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The Role of Strategic Behaviour in Ecosystem Service Modelling: Integrating Bayesian Networks With Game Theory

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ABSTRACT

Humans fulfil an active role, through management and economic activities, in the production of ecosystem services and related benefits. Different human groups may pursue different objectives, and their actions may affect each other's well-being. Bayesian networks have gained importance in ecosystem service modelling and we show how, in recent literature, this approach has attempted to address strategic behaviour issues. Using simple simulations, we illustrate that the strategic behaviour of stakeholders could be better modelled with an integration of game theory concepts in Bayesian networks. This approach may help to understand the rationale behind stakeholders' behaviour and foresee their actions. Furthermore, the comparison of environmental results with cooperative and strategic behaviours raises questions about the role of humans in the production of ecosystem services, and on the correct way to value their benefits.

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1. Introduction

The ecosystem service (ES) concept emerged in the 1990s (Costanza et al., 1997; Daily, 1997) and was mainly created to emphasise the importance of ecosystems for human well-being (e.g. provisioning services, regulating services, cultural services). Every ecosystem service definition identifies an unequivocal relationship between ecosystems and human life (Boyd and Banzhaf, 2007; Fisher et al., 2009). Several frameworks have been developed to stress the interrelationships between ecosystems and human benefit. One of the most cited approaches, the ecosystem service cascade (Haines-Young, 2011; Haines-Young and Potschin, 2009), describes the services as nature's gifts that linearly flow from biophysical structures and processes to human populations. Not all the ES cascade versions explicitly show the active role of humans in the generation of benefits, but several scholars recognize that benefits result from the combination of ESs and human inputs, such as the investments of labour, time, resources, and money (Boyd and Banzhaf, 2007; Lamarque et al., 2011). According to Fisher et al. (2008), the opportunity cost of these inputs must be subtracted in order to calculate the well-being generated by ESs. Cascade frameworks that explicitly include a human role are found in TEEB (2010) and Lamarque et al. (2011). Following these approaches, human contributions clearly emerge with management functions (especially in the case of public actors), and with processing/use functions (especially in the case of private actors) (see Fig. 1).

Theoretical ESs frameworks have given impulse to different types of mathematical models, most are focused on the biophysical component of the cascade (Gómez-Baggethun et al., 2010; Kareiva et al., 2011; Villa et al., 2014). Kelly (Letcher) et al. (2013) included Bayesian networks (BNs) in a large review of five approaches (together with Systems Dynamics, Agent-Based Models, Knowledge-Based Models, and Couple Component Models) for modelling complex environmental systems. Landuyt et al. (2013) and Mcvittie et al. (2015) showed the conceptual fit between BNs and the ES cascade framework, especially for economic valuation. Barton et al. (2012) discussed BNs in environmental and resource management using the driver-pressure-state-impact-response (DPSIR) framework.

Bayesian networks (also known as Bayesian belief networks) have recently gained importance in ES modelling thanks to its' high transparency, the possibility to combine empirical data with expert knowledge, and explicit treatment of uncertainties (Landuyt et al., 2013). An evolution of BNs are influence diagrams (IDs) also known as Bayesian decision networks, used to represent and analyse decision making under uncertainty. IDs are able to model and evaluate a complex decision-making process, where the process is not influenced by other participants. In reality, many decisions are made in complex environments, where a number of decision makers are involved in the same process (Zhou et al., 2013). IDs are not able to capture 'gaming situations' where people want to consider opposing agents that act according to beliefs about ones' own actions (Brynielsson and Arnborg, 2004). Actually, this is the field of game theory (GT), which is a theory of decision making under conditions of interdependence.

Bayesian networks and game theory have traditionally been regarded as orthogonal bodies of work (Lee and Wolpert, 2012). Several attempts have been recently made to integrate GT into BNs and into IDs (Brynielsson and Arnborg, 2004; Koller and Milch, 2003; Zhou et al., 2013). These studies have essentially regarded theoretical considerations and algorithms for computation, while a few applications can be found in the fields of military strategies (Bryan et al., 2010), pilot behaviour (Lee and Wolpert, 2012) and internet security (Yan et al., 2012). To the best of the authors' knowledge, no attempt has been made to integrate these two approaches in the field of ESs studies.

The objective of this paper is evaluating the possibilities and benefits of integrating Bayesian networks and game theory for the analysis of ecosystem services. We want to stress how the strategic behaviour of stakeholders is strongly related with many BN applications found in the literature. In several cases it is indirectly (i.e. unintentionally) included in the model. In others, conflicting objectives between stakeholders are clear, but ignored, or modelled with approaches different from GT. Finally, there are studies where strategic behaviour is not perceived in the BN, but only because the model focuses on a limited section of the ES cascade, deliberately ignoring human connections.

The paper is structured as follows. Section 2 presents the main characteristics of BNs and GT. In Section 3, we explain the criteria adopted to select, classify, and illustrate the BN related papers in the field of ESs; a similar procedure is followed to select a sample of papers that use GT. In Section 4, results of this literature review are presented. Section 5 discusses the results and presents a framework, based on a simulated situation, for the integration of BNs and GT. This is done at conceptual level using, as far as possible, commercial BN software as a tool for the analysis; the development of algorithmic applications for solving these cases is beyond the objectives of the paper. Section 6 concludes the paper.

2. Background

2.1. Bayesian Networks

BNs are a semi-quantitative modelling approach based on two structural model components: (a) a qualitative part represented by a directed acyclic graph (DAG) that denotes dependencies between the model's variables; and (b) a quantitative part represented by conditional probability tables (CPTs) denoting the strength of the links. Each variable contains a limited number of states. The dependencies between different variables are indicated in the DAG by arrows, which represent cause-effect relations and, since the graph is acyclic, feedbacks are not allowed. Both the DAG and the CPTs can be based on expert and stakeholder knowledge, or can be learned by empirical observations.

