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Potentials and Limits of Bayesian Networks to Deal with Uncertainty in the Assessment of Climate Change Adaptation Policies

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Abstract

Bayesian networks (BNs) have been increasingly applied to support management and decision-making processes under conditions of environmental variability and uncertainty, providing logical and holistic reasoning in complex systems since they succinctly and effectively translate causal assertions between variables into patterns of probabilistic dependence. Through a theoretical assessment of the features and the statistical rationale of BNs, and a review of specific applications to ecological modelling, natural resource management, and climate change policy issues, the present paper analyses the effectiveness of the BN model as a synthesis framework, which would allow the user to manage the uncertainty characterising the definition and implementation of climate change adaptation policies. The review will let emerge the potentials of the model to characterise, incorporate and communicate the uncertainty, with the aim to provide an efficient support to an informed and transparent decision making process. The possible drawbacks arising from the implementation of BNs are also analysed, providing potential solutions to overcome them.

1 Introduction

Adaptation to climate change impacts is an important component of countries' strategies to cope with the negative consequences of climate change. The policy focus is now gradually moving from mitigation only to mitigation and adaptation (Carraro and Sgobbi, 2008), as highlighted also by many recent international and national initiatives, such as for example the European White Paper on climate change adaptation (EC, 2009). The long-term analysis of adaptation strategies has traditionally emerged in the realm of long-term assessment of climate change impacts, in a continuous effort to overcome difficulties due to the large quantity of interacting factors and to the diversity of adaptation interventions.

The design of effective climate change adaptation policies often faces situations where there is considerable uncertainty in understanding how the system works and how particular decisions and actions will influence it. The uncertainty surrounding the scientific understanding of climate change causes and effects is further increased by the complex interactions which link the environmental and the socio-economic systems. On the one hand, anthropogenic processes can increase the vulnerability of the system to the impacts of climate change. On the other hand, socio-economic activities can be deeply affected by those impacts. Adaptation to climate change and uncertainty is clearly an issue for interdisciplinary research.

Climate change represents one of the most multi-faceted manifestations of global change of our time and, in particular, climate change adaptation studies, which analyse the impacts and the possible responses, are among the most complicated assessments that the scientific community has ever faced. Dessei et al. (2007) introduce an edition of Global Environmental Change dedicated to uncertainty and climate change, with an editorial which explains that uncertainty is pervasive in the climate change policy debate. The opinions range from the position of Patrinos and Bamzai (2005), who claim the need of robust science favouring more scientific research over policy actions, to the one of Yohe et al. (2004), who argue that uncertainty provides a reason to take specific policy action on the near term. Between these two positions there are a range of views about the implications of uncertainties for different types of policy responses, ranging from mitigation to adaptation (Congressional Budget Office, 2005; Stern, 2006).

The main goal of an analysis of adaptation to climate change and uncertainty should therefore look at the formulation of optimal policies under uncertainty. The important issue is to understand how such uncertainties might affect decisions about policy strategies, which implies choices concerning the timing of interventions, the characteristics of adaptation measures at the local level, but also the coordinated effort at the national and global level. Responses to reduce climate-related risks to environmental and human systems need to be part of an integrated management activity, which should aim at reducing the uncertainty of the issue through the application of specific tools and the active involvement of experts, stakeholders and public authorities, and should finally support informed decision making processes.

Climate change adaptation studies are characterised by uncertainties about the value of empirical quantities, and also about models' structural forms, which complicate the assessment of physical impacts and damages in future climate scenarios, and indirectly affect the uncertainty in determining the costs and benefits of adaptation policies. This rises new challenges for the way individuals, organisations and societies make decisions, and makes it difficult to design effective, equitable and efficient policies to adapt to the impacts of climate change.

When dealing with climate change policy issues, the uncertainties characterising the scientific understanding of the processes and the consequences on the environmental and the socio-economic systems can be translated into a cascade of four categories of uncertainties (Peterson, 2006): uncertainty about the path of emissions of greenhouse gases; uncertainty about the future climate; uncertainty about the impacts of climate change; uncertainty about optimal policies (see Figure 1).

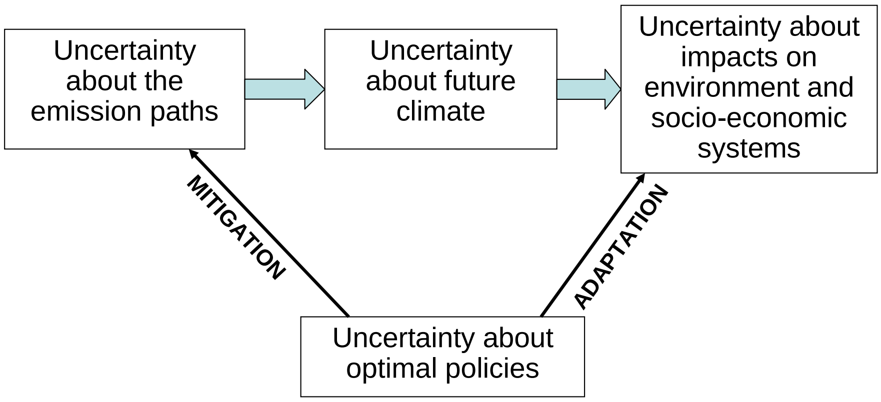

Figure 1: Representation of the four categories of uncertainty in climate change policy studies (source: adapted from Peterson, 2006).

These categories of uncertainty are both *epistemic* and *aleatory*. *Epistemic* or *parametric* uncertainty depends on limited information and imperfect knowledge, and can be reduced with further research, while *stochastic* or *aleatory* uncertainty is due to inherent variability and randomness in a system of phenomena that cannot be described deterministically, and is therefore irreducible (Pollino and Hart, 2007).

Several authors highlight the importance of assessing the uncertainty in climate change policy studies (see for example IPCC, 2005, Stern, 2006; Congressional Budget Office, 2005). In particular, Morgan (2008) suggests to apply a comprehensive approach based on three actions: characterising the uncertainty, incorporating it into the analysis, and communicating it to the policy makers. Many methodologies and tools suitable for dealing with the above three actions have been developed and reported in the scientific literature, but most of the existing studies focus only on one of the processes, failing to provide a comprehensive and transparent methodological framework for the management of uncertainty in decision-making processes.

