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Bayesian belief networks to analyse trade-offs among ecosystem services at the regional scale

Dries Landuyt[a,b,c,*], Steven Broekx[a], Peter L.M. Goethals[b]

[a] Unit Environmental Modelling, Flemish Institute for Technological Research (VITO), Boeretang 200, 2400 Mol, Belgium
[b] Laboratory of Environmental Toxicology and Aquatic Ecology, Ghent University, Jozef Plateaustraat 22, 9000 Ghent, Belgium
[c] Forest & Nature Lab, Ghent University, Geraardsbergsesteenweg 267, 9090 Melle-Gontrode, Belgium

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ABSTRACT

Knowledge on trade-offs and synergies among ecosystem services is crucial for the design of land use strategies that optimize ecosystem service delivery. Correlation coefficients, obtained through pairwise comparison of ecosystem service provision maps, have been put forward as suitable indicators to quantify these interactions. However, for more in depth analyses of trade-offs and synergies where driving forces of interactions need to be determined, more sophisticated methods are needed. Although Bayesian belief networks have been frequently mentioned as promising tools to investigate interactions among ecosystem services, up till now, no structured approaches to do so have been suggested. This paper presents a way to analyse trade-offs and synergies among ecosystem services together with their driving forces. Joint probability distributions of ecosystem service pairs, which can be calculated by using Bayesian belief network models, are used to quantify interactions. The paper demonstrates the approach by quantifying trade-offs and synergies among several ecosystem services in Flanders, Belgium. Our analysis identifies two bundles of ecosystem services which react synergistically. Wood production and several regulating services on the one hand and food production and soil formation on the other hand. Trade-offs are identified among food production and most of the other services that were included into the analysis. In addition to these general findings, the analysis shows that the identified interactions may change depending on the considered environmental conditions, specified through soil type, land cover and land use.

1. Introduction

Nature supplies a broad range of products and services that support human well-being (Daily, 1997). Typical examples of these ecosystem services (ES) include food production on agricultural land, wood production in forests and flood risk reduction by wetlands. Accounting for ES supply is increasingly becoming common practice in spatial planning studies (Hansen et al., 2015; Wilkinson et al., 2013). To evaluate alternative land use allocation scenarios, optimising ES delivery is being considered as an important objective (e.g. Broekx et al., 2013; Koschke et al., 2012). Attaining this objective, however, is far from straightforward. Natural and semi-natural ecosystems provide a broad range of goods (e.g. wood production, food production) and services (e.g. water quality regulation, climate regulation, recreation) of which the supply processes are closely related (Vangansbeke et al., 2016; Landuyt et al., 2014; Butler et al., 2013). Optimising the supply of one ES might diminish the supply of another (see Lee and Lautenbach (2016) for an exhaustive review of studied ES interactions). A phenomenon that is referred to as a trade-off, commonly defined as “when the provision of one ES is reduced as a consequence of increased use of another ES” (Rodríguez et al., 2006). While explicit consideration of trade-offs during decision-making is preferable, limited knowledge on trade-offs often leads to unintended side effects of management decisions in practice (Dugan et al., 2010; Allan et al., 2015; Rodríguez et al., 2006). Being able to identify and quantify trade-offs is one of the challenges that the ES research community are facing (Kremen, 2005).

Current efforts to quantify trade-offs can be classified into empirical (e.g. Cavender-Bares et al., 2015; Oñatibia et al., 2015) and model-based approaches (e.g. Maes et al., 2012; Haase et al., 2012). While empirical approaches are suitable to quantify trade-offs locally, limited data availability impedes the use of these

* Corresponding author at: Forest & Nature Lab, Ghent University, Geraardsbergsesteenweg 267, 9090 Melle-Gontrode, Belgium.
E-mail address: dries.landuyt@ugent.be (D. Landuyt).

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data-driven approaches at the regional scale. At the regional scale, trade-offs are generally assessed by comparing predicted instead of measured ES delivery rates. When grid-based spatial models are used, pixel-based comparison of ES delivery maps can reveal trade-offs or synergies. Scatter plots (e.g. Yang et al., 2015; Haase et al., 2012) and bag plots (Jopke et al., 2015) have been used to visualise these interactions. A frequently used indicator to analyse and quantify trade-offs and synergies is the Pearson's correlation coefficient (e.g. Chan et al., 2006; Raudsepp-Hearne et al., 2010; Yang et al., 2015), which is often corrected for spatial autocorrelation (e.g. through applying the CRH-test (Maes et al., 2012) or through data subsampling (Turner et al., 2014)). Correlation coefficients range between −1 and 1 and can characterise trade-offs and synergies through negative and positive values, respectively. The more the correlation coefficient differs from zero (indicating statistical independence), the stronger the interaction.

