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Probabilistic modeling of the relationship between socioeconomy and ecosystem services in cultural landscapes

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ABSTRACT

There is a strong relationship among cultural landscapes, socio-economy and the provision of ecosystem services. The goal of this paper is to study the relationships between socioeconomic changes and the generation of ecosystem services in cultural landscapes in Andalusia (Spain). In order to do that, a causal Object-Oriented Bayesian network (OOBN) approach was carried out. We proposed 3 socioeconomic scenarios: (i) no intervention (rural abandonment); (ii) rural intensification; and (iii) rural development (sustainability). We computed the relative change between the prior and posterior distribution of each variable considered in the model. We also computed the entropy of the ecosystem service variables (ESVs), as a measure of their uncertainty, before and after the introduction of socioeconomic changes. Afterwards, a statistical test was performed in order to find significant differences among the 3 scenarios, regarding the relative change of the state high of the ESVs. Moreover, a *t*-test was carried out to compare the uncertainty of the prior and posterior distributions of the ESVs. The results showed significant differences among the scenarios. OOBNs are a powerful tool to deal with complex socio-ecological systems. Moreover, the use of Bayesian networks provides a sound way of quantifying uncertainty in a transparent way.

1. Introduction

Cultural landscapes are the result of the coevolution of human beings and nature over time (Blondel, 2006), therefore, they contain cultural heritage (Plieninger and Bieling, 2012). These cultural landscapes (García-Llorente et al., 2012) are frequently heterogeneous systems composed of different patches with different degree of ecological maturity, capable of providing diverse ecosystem services. Therefore, they are multifunctional landscapes. The delivery (degree of flows) of ecosystem services is the result of a complex relationship between human cultural management and the ecosystem. Hence, cultural landscapes, shaped by traditional land-uses, play an important role in the generation of ecosystem services (Iniesta-Arandia et al., 2014), whose provision might be greater than in ecosystems highly intensified or natural (García-Llorente et al., 2012).

As a result of socioeconomic changes, traditional cultural landscapes are threatened by two opposite tendencies of land-use change: agricultural intensification and abandonment. Both processes are clearly visible in the Mediterranean basin (Schmitz et al., 2003) and affect the provision of ecosystem services. Agricultural intensification implies the homogenization of landscapes and the use of fertilizers and pesticides, leading to a loss of biodiversity and, sometimes, aquifer overexploitation and pollution. Land abandonment has a wide spectrum of impacts on cultural systems (Rey Benayas et al., 2007), which are typically context specific and not always well understood (Plieninger et al., 2014) but they usually involve cultural loss (Hötchl et al., 2005).

There is a strong relationship between cultural landscapes and the socio-economy that created and maintains these socio-ecological systems (Moreira et al., 2001; Schmitz et al., 2003; Peña et al., 2007). Therefore, it is important to know how socioeconomic changes affect the cultural landscape in order to implement suitable landscape conservation policies (Schmitz et al., 2003). Numerical analyses, mainly regression, have been carried out to study this relationship (De Aranzabal et al., 2008; Álvarez Martínez et al., 2011; Schmitz et al., 2012). However, cultural

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landscapes show a high complexity of elements, connections and cause-effect relations, even more if ecosystem services are considered in the model (Müller and Burkhard, 2012). One of the main challenges is related to handling uncertainty in data, where mathematically sound methods and algorithms for dealing with uncertainty are required. Probabilistic graphical models, and Bayesian networks (BNs) in particular (Pearl, 1988), provide a well-founded approach for handling complex domains endowed with uncertainty. The underlying formalism for uncertainty treatment is probability theory, according to which the uncertainty associated with the decisions made using BNs can be properly quantified using measures as, for instance, Shannon entropy (Shannon, 1948). BNs have been proposed as a tool to model cultural landscapes (Landuyt et al., 2013) since the potential inclusion of expert knowledge and empirical data, the suitability for participatory modeling or the explicit treatment of uncertainties make them an appropriate approach.

Object-oriented Bayesian networks (OOBNs) are a powerful tool to deal with large, complex, hierarchical BNs (Korb and Nicholson, 2003). Within a socio-ecological system context, representing a moderate degree of realism usually results in large networks, which are visually intractable. OOBNs can help manage the complexity of socio-ecological systems by means of encapsulation, i.e., a number of networks representing different parts of the system can be separately specified and then linked together. This kind of representation eases the construction of networks and allows them to be reused and combined into different models (Chee et al., 2016; Molina et al., 2009). Moreover, BN fragments are easily modified within an OOBN context (Weidl et al., 2005).