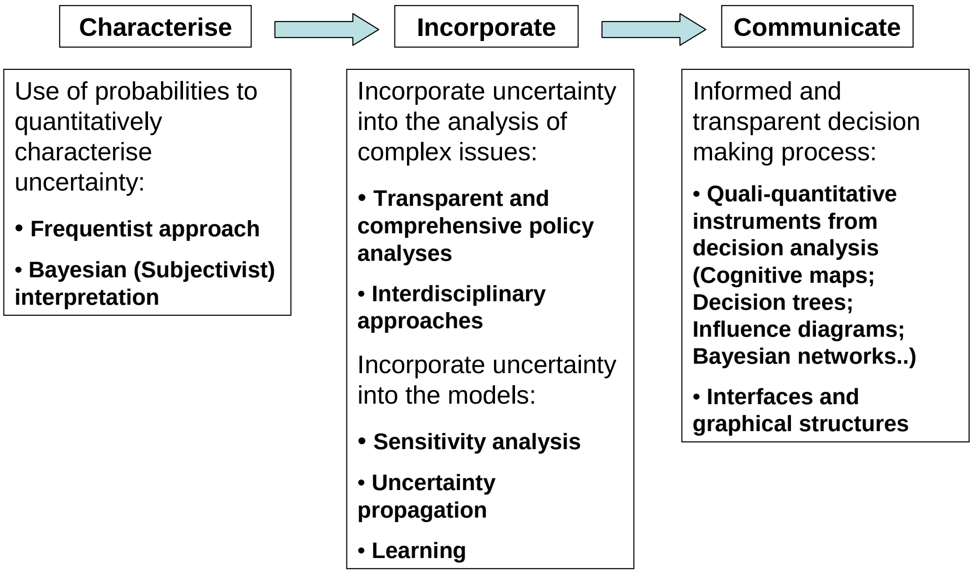

Figure 2: Synthesis of the main approaches applied to characterise, incorporate and communicate the uncertainty in climate change policy.

Probability is often considered as the best-known and most widely used formalism for quantitatively characterizing uncertainty (Morgan and Henrion, 1990), and the frequentist approach is usually applied, which is defined as objectivist since it assumes that probability is an objective property of theoretically infinite sequences of trials rather than of a single event. Since the frequentist approach deals with processes that are or can be imagined as repetitive in nature, it is often impractical for most real world decision problems. In contrast, the subjectivist or Bayesian interpretation considers the probability of an event as the degree of belief that a person has that an event will occur, given the relevant information known to that person. As a consequence, the probability is a function of the state of information, and not only of the event. Bayesian networks (BNs) are a new generation of probabilistic models, which apply the principles of the Bayesian philosophy, and are capable of modelling real-world decision problem using theoretically sound methods of probability theory and decision theory.

Three broadly applied approaches are generally used to incorporate the uncertainty into models: sequential learning, sensitivity analysis and uncertainty propagation. Analyses of learning can inform research priorities by recognising which uncertainties might be reduced to yield the largest benefits to today's decisions, allowing to compare an "act-then-learn" with a "learn-then-act" strategy. However, most existing models use a deterministic framework, and do not consider the uncertainty of the phenomena. The Bayesian probabilistic approach allows the user to consider decision processes as a sequence of choices in time, and not just as a “one-shot” game. Therefore it allows the implementation of an “adaptive” management approach, which is flexible enough to change as a result of new information about the effects of specific interventions.

The uncertainty in model’s parameters and structure is traditionally assessed by applying sensitivity or uncertainty analyses. A typical approach is Monte Carlo analysis (MCA), which considers random sampling of probability distribution functions as model inputs to produce hundreds or thousands of possible outcomes. The results provide probabilities of different outcomes occurring. MCA is not to be set against the use of BN models. It could instead be a complementary approach, which might be included in an application of a BN to assess the stability of the outputs to variations in the nodes’ CPTs.

Besides quantifying and incorporating uncertainties, the issue remains of how to communicate such uncertainty to decision and policy analysts. Decision analysis can be defined as a formal quantitative technique for identifying the best choices from a range of alternatives (Toth, 2001) and to explicit the trade-offs between adaptation alternatives, in order to guide an informed and transparent decision making process under uncertainty. Qualitative and quantitative decision tools can be combined into a single decision support system, which should be able to assess a decision problem considering its different parts: the qualitative structure of the problem, the available decision alternatives, the expected utility of choosing any of them, the importance of various sources of uncertainty, the value of reducing this uncertainty, etc. BNs can be applied as *quali-quantitative* instruments, whose user-friendly interfaces and graphical structures help the formalization of the system, through the engagement of experts or stakeholders in the decision process.

The objective of the present paper is to increase the understanding, awareness and acceptance of the climate change research community on the potentials of BNs as probabilistic graphical models which can support more informed and transparent decisions concerning climate change adaptation policies. The paper illustrates how BNs can be applied to characterise the uncertainty of the issue using subjective probabilities obtained both from data and from expert judgments, to incorporate it into the model through the Bayesian updating process, and to communicate it to the stakeholders and decision-makers through the graphical interface.

The next section of the paper introduces to the rationale behind the structure and features of the BN model. In the third section we present a review of selected applications of BNs to ecological modelling and natural resource management, which opened the way to the use of BNs in climate change policy analysis. Examples of those studies are reviewed in the fourth section. Section five identifies the many potentials of BNs in addressing complex issues such as climate change adaptation policy, together with the possible drawbacks arising from the review, and the possible solutions to overcome them. Section 6 concludes the article and synthesises the main findings.

2 Bayesian networks

Bayesian networks (BNs) are probabilistic models represented in a graphical structure for reasoning under uncertainty. The potential of the BN instrument lies in its dual structure. The graphical part illustrates and communicates, through a directed acyclic graph, the interactions among the set of variables, and mimics the causal structure of the modelled system. In addiction, BNs represent the quantitative strength of the connections between variables, allowing probabilistic believes about them to be updated automatically as new information became available, by applying the principles of Bayes' theorem. According to the Bayesian philosophy, a probability of an event is the degree of belief that a person has that an event will occur, given the relevant information known to that person, therefore it is a function of the state of information, and not only of the event.