Prior (unconditional) probabilities express the probability that some input parameter is in a particular state. Conditional probabilities represent the likelihood of the state of a parameter, given the states of input parameters affecting it. Finally, posterior probabilities represent the likelihood that some parameter is in a particular state, given the input parameters, the conditional probabilities, and the rules governing how the probabilities combine. Inference is based on the notion of evidence

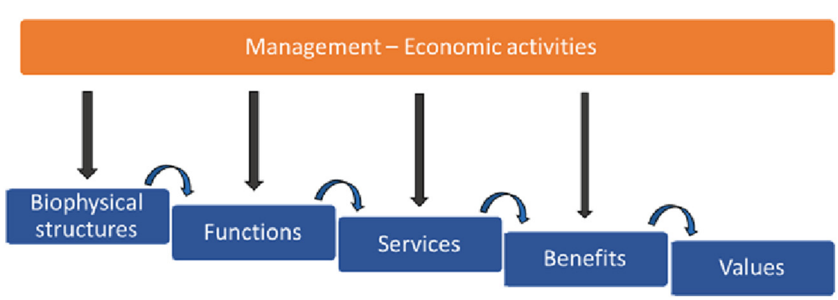

Fig. 1. Ecosystem service cascade with explicit human roles.

propagation, and refers to the process of computing the posterior marginal probability distributions of a set of variables of interest, after obtaining some observations of other variables in the model.

2.2. Influence Diagrams

An ID can be considered as a BN augmented with decision variables, utility functions, and precedence ordering (Kjærulff and Madsen, 2013). The decision nodes are variables whose values the agent chooses. The utility nodes represent the cost and/or the benefits generated by the decisions, enabling cost/benefit analysis of alternative options. Willingness-To-Pay functions, for example, can be easily integrated into utility nodes. Precedence ordering specifies the order of decisions, and the existence of information for decision makers. Solving a decision problem amounts to determining an optimal strategy that maximizes the expected utility for the decision maker, and computing the expected utility of adhering to this strategy (Kjærulff and Madsen, 2013).

2.3. Game Theory

Game theory is the theory of strategic interaction. A game is a mathematical instrument that serves the purpose of formalizing strategic interactions among agents (Lambertini, 2011). It is denoted by a set of players, a set of strategies, and a set of payoffs. GT assumes that each player rationally chooses a strategy in order to pursue the maximization of his payoff, being aware of the structure of the game, and that every other player will attempt to maximize their payoff. We consider an outcome to represent rational behaviour if it is a Nash equilibrium, where no agent has an incentive to deviate from his strategy. Probabilities are often used in games to represent uncertainty.

There are several classifications of games. Firstly, it is necessary to distinguish between cooperative games, where players pursue a common objective, and non-cooperative games, where players adopt self-interested behaviours, in open conflict with all other players. Secondly, there are games that are played simultaneously (in this case information is said to be imperfect, because players do not know the strategy adopted by rivals), and others sequentially (information is said to be perfect). Furthermore, we can have the case of incomplete information games, where some of the players do not know one or more relevant features characterizing the identity of other players. Uninformed players only know the exogenously given probability distribution of the rivals' types. In this case, the solution is called Bayes-Nash or simply Bayesian equilibrium (Lambertini, 2011).

There are two standard ways of visualizing a game: the strategic form (or normal form) that has the aspect of a matrix and is more suitable for simultaneous games, and the extensive form (or tree) used to formalize games with a time dependent sequencing of moves.

2.4. Integration Between Bayesian Networks and Game Theory

Koller and Milch (2003) retraces the literature over the possible extension of IDs to multi-agent scenarios, an idea that they consider to have been dormant for some time. They propose a representation of non-cooperative games as *multi-agent influence diagrams*, which represent decision problems with multiple players. Similar approaches to incorporate GT to IDs have been proposed by Zhou et al. (2013), with the name *game-based influence diagrams*, and by Lee and Wolpert (2012) with the name *semi network-form games*. These approaches benefit from the simplicity and efficiency of IDs for modelling complex decision problems, as well as the GT rationality for making decisions in interactive scenarios.

3. Methodology

Landuyt et al. (2013) reviewed 47 publications, from 2000 to 2012, which applied BNs to the study of ESs. Many characteristics of the networks, including the data source, the number of nodes, the geographic size, the model validation, and the software used were reviewed. We took this set of publications and we extended it with a Web of Science topic search on 'Bayesian networks' within the 'environmental sciences and ecology' research domain (October 2015), in order to consider papers published from 2013 to 2015. In this way, 35 new papers were selected.

All papers, old and new, were screened, eliminating cases where there is not a graphical representation of the network, or there are no links with the ecosystem service cascade framework. This resulted in a set of 67 publications (Table 1). Only a small percentage of these papers (16%) explicitly use the term 'ecosystem services'.

For every paper, we identified the type of ES that was modelled. Furthermore, we reviewed a few aspects that are relevant in a strategic behaviour perspective. Firstly, we checked how many stakeholders, institutions, or groups of stakeholders are explicitly included in the model (as nodes) as active agents, in the sense that they have a clear role in the modification, alteration, or management of the environment. Secondly, we considered the nature of these stakeholders, mainly if they are public or private agents. Then, in the case there were more than one active agent, we reviewed if the nodes representing agents' behaviour are positioned as independent nodes (i.e. as behaviours that happens simultaneously), or as cause-effect nodes (i.e. as behaviours that happens sequentially).

From the side of benefits, we checked how many and which (public or private) stakeholders (or groups of stakeholders) take advantage of the ES modelled in the network. For 'public' stakeholders we mean groups who enjoy public ESs (e.g. the population that enjoys climate regulation services).

Finally, we highlighted papers that try to value benefits or provide an anthropocentric judgment to the ESs level. BNs that take the form of IDs were selected and some cases are specifically described.

