55	0.41	0.34	0.55	0.44	0.46	0.47	0.48	0.45	0.49	0.30	0.39	0.33	0.52	0.40	0.44	0.46	0.29	0.40	0.47	0.44	0.41	0.33	0.42	0.44	0.36
1978-2954	0.24	0.25	0.25	0.25	0.28	0.25	0.26	0.24	0.24	0.27	0.29	0.24	0.24	0.28	0.24	0.27	0.26	0.24	0.28	0.27	0.25	0.24	0.25	0.24	0.25	0.25	0.28	0.25	0.27	0.27	0.28	0.25	0.25	0.27	0.21	0.26	0.23	0.25	0.27	0.29	0.26	0.22	0.26	0.28	0.23	0.27	0.24	0.25	0.26	0.26
2954-3929	0.13	0.14	0.13	0.14	0.18	0.14	0.14	0.13	0.13	0.16	0.17	0.14	0.13	0.15	0.16	0.21	0.16	0.13	0.15	0.14	0.17	0.11	0.14	0.14	0.10	0.15	0.20	0.10	0.16	0.15	0.15	0.14	0.14	0.15	0.15	0.17	0.16	0.12	0.17	0.18	0.15	0.16	0.17	0.16	0.14	0.17	0.17	0.15	0.16	0.18
>3929	0.12	0.09	0.08	0.09	0.10	0.11	0.07	0.08	0.12	0.07	0.05	0.15	0.13	0.09	0.24	0.21	0.18	0.15	0.05	0.07	0.20	0.15	0.16	0.19	0.10	0.18	0.19	0.10	0.14	0.11	0.09	0.13	0.15	0.09	0.34	0.18	0.29	0.11	0.16	0.10	0.14	0.34	0.18	0.10	0.19	0.16	0.26	0.18	0.14	0.20

Note GCM-RCM combinations: **1.** HadGEM2-ES/RCA4; **2.** IPSL-CM5A-MR/RCA4; **3.** CNRM-CM5/RCA4; **4.** EC-EARTH/RCA4; **5.** MPI-ESM-LR/RCA4; **6.** CNRM-CM5/CCLM; **7.** CMCC-CM/COSMO-CLM; **8.** HadGEM2-ES/RACMO22E; **9.** EC-EARTH/HIRHAM5; **10.**EC-EARTH/RACMO22E.