The graphical structure of BNs is composed of two elements (Cain, 2001): [1] a set of nodes representing system variables. Each node has a finite set of mutually exclusive and exhaustive states of the variable (its "state space"). The states or conditions of the variables can be categorical, continuous or discrete and variables must take one state value at a time; [2] a set of links representing causal relationships between nodes. The structure or typology of the network should capture qualitative and quantitative relationships between variables. Two nodes should be connected directly if one affects or causes the other, with the arc indicating the direction of the effect. If there is an arc from one node to another the former is called parent and the latter child node.

BNs graphical structure helps scientists and decision makers to build a realistic representation of the world in the form of a simple conceptual model. All the information should be represented at the appropriate level of detail using the right spatial and time scale. They are expressed in the network through the structure, the names of nodes and the names of states.

Figure 3 provides an example of BN applied to a case study assessing some specific impacts of sea level rise. Modelling choices have to be made to directly link dependent variables, and to characterise each node using mutually exclusive and exhaustive values.

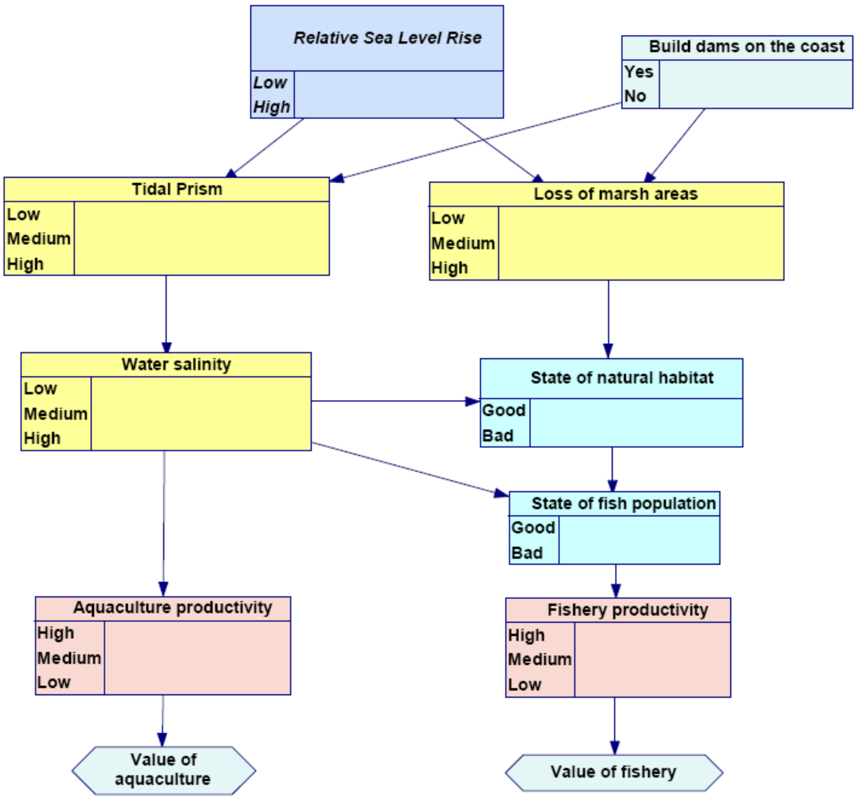

Figure 3 – Bayesian decision network considering an adaptation strategy ("Build dams on the coast") as decision node, and the economic value of aquaculture and fishery as value nodes.

The network depicted in Figure 3 is a Bayesian *decision* network (BDN), which contains "chance" (or sometimes "deterministic") nodes, but also "decision" nodes, which represent the decision being made at a particular point in time, and "utility" nodes, which explicit the value function measuring the desirability of the outcomes of the decision process.

Decision networks combine probabilistic reasoning with utilities, allowing to make decisions on a number of alternative actions, that maximize the expected utility. The expected utility is also known as the probability-weighted average utility over every possible outcome of a particular action.

The quantitative potential of BN models is introduced by a set of conditional probabilities (Conditional Probability Tables, CPTs) underling each node, which represent the belief that a node will be in a particular state given the states of those nodes which affect it directly ("parent" nodes). The CPTs contain entries for every possible combination of the states of the parent nodes and express how the relationships between the nodes operate (see Table 1).

	State of natural habitat	Good			Bad		
	Water salinity	Low	Medium	High	Low	Medium	High
State of fish population	Good	0.8	0.5	0.4	0.5	0.3	0.3
	Bad	0.2	0.5	0.6	0.5	0.7	0.8

Table 1: Conditional probability table for the node "State of Fish Population" included in the BN of figure 3.

The probability representing the knowledge of the subject before the research is conducted is called “prior”, and indicates the likelihood that an input parameter will be in a particular state. When new data or information became available, the prior probability updates and incorporates the evidence into a posterior probability. Evidence which has uncertainty associated with it can be considered in the updating algorithm in terms of “virtual” or “likelihood” evidence. The new outcome represents the probability that a variable will be in a particular state, given the input evidence, the conditional probabilities, and the rules governing how the probabilities combine.

In BNs, therefore, each link that indicates a dependence represents a conditional probability distribution, that is a description of the “likelihood of each value of the down-arrow node, conditional on every possible combination of values of the parents nodes” (Borsuk et al., 2004). A node with no incoming arrows (root node) can be described with a marginal or unconditional probability distribution.

BNs are built considering the conditional independence between variables. Two events are probabilistically independent when new information on one node leaves the probability of the other unchanged. It is possible to define the conditional independence among variables directly from the graphical structure of a BN. According to the Markov property, missing arcs, from a node to its successors in the sequence, signify conditional independence assumptions.

Numerically, BNs encode a joint probability distribution among variables, i.e. the probability that two events occur both: the occurrence of one event may change the probability of the other. Each change in the state of a node propagates along the network, through the updating of the joint probability distributions, with the iterative application of Bayes’ theorem. Changes in any node arise from the combined effect of changes in all the nodes linked to it, in accordance with the relationships expressed by the CPTs (Cain, 2001). In this way, the joint probability distribution for the entire network can be specified, and this relationship can be captured mathematically using the Chain Rule, whose equation states that the joint probability distribution for node X is equal to the product of the probability of each component Xi of X given the parents of Xi.