3.1. Game Theory Papers

Game theory has a long tradition in environmental and natural resource studies, and has been applied in fields like fisheries management, land management, water management, environmental management, pollution, and climate change (Albiac et al., 2008). Literature of GT applications is particularly rich for common-pool resources (Ostrom, 1990; Ostrom et al., 1994), which indicatively correspond with provisioning ecosystem services (e.g. fish stocks, pastures, water provision). However, there is now an increasing application of GT for the analysis and management of other services, such as supporting and regulating services (e.g. nutrient cycling, atmospheric and climate regulation) (Rodrigues et al., 2009).

A complete review of papers using GT is beyond the scope of this paper. However, a Web of Science and Scopus search on "game theory" and "ecosystem services" was performed, without time restriction, to select only papers specifically focused on the ES literature. Surprisingly, only eight papers published in peer-reviewed journals were found. Of these, four articles provide interesting elements for our discussion.

4. Review Results

4.1. Bayesian Networks

The review allowed classification of the papers into several categories. The first important division is between papers where humans have no explicit active role, and papers where humans do have some role.

In the first category, humans do not affect, positively or negatively, the provision of ESs. These papers do not consider either management interventions or economic activities from public or private actors. Several papers that analyse genetic resources, which are close to pure ecological studies, are included in this group. These studies are not interested

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Table 1
Scientific applications of BN models in ES modelling. (Pu = public, Pr = private, Mix = combination of public and private, 0 = no actors, * = more actors of the same category, C = cause-effect relation, I = independent relation).

Authors	Modelled ES	ID	Active actors	Relation	User actors	Socio-economic valuation
Adriaenssens et al., 2004	Genetic resources		0		Pu	
Ames et al., 2005	Water quality; recreation	X	Pu		Pr, Pu	Pu. and Pr. income; Pu. costs
Barton et al., 2008	Water quality; recreation	X	Pr		Pu	Pr. Costs; Public WTP
Borsuk et al., 2004	Genetic resources		Pr		Pu	
Borsuk et al., 2006	Genetic resources		Pr*	I	Pu	
Brandmayr et al., 2015	Water quality		Pr, Pu*, Mix	C, I	Pu	
Bromley et al., 2005	Food; fresh water provision; recreation		Pr		Pr, Pu*	Property price, benefit qualitative judgment
Carmona et al., 2013	Water regulation		Pr, Pu, Mix	C, I	Pr, Pu	Pr. income
Chan et al., 2010	Fresh water provision; water regulation		Pr*, Pu*, Mix	C, I	Pr, Pu	Public costs, benefit qualitative judgment
Dlamini, 2010	Regulating services		Pr, Pu	C, I	Pu	
Dyer et al., 2013	Water quality		0		Pu	Guidelines compliance
Farmani et al., 2009	Water quality; food; recreation	X	Pr, Pu	C, I	Pr*, Pu	Pr. income, Pu. costs, benefit qualitative judgment
Fienen et al., 2013	Water regulation		0		Pu	
Fu et al., 2015	Water regulation; genetic resources		Pu		Pu	
Gawne et al., 2012	Food		Pu		Pu	
Gieder et al., 2014	Genetic resources		Pu		Pu	
Grêt-Regamey et al., 2013a, 2013b	Carbon sequestration; wood; avalanche protection; habitat provision; recreation	X	Mix, Pr	I	Pu*, Pr*	ES value
Haines-Young, 2011	Climate regulation		Mix		Pu	
Haines-Young, 2011	Supporting services	X	Mix		Pu	Benefit qualitative judgment
Hamilton et al., 2007	Pest prevention		Pr		Pu	
Hamilton et al., 2015	Genetic resources		0		Pu	
Henriksen et al., 2007	Water quality; food; recreation	X	Pr, Pu	C, I	Pr*, Pu	Pr. income, Pu. costs, benefit qualitative judgment
Hines and Landis, 2014	Food; water regulation		Mix, Pu	I	Pr	Benefit qualitative judgment
Howes et al., 2010	Genetic resources		0		Pu	
Johnson et al., 2010	Pest prevention		0		Pu	
Johnson et al., 2013	Genetic resources		Pr, Pu	C	Pr, Pu	Pr. income
Keshtkar et al., 2013	Water quality	X	Mix		Pr, Pu	Pr. income, Pu. costs
Kragt et al., 2011	Water regulation, genetic resources		Pr, Mix	I	Pu	ES value
Krug et al., 2013	Genetic resources		0		Pu	
Lehmkuhl et al., 2001	Genetic resources		Pr, Pu	I	Pu	
Lucci et al., 2014	Supporting services		Pr		Pu	
Marcot et al., 2001	Habitat or supporting (population response to habitat management)		Pr, Pu	I	Pu	
Martin de Santa Olalla et al., 2007	Fresh water provision		Pr*, Pu*	C, I	Pr*	Pr. income
McDowell et al., 2009	Water quality		Pr		Pu	
Mcvittie et al., 2015	Water quality; water regulation	X	Pu		Pu	Satisfaction
Meineri et al., 2015	Genetic resources		0		Pu	
Meyer et al., 2014	Food; wood; recreation		Pr*,Pu	I	Pr*, Pu	Pr. and Pu. suitability
Molina et al., 2010	Food; fresh water provision		Pr*, Pu	C, I	Pr*	Pr. income
Murray et al., 2014	Pest prevention		Pr, Pu	I	Pr	
Nash and Hannah, 2011	Water quality		Pr		Pu	
Nash et al., 2013	Water quality		Pr		Pu	
Newton et al., 2006	Non-timber forest products		Pr, Pu	C, I	Pr	Capital level
Newton et al., 2007	Genetic resources	X	Pu		Pu	Pr. costs; loss of Pu. ES value
Pellikka et al., 2005	Genetic resources; recreation		Pr, Pu	C	Pr, Pu	ES value
Perez-Miñana et al., 2012	Climate regulation		Pr		Pu	Environmental costs
Pollino et al., 2007	Genetic resources		Pr		Pu	
Poppenborg and Koellner, 2014	Food; regulating services		Pr		Pr	Attitude
Pullar and Phan, 2007	Genetic resources		Pr		Pu	
Raphael et al., 2001	Genetic resources		Pr, Pu	I	Pu	
Rieman et al., 2001	Genetic resources		Pu		Pu	
Rigosi et al., 2015	Supporting services		0		Pu	
Roberts et al., 2013	Genetic resources		0		Pu	
Shenton et al., 2011	Genetic resources		Pu		Pu	
Shenton et al., 2014	Genetic resources; water regulation		Mix		Pu	
Spence and Jordan, 2013	Water quality; air quality		Mix		Pu	Benefit qualitative judgment
Steventon and Daust, 2009	Genetic resources		Pr		Pr, Pu	
Sun and Muller, 2013	Food		Mix		Pr	Income
Ticehurst et al., 2007	Genetic resources; cultural services; food; regulating services	X	Pu, Pr	I	Pr*, Pu*	Pr. income, Pu. costs, benefit qualitative judgment
Ticehurst et al., 2011	Supporting services		Pr, Pu	C	Pr, Pu	
Van Dam et al., 2013	Genetic resources, supporting services; food; water provision		Pr*	C, I	Pr, Pu	Pr. livelihood, Pu. benefit judgment
Van der Biest et al., 2014	Food; wood; climate regulation		Mix		Pr, Pu	Pr. and Pu. judgment
Van Putten et al., 2013	Food		Pr, Pu*	C	Pr	Income