However, following the definition of Rodríguez et al. (2006), stating that trade-offs are always induced through ES use, correlation coefficients do not always indicate such interactions. A positive correlation coefficients can, for example, be the result of a spatial association of services that is not caused through management (or use). Turner et al. (2014) refer to these correlations as being coincidental and present such a coincidental correlation between soil organic carbon storage and the provision of cultural services in Denmark. In this case, management actions oriented at optimising the supply of one service will not necessarily lead to an increased supply of the other service, hence a synergy that is less relevant for decision making. Although most authors refer to these interactions as conventional trade-offs and synergies, we prefer to make a distinction here because of their lower relevance for decision making and label them spatial associations instead. In this context, correlation coefficient might act as complexity blinders. More dynamic approaches that assess interactions among changes in ES delivery rates (e.g. Haase et al., 2012; Lauf et al., 2014) instead of interactions among static delivery rates (e.g. Maes et al., 2012; Turner et al., 2014) are able to differentiate between both trade-off types. A downside of this approach is that it requires extra modelling efforts as successive time steps (Haase et al., 2012) or alternative futures (Lauf et al., 2014) need to modelled. On top of the complexity argument provided above, the validity of correlation coefficients that are based on proxies for ES provision instead of measured data can be questioned as well. As proxies for ES provision are generally uncertain (Hou et al., 2013) and may deviate from measured data (Eigenbrod et al., 2010), correlation coefficients among them will be uncertain as well, an issue that is frequently ignored in the literature.

To fully account for the complexity of trade-offs and to be able to detect trade-offs that are relevant for decision makers, less black-box approaches are needed. Approaches that deliver additional information on why and how synergies and trade-offs appear. This can be achieved by applying models that explicitly account for causal relations within and in between delivery processes of multiple ES. At the same time, these approaches should be able to identify relationships even in case delivery rates can only be modelled or measured with a limited amount of confidence. Bayesian belief network (BBN) models are graphical, probabilistic models that are able to do so. They are increasingly being used in the ES modelling domain due to their capacity to integrate expert knowledge in the modelling process and their ability to account for uncertainties (Landuyt et al., 2013). Also to identify trade-offs, BBN modelling has been successfully applied (Van der Biest et al., 2014).

In this paper, we investigate the potential of BBNs to identify and quantify trade-offs among the supply of six ES in Flanders, Belgium. By doing so, we propose joint probability distributions (JPDs) and conditional joint probability distributions (conditional JPDs) as a new approach to calculate correlation coefficients and as a new visual indicator to characterise ES interactions. Using this approach, we investigate whether trade-offs among provisioning services and other ES, as found by Howe et al. (2014), can be detected in Flanders as well and analyse whether trade-offs and synergies can change depending on the environmental context (Charpentier, 2015; Castro et al., 2014).

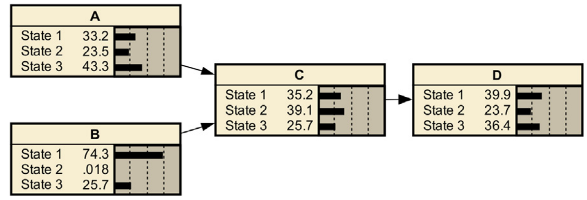

Fig. 1. Example Bayesian belief network model with four variables A–D.

2. Methods

2.1. Bayesian belief network modelling

2.1.1. Theoretical background

BBNs are graphical probabilistic models that encode the system being modelled as a network of nodes, representing the system's variables, connected through arrows, representing causal relations among the system's variables. This network of nodes is generally referred to as a directed acyclic graph or DAG, referring to the directed nature of the arrows and the absence of cycles or feedback loops within the graph. As all variables in a BBN are discrete or discretised continuous variables, the causal relation between a parent node X (at the origin of an arrow) and a child node Y (at the end of an arrow) can be quantified through a discrete conditional probability distribution $P(Y|x)$ for each discrete state x of parent node X. All these distributions are stored in the conditional probability table or CPT of child node Y. Note that for parentless variables, the input nodes of the model, $P(X|parents(X))$ simplifies to $P(X)$. By multiplying all conditional probability distributions ($P(X|parents(X))$), the JPD over the system's variables is obtained (Eq. (1)). This JPD allows a BBN to efficiently calculate the probability distribution of a variable given information on other variables within the model. In the context of ES, the model can, for example, predict the probability distribution over the states of the variable that represent ES supply given information on soil type, land use, etc.

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|parents(X_i)) \tag{1}$$

Eq. (1) is a simplified representation of the generally applicable chain rule of probability theory to calculate the JPD over a set of variables. Eq. (2) shows how the chain rule of probability theory simplifies to Eq. (1) by assuming a couple of independencies that are encoded in the graph represented in Fig. 1. Concerning model development, this implies that less conditional probabilities (two instead of three in this example) need to be defined by the modeller to calculate the JPD and, thus, to operationalise the model. For more detailed information on the theoretical background of BBNs, we refer to Jensen and Nielsen (2007).

$$\begin{aligned} &P(A, B, C, D) \\ &\textit{Chain rule of probability theory} \\ &= P(A) * P(B|A) * P(C|A, B) * P(D|A, B, C) \\ &\textit{Accounting for independencies encoded in the graph} \quad (\text{Fig. 1}) \\ &= P(A) * P(B) * P(C|A, B) * P(D|C) \end{aligned} \tag{2}$$