3 Applications of BNs to ecological modelling and natural resources management

Ecological models face a serious challenge when they need to integrate ecosystem patterns at a variety of special, functional or temporal scales, into coherent predictive models (Levin, 1992). In order to overcome this complexity and to be able to assess how uncertainties in each component of the model translate to uncertainty in the final predictions (Reckhow, 1994), Bayesian networks have been widely used in ecology and in the management of natural resources. BNs allow the user to easily update analyses in order to reflect evolving scientific knowledge and also policy needs (Walters, 1986). In recent years, BNs have been generally applied in ecological modelling to frame species-habitat relationships and population viability of terrestrial and aquatic vertebrates (Marcot, 2007, quoted in McCann et al., 2006).

A brief review of a selected set of papers dealing with BN applications in the field of ecology and natural resources management is provided below, to frame and introduce the potentials of such techniques in the much less explored field of climate change adaptation as discussed in the following sections.

Among the several applications of BNs to ecological modelling, one reference example could be found in Borsuk et al (2004), who propose a Bayesian network integrating several models of the various processes involved in eutrophication in the Neuse River estuary, North Carolina. The graphical form of the model explicitly represents cause-effect assumptions between system variables through conditional relationships, quantified using approaches suitable for the kind and scale of information available. The BN is developed as a synthesis model which combines diverse methods applied to the prediction of policy-relevant ecosystem attributes, including: process-based models statistically fit to long-term monitoring data, Bayesian hierarchical modelling of cross-system data gathered from the literature, multivariate regression modelling of mesocosm experiments, and judgements elicited from scientific experts. In this way, the BN model provides probabilistic predictions of ecosystem response to alternative nutrient management strategies.

BNs are applied to generate a holistic understanding of a complex ecological system under analysis also by Hamilton et al. (2005), who develop a BN to better understand the growth process of a marine cyanobacterium in Moreton Bay (Queensland, Australia). As in Borsuk et al. (2004), the network is capable of synthesis, prediction and uncertainty analyses. In this case the model is defined through an iterative process, starting from the engagement of scientists and stakeholders, which brings to the creation of a BN framework for integrating the available knowledge on the Lyngbya sp. bacterium. The BN provides an integrated model for understanding the bacterium dynamics in the Bay, using information from different sources, included expert judgments. A parallel process is carried out, focussing on management policies and ground actions at the state and local government level. A broader BN is finally created to integrate the management model into the scientific one, in order to predict the potential impact of management strategies and to develop scenarios relevant to future planning, benefiting from BN ability to identify areas of most influence, least information and greater sensitivity.

A similar approach for constructing and parametrising a BN model is followed by Marcot et al. (2001), whose purpose is to discover and then model the causal relationships between biotic factors, habitat conditions, and management for some vertebrate and invertebrate species in the Columbia River Basin (USA). Two different BN models are built, for aquatic and terrestrial wildlife, by combining the existing literature with expert judgments. The networks are then transformed into Bayesian decision networks (BDN), by adding utility nodes and decision nodes.

Decision making is often a driving force behind environmental modelling. BDNs have been widely applied to issues concerning the management of natural resources, by exploiting their potential to make predictions on the possible effects of different strategies and scenarios, and their capacity to assess the influence of uncertainty in understanding and variability in ecosystem response on costs and benefits assigned to model outputs, helping the competent managers to identify the optimal course of action. Borsuk et al. (2002) developed a Bayesian network to discern the relative causal importance of different hypotheses for the decline of fish catch in Switzerland. The network allowed the complex causal chain linking anthropogenic causes to ecological effects to be factored into an articulated sequence of conditional relationships. Each relationship was then quantified independently, using information from experimental investigation, field data, process-based models and elicited expert opinions. The BN was used to assess the historical importance of anthropogenic changes, but also to make previsions on the effects of possible management actions.

BNs have captured the interest of many researchers in water resource planning and management. Water systems comprise many different components (reservoir, catchment, fish, farms, etc.), which may differ also in nature (physical, social, economic, ecological, etc.). Therefore the integrated management of water resources (IWRM) deals with complex problems involving technological, environmental, economical and social aspects, and is characterized by a high degree of uncertainty. A model which aims at describing the whole system should integrate the models of the different components, without being too mathematically abstruse, or loosing information, accuracy or transparency. Cain (2001) proposes a document providing detailed guidelines for the implementation of BNs in IWRM. Using an hypothetical case study dealing with the management of resources in the Poya Ganga River (Sri Lanka), the author demonstrates the potential of the tool to synthesise data and information of different origins, with the involvement of scientific experts, local stakeholders and decision makers, with the aim to define effective management strategies.

Bromley et al. (2003), illustrate some of the advantages and problems encountered in the application of BNs as an aid to integrated water resource planning in the Lodon Catchment, South East England. The BN are developed as part of the MERIT project, and other BNs are then implemented for other catchment areas in Italy, Denmark and Spain. BNs are built up with the involvement of stakeholders groups, and link together different types of data, also coming from GIS estimates, in a way that allows integrated analysis.

			Model purpose				Input data type		
			Integration of variables from different domains	**Support to decision processes**	**Bayesian updating with available evidence**	**Prediction with future scenarios**	**Use of expert judgments**	**Engagement of stakeholders**	**Qualitative data from models**
Field of application	**Ecological modelling**	*Borsuk et al. (2004)*	X	X		X	X		
		Hamilton et al. (2005)	X			X	X	X	
		Marcot et al. (2001)	X	X	X		X		
	NRM/IWRM	*Borsuk et al. (2002)*	X	X	X	X	X		X
		Cain (2001)	X	X	X	X		X	X
		Bromley et al. (2003)	X	X	X	X		X	X
	Climate change	*Musango and Peter (2007)*	X	X	X	X		X	X
		Varis and Kuikka (1997)	X		X	X	X		X
		Oberholster et al (2005)	X		X	X			X
		Cuddy et al. (2007)	X	X		X		X	X
		Koiusavalo et al. (2005)	X	X	X	X	X		X
		Hall et al. (2005)	X	X	X	X			X
		Gu et al. (1996)	X			X			X

Table 2: Characteristics and purposes of the selected studies

4 Applications of BN to climate change policy issues

Similarly to the consolidated field of natural resources management, the assessment of climate change impacts and the evaluation of mitigation and adaptation strategies typically requires the consideration of a number of interacting processes operating at multiple spatial and temporal scales. But models developed to appropriately represent each of these processes are difficult to combine into a single predictive model.