Annex III-Analysis of variability of results







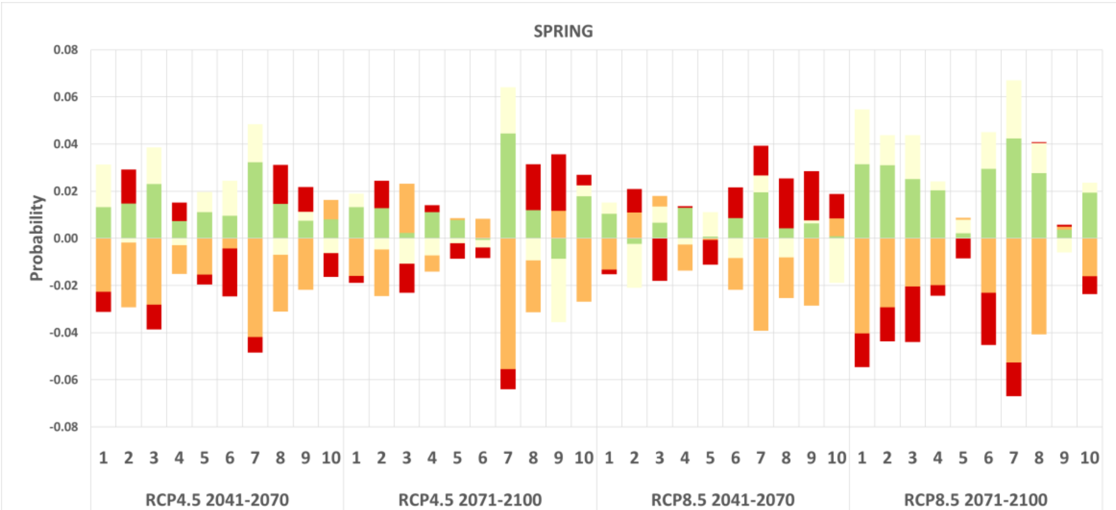