Table 1 (*continued*)

Authors	Modelled ES	ID	Active actors	Relation	User actors	Socio-economic valuation
Wang et al., 2009	Food		Pr		Pr	Benefit qualitative judgment
Waters et al., 2013	Food; genetic resources		Pr		Pr, Pu	Pr. income, Pu. benefit judgment
Williams and Cole, 2013	Water quality		Pu		Pu	
Wooldridge and Done, 2003	Genetic resources		0		Pu	
Zorrilla et al., 2010	Food; water regulation		Pr, Pu	C, I	Pr, Pu	Pr. income

in a specific anthropocentric valuation of the service provided. The service is measured on a physical scale, or is qualitatively evaluated (e.g. strong/weak, high/low) considering its physical status, and only one ES is usually considered. Although there is not an explicit attempt to value the service for its utility to humans, it is possible to understand which population category is benefited. Considering the characteristics of these studies, most relate to genetic resources and supporting services, the beneficiaries are large segments of the population, and we can consider these ESs as public services.

In the second category of papers, humans do modify the natural ecosystem service cascade through management and economic activities. Depending on the context, these interventions are done by public authorities, which should operate for the benefit of (relatively) large segments of the population, or by private citizens or firms that operate for their own benefit. In several studies, people (especially private actors) are included in the model only to show their negative effects on the flow (and consequently on the value) of the services. Private actors are always included in the model as homogenous groups (e.g. the farmers, the fishers) rather than as individuals.

Usually, when a single active actor (public or private) is included in the BN, he is also the beneficiary of the ES modelled. However, several exceptions do exist, especially when negative externalities caused by the behaviour of private actors are considered. In Lucci et al. (2014) and Nash et al. (2013), for example, the behaviour of farmers affect the normal ecological equilibrium, causing different levels of phosphorus or nitrogen diffusion in the environment, and affecting the welfare of large parts of the population.

Van Putten et al. (2013) presents the opposite situation where the returns of Australian fishers depend on several public decisions. Furthermore, decisions are taken by two countries, Australia and Papua New Guinea, which have different objectives (Papua New Guinea, in particular, is not directly interested in the welfare of Australian fishers).

In many studies, we find the simultaneous presence of several active actors, in the form of public authorities and/or private groups. In some circumstances, the BN is built with nodes that already are the result of an interaction between public and private actors. This is a typical situation of BNs that present scenarios, where scenarios are a combination of public and private behaviours (Keshtkar et al., 2013; Van der Biest et al., 2014). In other BNs, nodes are originated by more complicated forms of interaction. For example, in Brandmayr et al. (2015), there is a node measuring the level of communication between two actors, while in Carmona et al. (2013), there is a node measuring the level of private compliance to public rules.

When different active stakeholders are included in the model, a cause-effect relationship between their behaviours can be recognized (or not, if behaviours are independent of each other). Very complex models may represent both independent and cause-effect relations between stakeholders' behaviours (Brandmayr et al., 2015; Carmona et al., 2013). When there is a cause-effect relationship, it is quite common that the choice of private actors is conditioned by the decisions of public authorities (Johnson et al., 2013; van Putten et al., 2013), normally under the form of management or policy options.

The most interesting cases (for our scopes) are those where multiple beneficiaries (public or private) coexist. In these cases, the benefits obtained by different stakeholders are more or less explicitly compared, and trade-offs between them are considered (Carmona et al., 2013; Keshtkar et al., 2013; Van Dam et al., 2013; Van der Biest et al., 2014; Waters et al., 2013). In most of these studies, different people groups utilize different ESs: trade-offs include both balances between people groups (thus raising equity and/or externality issues), and balances between different ESs (thus raising problems of measurability and accountability).

Normally, the benefit (or value) variables of different ESs are included in the BNs as final outputs of the model, so that there are not direct cause-effect relationships between them. However, special situations do exist. In Johnson et al. (2013), we find a case where the level of private benefits of Namibian farmers cause different behaviours and dynamics that affect the cheetah population (which represents a source of public, non-use, ecosystem services and benefits).