As discussed in the previous section, BNs can provide a possible solution to this problem, since they represent cause-and-effect relationships between system variables that may not be clarified under other approaches, and allow the complex causal chain linking management actions to environmental or socio-economic consequences to be formally structured into an articulated sequence of conditional relationships. Moreover, the selected examples of BN models applied to ecology and NRM provided sound frameworks within which uncertainty could be represented and analysed pragmatically, and their versatility in collecting and integrating disparate knowledge from all the areas of interest, made them well suited for applications in the analysis of climate change policy. Below, successful examples of applications of BNs in the field of climate change policy are briefly reported, to support the identification of potentials and limits presented in Sections 5 and 6.

Gu et al (1996) apply the BN approach to deal with the uncertain information associated with climate prediction, in order to examine the risk or benefits to crop production in Scotland. The BN relates a model describing faba bean growth with a weather generator model, and it is able to answer queries on faba bean production under various climate predictions. The study also discusses the advantages deriving from the combination of belief network techniques with Geographical Information Systems (GIS) as a means of scaling from local to regional predictions for crop production.

Hobbs (1997) analyses the advantages of a Bayesian approach for assessing uncertainties in climate change, in terms of basing inference and decisions on a coherent and normatively theoretical framework. He summarises the application of Bayesian analysis to detection of climate change, estimation of model parameters, and wetland management under climatic uncertainty. He compares the Bayesian methodology with alternative paradigms for analysing uncertainty, such as fuzzy sets and Dempster-Shafer reasoning, and concludes that Bayesian analysis is a practical and theoretically sound tool for making inferences about climate change and for making decisions based on those inferences, and it is relatively easy to understand.

With the aim of combining data from different sources, including information elicited from the experts, Varis and Kuikka (1997) develop a Bayesian impact matrix approach (BeNe-EIA, an acronym from Belief Network approach to Environmental Impact Assessment), to elicit expert judgment and assess the impacts of climate change. The approach combines information from two assessment matrices compiled by the experts, that contain the probabilities of change in the attributes included in the analysis and the strengths of interdependencies between the attributes. One or more experts are used to define a Bayesian prior distribution for each of the selected attributes, and the inter-attributes links, of the system under study. Posterior probabilities are calculated interactively, indicating consistency of the assessment and allowing iterative analysis of the system. Therefore the approach uses Bayesian network techniques to calculate posterior probability distributions for each of the attributes. A network model is produced, which is aimed at aiding quantification and managing the inconsistencies in the elicitation process.

Also Hall at al (2004) develop a Bayesian *decision* network as a formal mechanism for structuring large quantities of evidence from a variety of sources, and respond to policy questions about the potential impacts of climate change. The research was commissioned by the UK government to establish the extent to which the unusually damaging floods of 2000 were a manifestation of hydrological climate change. Influence Diagrams are populated with probabilistic measures of belief to provide a graphical representation of uncertainty, which helps to synthesize complex and contentious arguments into a relatively simple, yet evidence-based, graphical output.

Oberholster et al. (2005) combine historical data with new evidence, implementing a BN to predict the concentration of sub-surface chlorophyll, as an indicator of plankton production. Estimates of plankton primary production are essential to understand the functioning of the marine ecosystem and the possible impacts of climate change on the marine food web. Bayesian Networks are comprised of two parts: a learning engine and an inference engine. The learning engine finds patterns in historical data and the inference engine takes these patterns as input and predicts likely trends. Topic maps are used to represent and store the Bayesian network structure and beliefs. The topic maps serve as a mechanism for passing information between the Bayesian network component of the system and the interface. BNs are applied to combine environmental and satellite data with an existing archive of 10 years worth of sub-surface ship readings, to provide predictions of chlorophyll profile and estimate plankton primary production of a given point in the ocean, when environmental or satellite data are made available, including climate change projections to assess potential impacts on the marine ecosystem.

Koivusalo et al. (2005) develop a Bayesian network tool inside a Decision Support System (DSS), as part of the CLIME project, which assesses the effects of climate change on lake dynamics. The aim is to integrate experts' knowledge and simulation model results in a form of a decision support system (CLIME-DSS) that illustrates and summarizes the main results of the project to interest groups outside the research community. The DSS is based on a causal BN, that summarizes the main relationships between climate variables and lake characteristics. The model is built using data elicited from the experts together with the results of an environmental simulation model focusing on watershed hydrology and Dissolved Organic Carbon (DOC). The methodology is applied to a case study which assesses the impacts of climate change on the concentrations of DOC in catchment run-off. An expert survey is firstly conducted to determine the variables characterizing DOC processes, and to identify the causal dependencies between the variables in comparison with the variables included in the DOC model. Subsequently, the Bayesian network is parameterized, characterizing the response of DOC concentrations to changes in climate. Finally, it is explored how the Bayesian network can be applied to regionalize the model results from one location in Europe to another.

Musango and Peter (2007) demonstrate the usefulness of employing Bayesian networks to integrate in a single framework environmental, social and economic variables that may be impacted by climate change in the South African agricultural sector. Various climate change scenarios are considered with decreasing rainfall and increasing evapotranspiration. The effects of damming and population increase are also included, and the net water-usage resulting from various agricultural strategies is compared to projected decreases in water availability due to climate change. The model compares the potential total value added of the activities with and without the potential impacts of climate change. The ability to present the sensitivities between key variables, for which varying degrees of data scarcity and uncertainty occur, provides agricultural sector researchers with a facilitation tool that helps to formulate climate change mitigation and adaptation strategies.