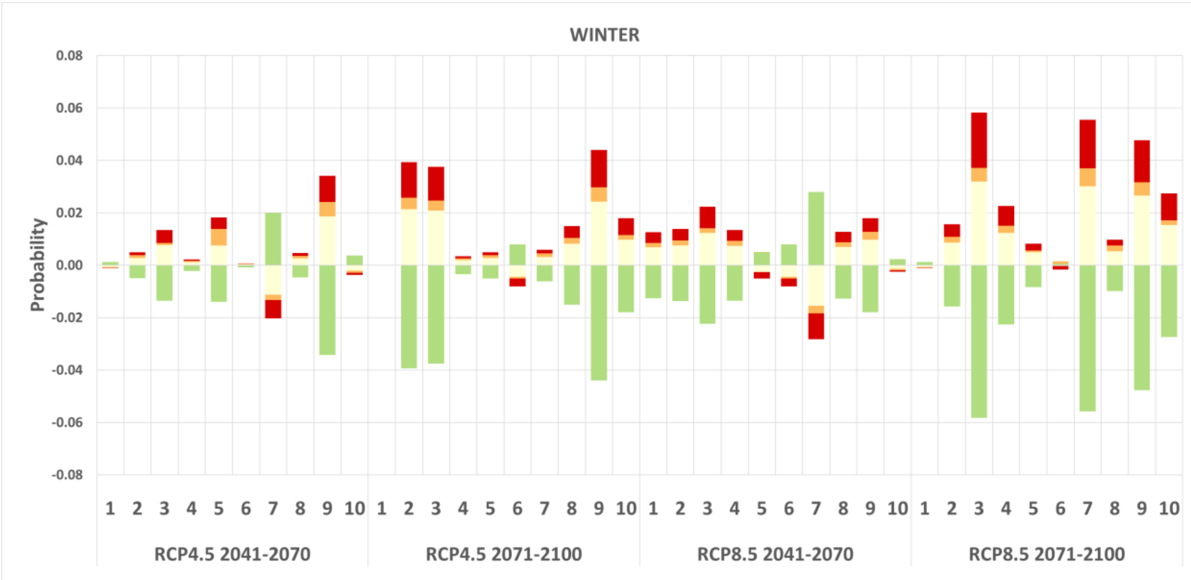
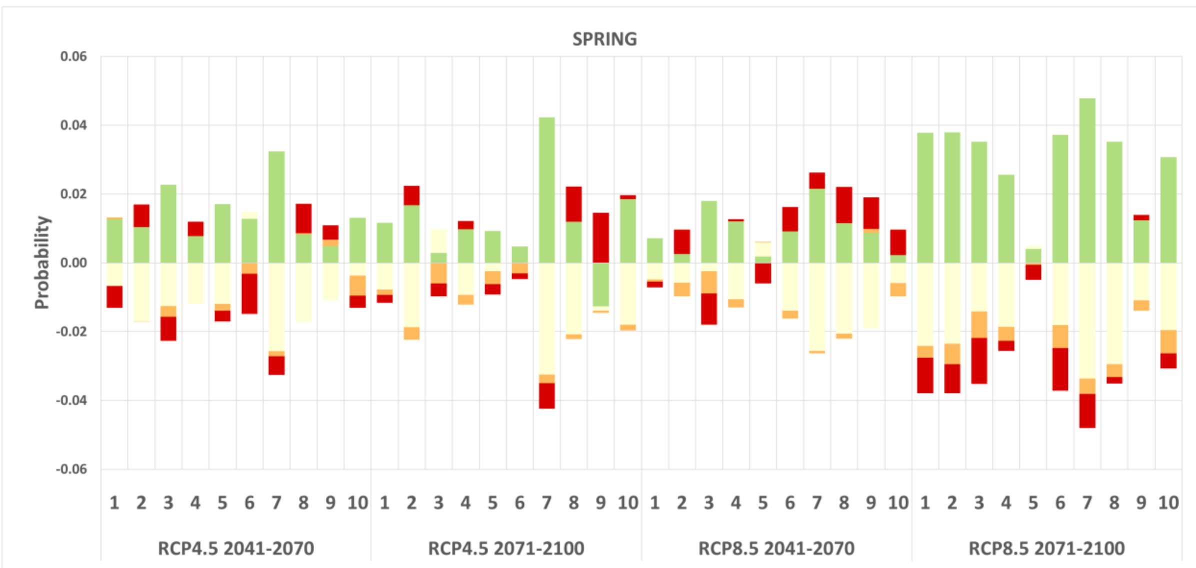
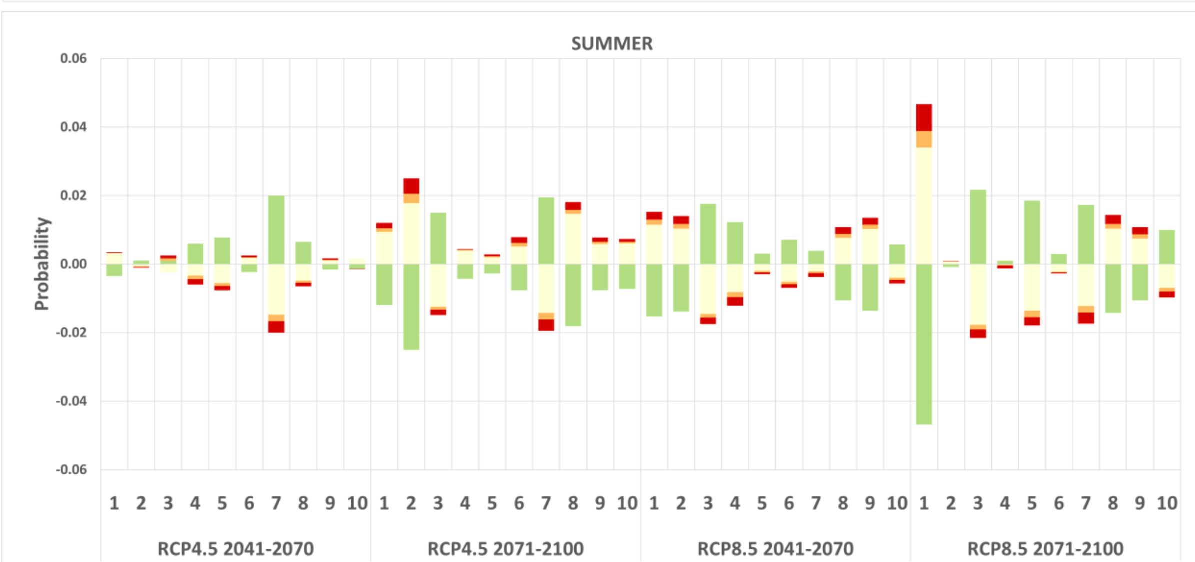