4.2. Socio-economic Valuation

Different strategies are used to value the benefits of ESs for human well-being. In a few papers, the term 'ecosystem services' is explicitly used, and authors provide an economic value for their benefits. If more than one ES is considered, as in Grêt-Regamey et al. (2013a, 2013b), this approach clearly permits us to compare or sum them up. This is more commonly done in IDs through utility nodes. Sometimes, costs are explicitly included in the model (Keshtkar et al., 2013), but in many other cases, one should suppose that benefits are already considered as net benefits.

Other approaches are provided, which obtain an integrated valuation of, or a comparison between, different ESs. Note the following examples.

Van Dam et al. (2013), in a rural African context, compare two qualitative indices that they call respectively 'livelihoods outcomes' and 'ecosystem function'. The first one is the valuation of several farmer outcomes (including fish yield, crop production, and drinking water supply), while the second is the valuation of several ESs (including biodiversity) that benefit a larger population.

In Spence and Jordan (2013), two public ESs provided by wetlands are considered: N_2O emission control and water quality. They are previously considered separately (with two scales that cannot be compared), and then joined in a sole variable named 'ecosystem service interaction'.

Van der Biest et al. (2014) consider three ESs provided under different land use scenarios. Two services benefit the population through private productions (farm and wood production), while the third is a public service (climate regulation). All are valued with an index on a 0–5 scale, and then included in a bundled index.

In Meyer et al. (2014), pixels of territory have been simultaneously judged for their suitability for different uses (agriculture, forestry, conservation, residential development). The study only compares several suitability scores, without explicit trade-off indications.

When ESs provide private benefits for specific stakeholders groups (e.g. farmers, fishers), it is quite typical to use indices such as the level of income (papers may use different terms such as revenue, margin, return) (Carmona et al., 2013; Johnson et al., 2013; Keshtkar et al., 2013). In these cases, only the welfare for the producer is considered, and not the welfare obtained by the consumers. In other papers (Hines and Landis, 2014), a qualitative judgment is expressed to value the economic activity (e.g. fisheries) or the public benefit related to the flow of ESs.

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4.3. Influence Diagrams

Influence diagrams encompass different levels of complexity. Relatively simple models include just one decision node and one utility node. This is the case of Mcvittie et al. (2015), which use a 'satisfaction' variable in order to provide a final valuation to the delivery of two different ESs (water quality and flood prevention). Slightly more complex models include one decision node and several utility nodes, which can be compared and summed-up (Grêt-Regamey et al., 2013a, 2013b). In these cases, ESs can benefit different population categories, such as private producers (e.g. farmers benefited by food production) and larger citizens groups (e.g. world population benefited by carbon sequestration).

In some situation, not all desired outcomes are modelled as utility nodes. In Ames et al. (2005), management decisions taken by one public authority are associated with the net revenue (utility) to the state and local community as a result of recreational reservoir use. However, the model includes another outcome, modelled as a chance node (water phosphorus concentration), which is functioning as a control variable. Only if specific values of this variable are guaranteed, can utility be maximized.

There are a few cases where the contrast between different actors is quite explicit. In Barton et al. (2008), farmers are actively involved with four nutrient abatement measures, which are linked to four abatement costs (for farmers) and one public benefit, expressed as household willingness-to-pay for bathing suitability. Then, total net benefit is calculated. Households' payments over and above their current water bill should compensate farmers. In a later work on the same case study, Barton et al. (2016), discuss about the motivations and preferences of different stakeholders' groups.

We find an even more interesting situation in Henriksen et al. (2007), where there is one decision (node) taken by a public authority, and where the utility (node) represents farm revenue. Many other chance nodes are included in the model to represent public benefits (water quality, biodiversity) and private benefits (fishing) for other stakeholders. Public decisions, through compensation payments, try to affect farmer behaviour. Farmers may (voluntarily) join farming contracts prescribing no pesticide application. The utility node calculates the net benefit of farmers considering compensations and decreases in revenues. Thus, the public decision node is linked to the utility of private actors. Private behaviour (percentage of contract acceptance) is not driven by a maximization procedure, but through a not clearly defined relationship (specified in the CPT) with the amount of compensation. In a successive paper (Farmani et al., 2009), the same case study is analysed in a multi-criteria approach to find Pareto-optimal solutions.

4.4. Game Theory Papers

Only four papers present significant applications of GT in ESs modelling. These include simultaneous games, sequential games, and incomplete information games. In all papers, there is a comparison of the results obtained with strategic behaviour and the results obtained with cooperation, a proof of the importance provided to management and rules in this field of studies. In two cases (Rodrigues et al., 2009; White et al., 2012), GT is coupled with ecological dynamics, including elements such as growth models and predation-competition relations. Several combinations of private and public (or no-profit) agents are modelled, with interesting examples of positive and negative externalities.

Rodrigues et al. (2009) present a situation where two private landowners must choose between forest conservation and deforestation. Deforestation provides a high return to the landowner, but degrades the regulating services produced on the parcel managed by the other landowner. Ecological and socioeconomic factors influence the equilibrium, and the emergence of social dilemma as in the stag hunt and prisoner's dilemma games.

In White et al. (2012), players are different private groups (fishery sectors) that compete for different sets of common goods (i.e. fish stocks) in complex ecological relations. Not all groups of fishers have improvements with cooperative behaviour, and transfer payments to share the overall gains among the sectors are necessary as a result.

Buckley and Haddad (2006) model the behaviour of restorationists and farmers. Utility of restorationists is a function of the level of ESs, and they can buy land from farmers to increase the service provision. Farmers may make defensive investments in their lands if they feel there is a risk of negative externalities from nearby restoration. Defensive investments inhibit ESs and entail negative payoffs for restorationists. In an incomplete information framework, two kinds of probabilities are included by the authors. The first is the probability perceived by farmers that damage to production occurs due to restorationists' behaviour. The second is the probability perceived by restorationists of farmers' behaviour, linked to the assumption that two types of farmers can exist: one who expects positive payoffs from investments and one who does not.