At the Integrated Catchment Assessment and Management (iCAM) Centre of the Australian National University a research project is in progress, which develops a BN inside a DSS to study the impacts of climate change on natural resource management (NRM) in the Central West catchment area (Cuddy et al., 2007). The DSS will help to assess NRM options under different climate change scenarios, and aid decision making to lessen impacts on catchment assets. The research started with a consultation of local and regional stakeholders, to conceptualize the system's variables and interactions. The system framework includes: climate change scenarios applicable for the region, important system components and assets as identified by stakeholders, catchment management goals identified by the Central West Catchment Management Authority and the stakeholders. The framework will be then converted into a Bayesian Decision Network, in order to allow for a complex and broad range of impacts to be explored using a simple interface.

The literature survey presented above clearly shows that the applications of BNs to climate change have a lot in common with the much broader field of applications to environmental issues. First of all they share the need to structure evidences coming from a variety of sources in a single model. A second aspect is the possibility to make projections on the effects of alternative management options on the system under analysis, and to carry out an adaptive management approach by updating the model with available evidence. Another important issue is the incorporation of uncertainty into the analysis (a pervasive problem in climate change research), for which Bayesian reasoning is specifically suited and increasingly used, with the support also from the Intergovernmental Panel on Climate Change (IPCC), who has given increasing attention to the Bayesian approach in particular for the management and reporting of uncertainties since the Third Assessment Report (IPCC, 2001). Lastly, a peculiar feature of Bayesian statistical models is their ability to combine information from a multi-model ensemble. The section that follows will attempt to provide a comprehensive assessment of the potentials of BN's in climate change research, with specific emphasis on supporting the development of adaptation policies.

5 Potentials and limits of BNs for climate change adaptation policies

Drawing on the reviewed applications of BNs in environmental management and more specifically in climate change research, the present section firstly describes the benefits that can be provided by the implementation of such techniques in the policy making process, and then discuss the possible drawbacks, together with the solutions to overcome them.

The potentials arising from the applications of BNs can be easily brought back to the three actions, exposed in the introduction, that lead to a comprehensive and effective process of uncertainty management in the assessment of climate change adaptation policy: characterising, incorporating and communicating the uncertainty (Table 3).

Management of uncertainty in BNs		
Characterising	***Incorporating***	***Communicating***
Handling aleatory/epistemic uncertainty through a probabilistic model	Adaptive management through probability propagation and belief updating	Supporting policy decision processes through Bayesian decision networks
Handling epistemic uncertainty through the integration of expert judgments and data from different sources	Examining alternative management scenarios	Improving communication among different actors through the graphical interface

Table 3: Synthesis of the main advantages provided by the application of BNs in climate change policy studies

BNs use probability as a measure of uncertainty, in order to estimate risks and uncertainties better than deterministic models. The probabilistic representation of the interactions among variables prevents overconfidence in the strength and effectiveness of the responses obtained by applying specific interventions. As new evidence becomes available, and it propagates updating the

Bayesian networks' CPTs, the uncertainty diminishes and the knowledge of the true values of the variables improves. BNs therefore provide a "robust and mathematically coherent framework" for modelling uncertain and complex domains (Uusitalo, 2007), since they make it possible to treat uncertainty explicitly.

Most of the studies considered in the review have to deal with incomplete evidence leading to beliefs that fall short of knowledge, with fallible conclusions and the need to recover from error. BNs are therefore applied as sound frameworks within which uncertainty can be represented and analysed pragmatically.

As expressed in the introductory section, climate change problems are often complex and multifaceted, and are usually addressed with a *reductionist* approach, which focuses on small areas of the problem. Bayesian networks provide a rational method for integrating the best information from a variety of fields and sources. Since the work of Varis and Kuikka (1997) BNs have been used to overcome uncertainty and fragmentation of existing studies, through the provision of integrated analytical approaches. Musango and Peter (2007), for example, demonstrate how BNs may be used to derive key thresholds and sensitivities within the uncertain projections of climate change impacts on agriculture, to test the potential adaptation strategies, while highlighting the serious research deficiencies.

A specific advantage emerging from the examined literature is that BNs do not necessarily need a wide sample size of data to perform an accurate analysis, while incorporating in a mathematically coherent way data of different accuracy and belonging to different sources (Uusitalo, 2007). Even more importantly, BNs provide a solution for the integration of quantitative information, obtained by models and empirical data, with qualitative knowledge, provided by experts and stakeholders. BNs thus allow users to deal with a range of different domains (environmental, social, political, economic, etc.), linked together through probabilistic dependencies, including also those variables for which no quantitative data and/or models exist yet, while expert opinion are available and could be used to – temporarily – fill existing gaps for supporting urgent decisions and policy developments.

As it should be evident from the above analysis, the main strength of BNs probably lies in their flexible structure, whose variables can represent any physical, social, economic or institutional factor, either tangible or intangible, and can include information from different sources, mainly expert knowledge and model or empirical data, in order to capture ideas effectively. Conditional Probability Tables underlying each node of the network, are based upon data-based and/or knowledge-based approaches.

As pointed out by Hamilton et al. (2005), the process of BN development in itself facilitates: a deeper understanding of variables and interactions; a greater maturity in reasoning about the problem during successive iterations of the model; the awareness of the role of individual scientists' research in the larger picture; and a recognition of the need to coordinate data and models arising from the different research projects.

BNs show specific opportunities also when applied to condition upon new information. The process of conditioning, also defined as probability propagation or belief updating, is carried out through a "flow of information" among the variables of the network (Korb and Nicholson, 2004). In those cases, BNs' priors are updated with data, to obtain a synthesis of old knowledge and new information, which can be further used as a prior in a new analysis. This flexible mechanism allows to perform an adaptive management approach, which changes as a result of new information about the effects of initial interventions, and which is at the basis of the concept of climate change adaptation. The updating process thus provides an explicit, structured and systematic approach that allows learning from experience and facilitates more robust and transparent planning and management processes. In particular, Bayesian decision networks (BDNs) represent a useful tool to be applied together with decision analytic tools to aid management choices. Indeed, while BNs allow the user to quantify uncertain interactions among random variables, in order to determine the impact of observations, BDNs support exploration of decision makers' options and preferences, and help to determine the preferred solutions.