The goal of this paper is to study the relationships between socioeconomic changes and the provision of ecosystem services in cultural landscapes in Andalusia (Spain). Through OOBNs, we model and analyze: (i) the current socioeconomic scenario of rural abandonment; (ii) a scenario of rural intensification; and (iii) a scenario of socioeconomic rural development. The paper is divided as follows. Section 2 briefly introduces Bayesian networks and OOBNs. In Section 3 we describe the methodological aspects carried out. Section 4 presents the results obtained for each proposed scenario. In Section 5 we discuss the results. The paper ends with conclusions in Section 6.

2. BNs and OONBs

2.1. Bayesian networks

A Bayesian network (BN) is a statistical multivariate model for a set of random variables $\mathbf{X} = \{X_1, \ldots, X_n\}$, which is defined in terms of (1) a directed acyclic graph (DAG), where each vertex represents one of the variables in the model and the presence of an edge linking two variables indicates the existence of statistical dependence between them; and (2) a conditional distribution $p(x_i|pa(x_i))$ for each variable X_i, $i = 1, \ldots, n$ given its parents in the graph, denoted as $pa(X_i)$.

In the discrete case, the relationship between variables is quantified by conditional probability tables (CPTs) associated with each node. The CPTs together compactly represent the full joint distribution of the variables in the network (Nicholson and Flores, 2011), which is therefore represented in a factorized way as

$$p(x_1, \ldots, x_n) = \prod_{i=1}^{n} p(x_i|pa(x_i)) \quad \forall x_1, \ldots, x_n \in \Omega_{x_1,\ldots,x_n} \tag{1}$$

where Ω_{x_i} represents the set of all possible values of variable x_i and $pa(x_i)$ denotes an instantiation of the parents of X_i.

The structure of the network can be obtained by expert elicitation, thus providing it with an inherent causal character. Representing real world problems in a causal way contributes to increase the explanatory power of the model.

Once the network structure is set up and the CPTs are learned, new pieces of information (evidence, e) can be introduced in the network. This evidence, e, propagates throughout the network, producing a new posterior probability distribution $P(X|e)$ for each variable in the network. There are a number of efficient exact and approximate inference algorithms, such as Variable elimination (Zhang and Poole, 1996) or Penniless propagation (Cano et al., 2002), for performing this probabilistic updating, providing a powerful combination of predictive, diagnostic and explanatory reasoning (Chee et al., 2016).

2.2. Object-oriented Bayesian networks

In this paper, we follow the definition of OOBN used in Kjærulff and Madsen (2008), as implemented in the Hugin software package.[1] An OOBN is a BN that contains ordinary nodes and object nodes, which represent instances of other classes (sub-networks). Thus, an object node may encapsulate multiple sub-networks, giving a composite and hierarchical structure (Korb and Nicholson, 2003).

Objects are connected to other nodes via some of its own ordinary nodes, which are known as *interface nodes*, whereas its remaining nodes are kept hidden. Interface nodes are divided into *input* and *output* nodes. Within an OOBN class, input nodes are root nodes and act as placeholders of ordinary nodes of another class. On the other hand, the output nodes are real nodes within an OOBN class and can be parents of nodes of another class or can be bound to an input node of another class, as long as cycles are not introduced.

Fig. 1 shows an example of OOBN with 2 classes, **A** and **B**, where class **B** is expanded in 1a and partially expanded in 1b, i.e. just interface nodes are shown. In this example, class **A** contains 3 hidden variables (X_1, X_2 and Z), 1 output variable (X_3), which is bound to node X_3 in class **B**, and 1 object (**B**), which is an instance of class **B**. Class **B** has 1 input node (X_3), which has been mapped from class **A**, 2 hidden nodes (Y_1 and Y_3) and 1 output node (Y_2), which is parent of node Z in class **A**.

Equivalently to single BN models, new pieces of evidence can be introduced to any variable, so that a new posterior probability distribution is produced for each variable in the complete OOBN. Fig. 2 shows an example of an OOBN when a piece of evidence is introduced.

3. Material and methods

3.1. Study area

The study area is Andalusia (Fig. 3), a region in southern Spain which occupies an area of 87 000 km^2 and whose latitude and longitude is between 36°N–38°44′N and 3°50′W–0°34′E. Andalusia's climate belongs to the Mediterranean domain, alternating mild, rainy and humid winters with dry and warm summers. The average annual temperature usually does not drop below 15 °C, as a consequence of the ocean influence. On the other hand, rainfall shows a high spatial variability, ranging from 170 mm/year to 2180 mm/year.

The study area ranges from 0 to 3460 m above the sea level. The main mountain ranges of Andalusia are the Sierra Morena mountain range (in the North) and the Baetic systems (in the South), which are separated by the Baetic depression, the lowest territory in Andalusia. Concerning slope, the flattest areas correspond to the Littoral and the Baetic depression, through which the Guadalquivir

[1] http://www.hugin.com.

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