Figure 1III Variations in the probability of each NO3 loading classes respect to the baseline (i.e. 1983-2012) under different scenarios and GCM-RCM combinations


WINTER
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
-0.08
Probability
1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10
RCP4.5 2041-2070
RCP4.5 2071-2100
RCP8.5 2041-2070
RCP8.5 2071-2100


SPRING
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
Probability
1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10
RCP4.5 2041-2070
RCP4.5 2071-2100
RCP8.5 2041-2070
RCP8.5 2071-2100


SUMMER
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
Probability
1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10
RCP4.5 2041-2070
RCP4.5 2071-2100
RCP8.5 2041-2070
RCP8.5 2071-2100

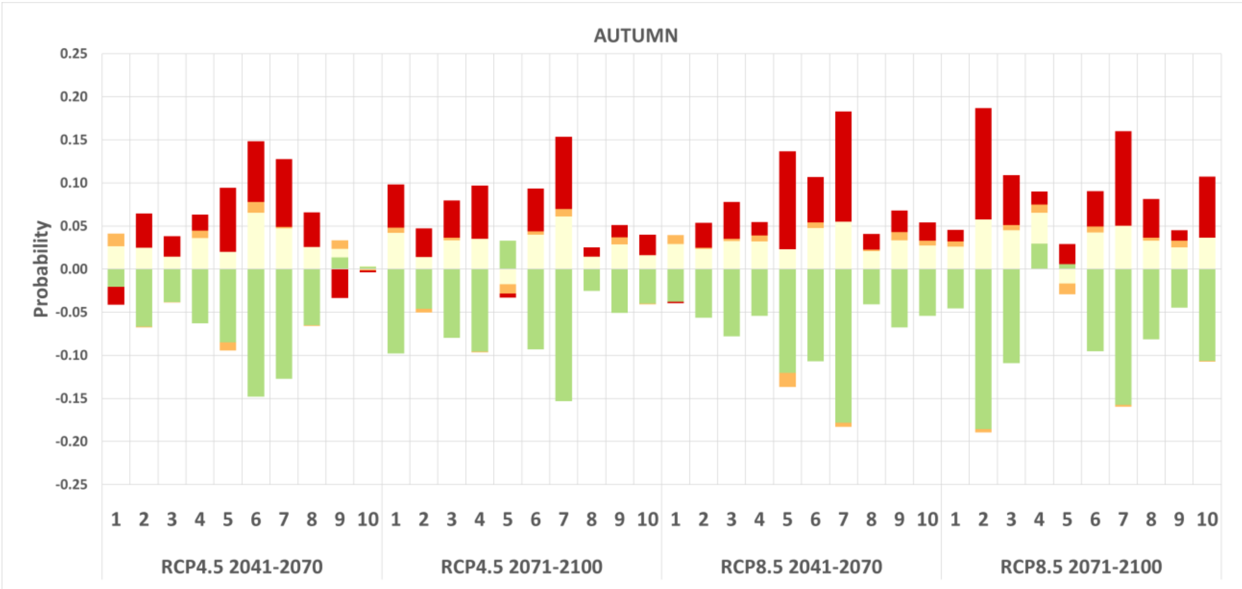


Figure 2III Variations in the probability of each NH4 loading classes respect to the baseline (i.e. 1983-2012) under different scenarios and GCM-RCM combination

List of relevant contributions

Peer reviewed papers:

Sperotto A., Molina J.-L., Torresan S., Critto A., Marcomini A., 2017. Reviewing Bayesian Networks potentials for climate change impacts assessment and management: A multi-risk perspective. *Journal of Environmental Management*, *202*, 320–331.

Sperotto A., Torresan S., Gallina V., Coppola E., Critto A., Marcomini A., 2016. A multi-disciplinary approach to evaluate pluvial floods risk under changing climate: The case study of the municipality of Venice (Italy). *Science of The Total Environment*, *562*, 1031–1043.

Gallina V., Torresan, S., Critto A., **Sperotto A.**, Glade T., Marcomini A., 2016. A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment in, *Journal of Environmental Management*,168,123-132.

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Proceedings of national and international conferences:

Sperotto A., Torresan S., Molina J.L., Pulido Velazquez M., Critto A., Marcomini A., Assessing water quality responses under climate change. *Proceedings of the European Conference on Climate Change Adaptation-ECCA 2017*, Glasgow (UK), 05-09 June 2017.

Sperotto A., Torresan S., Molina J.L., Pulido-Velazquez M., Critto A., Marcomini A.: Multi-risk assessment of climate and land use changes on water resources: A Bayesian Network approach. *Proceedings of the Land Use and Water Quality Conference-LuWQ2017*, The Hague (NL), 28-2 June 2017.

Sperotto A., Torresan S., Molina J.L., Pulido-Velazquez M., Critto A., Marcomini A., A Bayesian networks approach for the multi-risk assessment of climate change impacts on water resources. *Proceedings of the SISC Annual Conference on "Climate challenges and solutions under the 2°C target"*, Cagliari (Italy), 19-20 October 2016.

Gallina, V., Torresan, S., Critto, A., Zabeo, A., **Sperotto, A.**, Glade, T., Marcomini, A., Multi-risk evaluation of climate change impacts in coastal zones. *Proocedings of the 12th International Conference on the Mediterranean Coastal Environment-MEDCOAST 2015*,

Varna (Bulgaria), 06-10 October 2015.

Torresan S., **<u>Sperotto A.</u>**, Gallina V., Furlan E., Critto A., Marcomini A., Developing climate risk and adaptation services in coastal zones: an integrated bottom-up approach applied in the North Adriatic coast. *Proceedings of the SISC Annual Conference on "Climate Change: Scenarios, Impacts and Policy"*, Venice (Italy), 29-30 September 2014.

Working papers:

Rianna G., Alessandrini C., Pecora S., Cristofori D., Ferroni G., Ricciardi G., Noce S., **<u>Sperotto A.</u>**, Pham V., Torresan S., Critto A., 2017. Deliverable T1.1.1 Country Reports About the Implementation of Sustainable Land Use in Drinking Water Recharge Areas (Italy)-Peer review of land use and water management practices, *PROLINE-CE Project.*

Rianna G., Cristofori D., Noce S., **<u>Sperotto A</u>**., Pham V., Torresan S., Critto A., 2017. Deliverable T1.2.1 Country-specific best management practice reports (Italy)- Review of best management practices for drinking water supply issues, *PROLINE-CE Project.*

Torresan S., **<u>Sperotto A</u>**., Giannini V., Gallina V., Critto A., Marcomini A.,2014. Deliverable 8.4 Cross-cutting conclusions. Integrated case study: Veneto and Friuli Venezia Giulia, Northern Adriatic Sea, Italy. *CLIM-RUN Project.*

Books:

Isigonis P., Torresan S., **<u>Sperotto A</u>.,** Zabeo A., Critto A., 2014. Review of organisations, methods and tools for the provision of relevant climate services for different sectors of society, *Sustainable energy and environmental risk analysis: the scientific support to decision making in Europe and Asia*, Paolo Farah, pp. 1-28.

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