In a decision/policy making context, the capability of BNs to estimate the possible impact of uncertainty on the options considered is of great relevance. BNs can thus provide insight on the chance that different interventions may have a particular expected effect, and then investigate the consequences of such uncertainty, balancing the desirability of the specific outcomes against the chance to obtain them. Moreover, the consequences of different management choices can be analyzed considering also the risk of highly undesirable outcomes.

Last but not least is twofold potential of BNs graphical structure, mentioned in the various studies examined. On the one hand, the diagram conceptualizing the system under analysis helps to explicitly model causal relationships and hence can be used to gain a deeper understanding about the problem domain. On the other, the communication of information to decision makers and the active participation of people without technical abilities improves with the use of the BN's graphical structure, representing all the variables and relationships of the system.

Besides highlighting the several potentials of BNs, the analysis of the theoretical background and the reviewed applications of the models allows the identification of restrictions and pitfalls arising from their implementation, summarised in Table 4, all together with possible solutions.

<table>
<tr><th></th><th>Represent complex problems</th><th>Acyclic graphs</th><th>Represent continuous variables</th><th>Integrate expert judgments</th></tr>
<tr><td rowspan="4">Limits</td><td>Computationally hard problems</td><td rowspan="4">BN cannot incorporate feedback loops</td><td rowspan="4">Discretization processes: delicate and often subjective</td><td rowspan="4">Risk of errors or biases in the estimates</td></tr>
<tr><td>High amount of information needed</td></tr>
<tr><td>Time consuming</td></tr>
<tr><td>Financial costs</td></tr>
<tr><td rowspan="4">Possible solutions</td><td>Process of simplification of the BN</td><td rowspan="4">Use of Dynamic Bayesian networks, with different time slices</td><td rowspan="4">Use of specific software packages and statistical languages</td><td rowspan="2">Use of structured methods for expert elicitation</td></tr>
<tr><td>Compact and manageable BN</td></tr>
<tr><td>Use of sub-models</td><td rowspan="2">Combination of expert judgments with hard science data</td></tr>
<tr><td>Techniques to handle complexity (e.g. MCMC; HBN; OOBN; IPT; DBN)</td></tr>
</table>

Table 4: Synthesis of the identified limits of BNs and possible solutions

Environmental issues, and even more those issues that include both the environmental and the socio-economic dimensions, are often assessed from a variety of narrow and specialist perspectives, making it difficult to simultaneously bear the best scientific information from distinct fields, including also the participation of multiple experts and/or stakeholders, and identifying management objectives. BNs can perform such a function, providing a rational method for the integration of data from different sources (Woolridge and Donne, 2003), and at the same time they allow the user to incorporate prior knowledge and posterior evidence in order to more accurately model a complex system, which may be difficult when using other techniques. However, BNs are often considered not ideally suited to situations where the complexity must be represented in great detail or where cause-effect relationships are not enough to understand how the system works. Cain (2001) points out that the representation of uncertainty requires information on what that uncertainty might be, which increases the amount of information required to feed the model.

Exact or even approximate inference in an arbitrary network is considered NP-Hard in time complexity (Heckerman and Wellman, 1995). This means that there is no known polynomial time algorithm that can provide the inference. Instead, exact inference requires time that is exponential in the number of variables. Networks with more than just few nodes quickly become intractable to use (Mead et al., 2006).

In order to represent independencies explicitly and to optimally handle the causal structure of the model, also from the computational point of view, BNs should be compact. The amount of nodes, states and links need therefore to be limited, to obtain more manageable conditional probability tables (CPTs) and to facilitate the understanding of the model functioning to other people (e.g. stakeholders and decision makers).. Moreover, it usually takes a long time and significant costs to collect and collate the data. Both time and financial costs are related to the size and complexity of the BN created. There exist several ways to make BNs more manageable. A complex BN can be for example divided in simpler sub-models, which are easier to compile and linked to each other. Some of the BN models proposed in the reviewed studies explicitly underwent a simplification process, such as for example the network developed by Borsuk et al. (2004), which was reduced from 35 nodes and 55 arrows down to 14 nodes and 17 arrows.

In the latest years, several techniques have been proposed to handle BNs complexity (Mead et al., 2006), e.g. Markov chain Monte Carlo (MCMC) simulations, hierarchical (HBNs) and object oriented (OOBNs) Bayesian networks, interval probability theory (IPT), and dynamic Bayesian networks (DBN). MCMC techniques represent a Markov chain of possible states where each one is a unique configuration of the network, and estimates posterior probability distributions. By using approximate inference, networks with more than a few nodes become tractable. HBNs and OOBNs extend BNs to increase their ability to manage complex structure by allowing the nodes of the network to be instances of other networks, and therefore improving the efficiency that results from the additional structure information. IPT expresses the uncertainty in the prediction when it separates the support for a proposition from support for the negation of the proposition, and in this way expresses ambiguity in probabilistic predictions or estimates. Finally, DBNs represent the change of the BN model over time connecting nodes in different time slices.

BNs are acyclic directed graphs that cannot incorporate feedback loops: they do not allow to return to a node simply by following directed arcs. Relationships must represent either one-way causal influences at a particular instant in time, or net influences on eventual steady-state conditions. This could represent an important limitation in climate change modelling. A solution could be the use of dynamic BNs, where temporal dynamics can be incorporated using different time slices. This approach would relax some of the feedback restrictions typical of the standard directed acyclic graphs used for BNs. However, dynamic BN could result very tedious and complex, considering the intra and inter-slice interactions and dependence among variables. Such a model requires significantly more information to quantify the time dynamics, and the level of uncertainty usually increases when looking further into the future. A robust analysis should therefore be limited to few time steps, taking into account that an insufficient consideration of dynamic aspects of system behaviour could provoke unexpected consequences, that are not adequately captured by the probabilistic predictions.