Finally, in Bode et al. (2011), two environmental organizations want to buy land in order to protect two different ESs (e.g. two animal species). The two ESs partially overlap on the territory, and the protection decision of one organization entails positive externalities for the other organization. Again, it is shown that cooperation provides larger social value than strategic behaviour.

5. Integration of Methods and Discussion

The review shows that, in many situations, BN studies touch strategic behaviour issues, especially when they take the form of IDs. Case studies where BNs or GT are applied are very similar, and one could imagine the GT framework as a natural extension of IDs: when two or more agents have different objectives, and the decision of one can affect the utility of others (i.e. externalities). This happens quite often in the field of environmental studies.

In this section, we want to show how a simulated case study, related to the use and management of ESs, can be modelled in different ways using BNs, IDs, and with an integration of BNs and GT. All models may be appropriate and choice depends on specific situations, objectives, and available information. The examples have been developed using GeNIe 2.0 (an open source BN program), and we will highlight how this tool can be used to integrate BNs and GT.

Let us assume a situation of a lake-based fishery. There is a sole ecosystem service index that, for simplicity, includes water quality and fish stock health. The ES level can be high, low, or very low. Fishers can decide to make an investment that improves the efficiency of their equipment, or not.

5.1. Model 1

In this initial model, there is only one fisher (or one fisher group, which is the same thing). The BN includes two chance nodes (ES level and investment choice) and three utility nodes (costs, gross benefit, and net benefit), without any decision node. If the fisher invests, then he has a cost of 20, otherwise he has no costs. The gross utility (Table 2) depends on both the state of the ecosystem and the investment decision.

The highest net utility (Gross Benefit – Costs) is obtained when the ES state is high and the investment is done. Note that in the case of high and low ES level, higher net utility is obtained if the investment is done; however, if the ES state is very low, there is higher net utility

Table 2
Expected benefits (Model 1).

ES Level	High		Low		Very low	
Investment	Yes	No	Yes	No	Yes	No
Gross utility	150	100	75	50	40	30
Net utility	130	100	55	50	20	30

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Table 3
Expected gross benefit for Fisher 1 (Model 3).

$U(I_1,I_2,ES)$	ES = High		ES = Low		ES = Very low	
	I_2 = Yes	I_2 = No	I_2 = Yes	I_2 = No	I_2 = Yes	I_2 = No
I_1 = Yes	70	150	35	75	20	40
I_1 = No	20	100	10	50	5	30

Table 4
Expected net benefit of both fishers in a strategic form (Model 3).

$U(I_1,I_2,ES)$	ES = High		ES = Low		ES = Very low	
	I_2 = Yes	I_2 = No	I_2 = Yes	I_2 = No	I_2 = Yes	I_2 = No
I_1 = Yes	50, 50	130, 20	15, 15	55, 10	0, 0	20, 5
I_1 = No	20, 130	100, 100	10, 55	50, 50	5, 20	30, 30

without investment. The prior probabilities of both ES level and investment choice nodes can be modified in order to calculate the expected net utility.

5.2. Model 2

The previous BN can be easily converted to an ID, where the only difference is that investment is represented by a decision node. The solution of the network coincides with the decision that maximizes the expected net utility. The result is different if we build a network with (or without) an informational link from the ES node to the investment node (i.e. if the fisher knows the real state of the environment, or only knows the prior probabilities of the different states). In the first situation, the decision is easy to take consulting the expected net utility table (Table 2): the fisher decides to invest if the ES level is high or low, but not if it is very low. If he only knows the prior probabilities of the ES level, he has to calculate the expected utility. For example, when the probabilities for each ES state are: 20% high, 40% low, and 40% very low, expected utility is 56 ($130 * 0.2 + 55 * 0.4 + 20 * 0.4$) in the case the fisher invests and 52 if he does not invest (results are automatically calculated by the software).

5.3. Model 3

Now suppose that two fishers (or two fishers' groups) with similar characteristics[1] use the lake. Suppose also that the utilities calculated in Models 1 and 2 for the first fisher are true only in the case the second fisher does not invest. In fact, increased fishing effort affects the sustainable production of fish, and fishers decisions affect each other's long-run gross benefit (Mulazzani and Malorgio, 2013).

Table 3 shows the expected utility for the gross benefit of Fisher 1 in the strategic form used for the representation of simultaneous games. Utility is a function of the investment decision of both players (I_1 and I_2) and of the ES state. If Fisher 2 decides to invest, gross benefit for Fisher 1 drops considerably compared to the gross benefit seen in Table 2.

Now, let us consider the net benefit of both fishers in a matrix, typical in GT representations, where the first number is the utility (i.e. payoff) of Fisher 1 and the second number the utility of Fisher 2 (Table 4).

Again, we have to consider if players know the real state of the ES or not (i.e. presence of informational links). In the first case, Table 4 can be used to foresee the rational outcome (Nash equilibrium) in the three situations of high, low, and very low ES level. The values included in Table 4 are automatically calculated by GeNIe for the utility nodes 'Net benefit 1' and 'Net benefit 2'; however, they have to be rearranged manually in order to be seen in a strategic form comparing the utilities of both players. The solution of the game is different from the solution calculated by BN software.[2] In the BN logic, the best outcome is the one providing the highest total utility, which is the sum of Fisher 1 and Fisher 2's net benefits. On the contrary, the strategic behaviour of the two players is aimed at their own private benefit. This entails that only in the situation of very low ES level, the strategic decisions of the fishers lead to a situation where total utility is maximized. Outcome I_1 = No, I_2 = No is the Nash equilibrium (neither players have incentive to change their strategy) and the situation that maximizes total utility ($30 + 30$).

In the two cases of high and low ES level, the outcome I_1 = No, I_2 = No, which is the situation that maximizes total utility, is not a Nash equilibrium. Both players have incentives to change their decision, and equilibrium is found only in the situation of I_1 = Yes, I_2 = Yes, where total utility is lower. This is a classic prisoner's dilemma situation, which is typical in the management of common-pool resources which lay in the heart of the tragedy of the commons' (Rodrigues et al., 2009).