BNs ability to consider continuous data often results limited. The usual solution is to discretize the variables, although the process could rise some difficulties. First of all, the discretization captures only the rough characteristics of the original distribution and we may loose statistical power if the relationship between the variables is, in fact, linear (Uusitalo, 2007). Discretization methodologies are often based on subjective knowledge and not on automatic approaches. However, it should be noticed that also the use of continuous probabilities risks to include a certain degree of subjectivity, for example if a specific shape of the distribution is externally imposed. Discretization involves delicate processes, since the number of intervals which are defined, and the division points, will make an important difference in the resulting model. While several BN software do not allow to deal with continuous variables, new methodologies and packages are being developed to take them explicitly into account. Most existing BN software packages make it possible to build and implement BNs without technical knowledge about the belief updating algorithms and the programming languages. BN software products are experiencing a constant development and their features makes them easy to apply to different fields of knowledge. They are more and more diffused to support the research efforts in an ever-widening range of domains.

BNs are a useful tool to integrate expert knowledge into the analysis and eventually combine it with model or empirical data. The use of expert judgment plays a particularly important role in environmental management. Most of the researches analysed in the review integrate empirical data and information from models with knowledge elicited from the experts (eg. Varis and Kuikka, 1997, Hamilton et al., 2005, etc.). However, the expert judgment elicitation process brings along several difficulties, mainly associated with collecting and structuring the information in a form that can be converted into probability distributions. The way in which expert judgment is introduced into a BN can lack transparency and rigor. As Morgan and Henrion (1990) point out, collection of quantitative knowledge from humans is prone to overconfidence, that may result in biased outcomes. Humans find it easier to assess qualitative than quantitative data. It seems cognitively difficult to think of conditional distributions with several conditioning factors. That is another reason to simplify the BNs' structure by reducing the amount of parent nodes and states of the variables, and by omitting less important variables. BNs allow to decompose, according to the conditional independences, the whole problem to lower-dimension sub-models, which can be more easily fed and solved also with expert data.

Uusitalo (2007) proposes an approach to organize elicitation into BNs. It is important to firstly decide whether to use expert knowledge both to define the model structure and the probability distributions, or to have instead a pre-defined structure and fill in the CPTs with expert judgment. The first option would be more appropriate for the analysis of complex phenomena such as the global climate change, when it is advisable to ask the experts to create first the model structure according to their own beliefs, and then give estimates of the relevant probability distributions related to the model. In order to be more effective and robust, BNs shouldn't rely only on data elicited from the experts, but should try to combine the qualitative structure, based on expert knowledge, with the quantitative probabilities obtained using hard data. Finally, BNs can be malconstructed and should then be reviewed by an experienced BN expert for consistency. (Henriksen et al., 2006)

6 Conclusive remarks

The analysis of the literature of Bayesian network applications carried out throughout the paper, demonstrates that they may provide an innovative operational approach for assessing and incorporating probabilities, and therefore uncertainty, into analyses and decision makers' choices. In particular, for what concerns climate change adaptation, BNs emerge as a flexible approach providing analysts and decision/policy makers with a tool to facilitate learning, and enhance analysis performances, thus improving adaptive management and decision making,. The review illustrated how the opportunities and advantages offered by the BN instrument are applied to different research contexts dealing with environmental and climate change issues, and demonstrated the capacity of the tool to characterise, incorporate and communicate the uncertainty in the assessment of adaptation policy options. It appears evident that such potentials of BNs, could facilitate the design of effective, equitable and efficient adaptation policies, focusing in particular on the choice between a precautionary action and a delayed intervention.

The question of whether to act now or wait to learn more is central to the climate change adaptation debate. In that context the implementation of the BDN model may provide an innovative approach to move beyond the incorporation of uncertainty in climate change analysis and account for learning, through the acquisition of new information that leads to the reduction of uncertainty over time. Most of the analysed BN models, applied to environmental or climate change studies, provided a support for adaptive management, in an effort to structure an informed and transparent decision making process which was able to consider a sequence of choices in time, and not just a "one-shot" game. BNs were applied as sound frameworks within which uncertainty could be represented and analysed pragmatically, and were sometimes coupled with the development of Monte Carlo analyses, to better assess the stability of the outputs to variations in the nodes' CPTs. The BN tool could therefore guide the choice and implementation of adaptation policies, following a precautionary approach that overcomes the uncertainty of future projections and models' estimates.

Given the relevance of the issue of interfacing the scientific and the policy spheres within the same debate about adaptation policies, BNs' potential to integrate qualitative and quantitative information and to synthesize complex and contentious arguments into a relatively simple graphical output appears of greater relevance. A BN model can integrate the different components without being too mathematically abstruse, or loosing information, accuracy or transparency. Existing simulation models, which appropriately represent our level of understanding about the functioning of the climatic or socio-economic systems, can be used as a basis for identifying and quantifying the variables and the set of relationships in a BN. However, BNs should not be seen as a suggested replacement for other models in current use, but rather as integrators of several forms of knowledge, whether expressed as a process-based description, a data-based relationship, or a quantification of expert judgment. At this regard, as in most of the reviewed studies dealing with the management of natural resources and climate change, BNs need to be coupled with specific and broader DSS approaches and tools, in which BNs can be considered as a facilitation tool which could help both researchers and policy-makers to assess the effects of climate change and respond to policy questions about adaptation strategies.

The user-friendly graphical structure of the reviewed networks encourage the involvement of stakeholders and decision-makers in the implementation process, improving the communication between science and society, and the diffusion of information. The possibility to incorporate data elicited from the experts in climate change adaptation studies would favour the interchange and the comparison of available knowledge among different domains, and would therefore manage the intrinsic complexity of the issue.

Despite the unquestionable strength of the instrument, still relatively few applications of BNs to climate change policy issues are available in the literature. While Bayesian reasoning and analysis are extensively applied to assess the uncertainty in climate change science, BNs are still poorly utilised as a decision support tool in the policy area.

It may be expected that the growing development of new computational methods and techniques, the diffusion of user-friendly BN's software, and the vast application of BNs to ecology and natural resource management issues, will improve BNs' abilities and range of potential applications, but the limitations mentioned in the previous section should be carefully considered at least until when a new generation of approaches and tools will become available, thus overcoming in particular the problem of managing the fast growing and often unmanageable complexity of networks and the challenging management of feedback loops.

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