If the ES level is unknown, players have to calculate, according to the prior probabilities, the expected utility of each decision, as in Model 2, but now they have to consider the potential decision of the other fisher. The expected utilities of the four theoretical outcomes (I_1 = Yes, I_2 = Yes; I_1 = Yes, I_2 = No; etc…) are calculated by GeNIe independently for the two players (utility nodes 'Net benefit 1' and 'Net benefit 2'), and then they have to be rearranged manually in a strategic form.

5.4. Model 4

Here, a third player is added, a public authority that has the possibility to affect, through management, the state of the ES. Suppose a CPT for the ES level node as given in Table 5.

The objective of the public authority is to maximize the total net benefit (i.e. the social benefit) produced by the economy. In this example, the public authority moves first; successively, the two fishers move simultaneously. Suppose that fishers know the state of the ES (i.e. they know the result of management).

As in any sequential game with complete information, the first player does not know the move of the other players but he knows their payoffs, so he can imagine how these players will react. Thus, the management authority knows that if the ES is very low, fishers will not invest and social benefit will be 60 ($30 + 30$). With low or high levels of ES, fishers will invest and social benefit will be respectively 30 ($15 + 15$) or 100 ($50 + 50$). Paradoxically, social benefit is higher

Table 5
CPT for ES level (Model 4).

Management	Good	Poor	None
ES = High	0.9	0.05	0
ES = Low	0.1	0.9	0.1
ES = Very low	0	0.05	0.9

Table 6
CPT for investment (Model 5).

Ecosystem service level	High	Low	Very low
I = Yes	100	100	0
I = No	0	0	100

[1] Instead of a second fisher, we could consider a different stakeholder, for example an authority that catches fish for restocking purposes.

[2] Note that, due to the traditional objectives of BNs, GeNIe (as other commercial software) modifies the model configuration illustrated in Fig. 2 adding one informational link between the nodes 'Investment 1' and 'Investment 2' to reflect knowledge of earlier decisions. However, the inclusion of this new link does not affect the validity of the expected utility tables produced by GeNIe for the nodes 'Net benefit 1' and 'Net benefit 2'. On the other hand, users must be aware that solutions calculated by the software for the decision nodes 'Investment 1' and 'Investment 2' have to be ignored, since the software searches for the outcome that maximizes 'Total net benefit', and the order of decisions is taken into consideration.

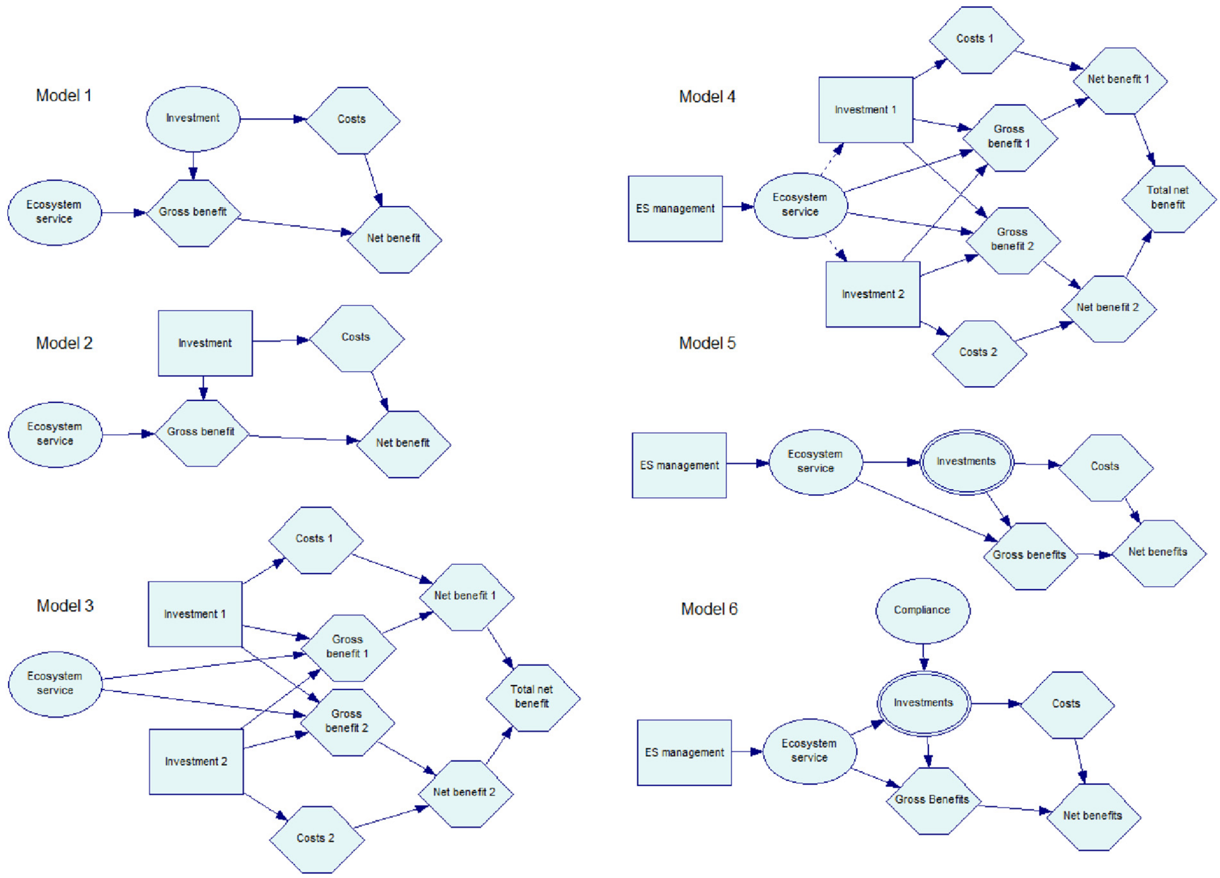

Fig. 2. DAGs of alternative models. Rectangles represent decision nodes; diamonds represent utility nodes; ovals represent chance nodes; double-line ovals represent deterministic nodes; dashed arrows are informational links.

with very low ES rather than low ES. Knowing this, the public authority has to decide if they should provide good management of ESs, poor management, or remain without management. At this scope, the authority must calculate the expected utility on the base of the CPT for the ES node.[3] Thus, it results that the best strategy is good management, followed by no management, and (the worst case) by a poor management.

The total net benefit for the different options of the public authority is calculated as follows: 'Good management': $100 * 0.9 + 30 * 0.1 = 93$; 'Poor management': $100 * 0.05 + 30 * 0.9 + 60 * 0.05 = 35$; 'No management': $30 * 0.1 + 60 * 0.9 = 57$. In this case, the software only provides (for the 'Total net benefit' node) the values of expected utility given the states of 'Ecosystem service', 'Investment 1' and 'Investment 2'. The calculation of the expected utility of each authority strategy must be done manually.

5.5. Model 5

If researchers are not interested in an explicit modelling of players, Model 4 can be simplified, substituting the decision nodes of both fishers with a sole chance, or even a deterministic node, the states of which (differently from Model 2) depend on the state of the ES node (we are still assuming that fishers know the state of the ES). In fact, accepting that fishers behave on the base of the already mentioned strategic rationality, we can assume that the behaviour of every fisher will be equal and deterministically given as shown in Table 6. In other words, this approach internalizes in a single node the strategic behaviour of Fisher 1 and 2: they invest if ES is high or low, but they do not invest if it is very low.

A network like this can be solved without problems using normal ID routines, and would provide (at both 'ES management' and 'Net benefit' level) the same results calculated manually for Model 4. Such modification makes the model easier to manage, at the cost of a less explicit understanding of stakeholders' rationality.

5.6. Model 6

We conclude this set of examples with a case of incomplete information (i.e. one player does not know the preferences of other players). Suppose that the public authority, in order to avoid a 'tragedy of the commons' situation, has forbidden that fishers make investments, but the authority does not know if fishers will comply with the new rule (i.e. it does not know the attitude of fishers to compliance). This lack of information can be modelled in a BN framework by adding a chance node (i.e. 'Compliance' probability), functioning as a parent node of investment, to Model 5. In the case fishers are not compliant, they behave strategically as explained for Model 3 and shown in Table 6. Considering the prior probabilities of compliance, the public authority calculates the expected net benefits of the management options. The higher the compliance probability, the higher the expected net benefit,[4] and it is possible to see which compliance probability is necessary to ensure that the expected benefit of 'Poor management' is at least as high as the expected benefit of 'No management'.

[3] For simplicity, we assume that management implementation has no costs.

[4] For example, with a compliance probability of 0.2, expected net benefits are as follows: 112,4 for 'Good management'; 48,6 for 'Poor management'; and 58,4 for 'No management'. As for Model 5, this case is solved without problems using normal ID routines.

6. Conclusions

Bayesian networks and game theory present several points of convergence. Both approaches are characterized by high transparency, the possibility of combining empirical data with expert knowledge, and explicit treatment of uncertainties. Furthermore, there are similarities in the tools (matrixes, graphs) for the representation of cause-effect relations and utility functions.

Literature review showed that many ES studies using BNs implicitly try to approach strategic behaviour. The models simulated in the discussion session showed how GT can be integrated in a BN framework to increase the potentiality of this analysis. In Model 3, the BN provides the expected utilities of the players for the different outcomes, and the researcher has to consider these values to select the outcome representing the Nash equilibrium. In Model 4, a few manual calculation is necessary (starting from the values obtained by the BN) in order to find the equilibrium. As an alternative, a classic BN (or ID) can be accurately drawn in order to incorporate strategic behaviour without an explicit GT representation (Models 5 and 6).

We considered simultaneous games, sequential games, and incomplete information games in both private and public perspectives. The integration of GT logic in BNs has been performed at a conceptual level, without necessity for specific algorithmic applications or new software. Commercial BN software do not permit to find (automatically) the solution of models where several decision and utility nodes represent the interests of different agents. We expect that this paper will be useful in fostering the development of specific algorithms and programs (Brynielsson and Arnborg, 2004; Koller and Milch, 2003; Zhou et al., 2013).

Different levels of refinement can be added to the basic models we have used as examples. One development direction that can be investigated is the introduction of time-slicing to model the reaction of players as a consequence of the results obtained in previous time steps (and of the other stockholders' strategies). Somehow, this approach would bring BNs closer to Agents Based Models (ABMs), where numerical solutions (i.e. simulations) about the behaviour over time of an agents' population are studied instead of analytical solutions (Righi and Takacs, 2014). Unlike ABMs, the combination of BNs and GT is more appropriate when analytical solutions can be found, that is when the model is not too complex (i.e. there are few players and few decisions). In this context, it is good for pedagogical examples, and it can contribute to social learning and decision analysis.

Integration of GT and BNs may help understand the rationality of stakeholders' behaviour, even to foresee their actions. Literature review and simulations have highlighted how human agents, including public and private players, may largely affect the value of ecosystem services' benefits. Management actions and economic activities have a critical role for the fulfilment of ESs potential. Actually, this raises several questions on what share of the value is really provided as a gift of nature, and what share is provided by human decisions in the form of cooperative or strategic behaviours. In particular, benchmark values should be calculated under the conditions of optimal coordinated management (i.e. maximum social benefit) driven by a 'rational social planner', and optimal uncoordinated management (i.e. Nash equilibrium) driven by private forces (Scheffer et al., 2000; White et al., 2012).

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