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Inference reasoning on fishers' knowledge using Bayesian causal maps

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ABSTRACT

Scientists and managers are not the only holders of knowledge regarding environmental issues: other stakeholders such as farmers or fishers do have empirical and relevant knowledge. Thus, new approaches for knowledge representation in the case of multiple knowledge sources, but still enabling reasoning, are needed. Cognitive maps and Bayesian networks constitute some useful formalisms to address knowledge representations. Cognitive maps are powerful graphical models for knowledge gathering or displaying. If they offer an easy means to express individual judgments, drawing inferences in cognitive maps remains a difficult task. Bayesian networks are widely used for decision making processes that face uncertain information or diagnosis. But they are difficult to elicitate. To take advantage of each formalism and to overcome their drawbacks, Bayesian causal maps have been developed. In this approach, cognitive maps are used to build the network and obtain conditional probability tables. We propose here a complete framework applied on a real problem. From the different views of a group of shellfish dredgers about their activity, we derive a decision facilitating tool, enabling scenarios testing for fisheries management.

1. Introduction

1.1. Context

Most of environmental issues and management are currently based on scientific and/or technical knowledge. Other sources of knowledge (empirical or traditional) have been ignored or minimized for a long time.

Nowadays, there is a trend to more incorporate all various perceptions, in particular coming from end-users like farmers or fishers, taking account of ground realities (Haggan et al., 2007), (Oliver et al., 2012). In addition, decisions taken on these grounds should be more easily accepted by stakeholders, within a more effective management process: public participation is a key ingredient of good governance (Pita et al., 2010).

In a recent exploratory study regarding farm management decision support (Daydé et al., 2014), the authors emphasize the need to understand mental choice process because traditional decision support systems assume idealized situation, with exhaustive knowledge, that does not necessarily exist. In real world, much processing is done in a *qualitative manner*.

This paper addresses some management issues related to scallop (*Pecten maximus*) dredging in the Bay of Brest (Western France). We aim here at building a model from fishers statements, considered accurate as a premise, in order to improve management decisions.

The main contribution of this work is to show how stakeholders' knowledge can be used for qualitative decision support, through simple scenarios testing, and hence, to facilitate the making decision process.

The typical scallop dredging season in this bay runs from mid-October to late March, with three days of fishing allowed per week. During these periods, the scallops are sold alive. However, from time to time, an ASP toxin (amnesic shellfish poisoning) is detected within the bay, which forces all fishers to freeze their scallops, to be sold at a lower price. Scallop fishers have been experiencing the evolution of this natural resource and its environment for many decades. After an increasing fishing effort during the first half of the 20th century, the stock of scallops fell within a few years from an annual production of about 2500 tons in early 1960s to hundred tons in 1970s. A nursery program was thus initiated in the 1980s, thanks to the Tinduff hatchery leading to annual planting operations. Annual catches rose back to about 350 tons. Furthermore, a "shellfish fishing license" system was introduced in order to finance the hatchery program and to maintain a limited fishing effort (less than 60 boats).

1.2. Working with and for stakeholders

Stakeholders knowledge is intended here to be used to support stakeholder decision (fisheries board in the first place).

A recent paper, (Voinov and Bousquet, 2010) reminds us that even if stakeholder collaboration has become part of nearly every modeling

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effort, their involvement has often been nominal. The authors nevertheless insist that decisions are implemented more easily and more successfully when they are driven by stakeholders. In their panorama of existing techniques, they recognize much promise in integrating cognitive mapping with Bayesian networks.

Dealing with decision support, Pielke (2003) insists on two different issues. First, conventional modeling and prediction approaches cannot simultaneously meet the needs of both science and decision making. He also raises the matter of uncertainty, that decision makers would like to quantify and reduce. But he advocates that a *good* model is not necessarily an *accurate* one. Here, prediction is part of a management decision process, it does not pretend to provide numerical or time-accurate prediction.

Whoever they are, using stakeholders knowledge usually means finding a way to deal with qualitative data, which was already noted 25 years ago: much ecological knowledge is qualitative and fuzzy, expressed verbally and diagrammatically (Rykiel, 1989).

1.3. Prediction and complex systems

The common challenge of prediction about complex systems is to answer *qualitative* questions based on partial knowledge (Kuipers, 1994). Usually, these questions were answered through formulating and analyzing differential equations. But ordinary differential equations do not fit to qualitative reasoning: they assume complete and precise models of dynamic systems, which are unrealistic and sometimes unnecessary. Hence, the use of qualitative differential equations was advocated.

Other works brought mathematical foundations for qualitative reasoning, and with different formalisms: signed algebra and order of magnitude for example. They have shown how qualitative simulation could be held. For (Travé-Massuyès et al., 2003) qualitative methods unified with numerical or statistical modeling approaches can outperform either pure qualitative or pure quantitative approaches. Some recent works followed this path, like (Largouët et al., 2012), who used traditional trophic models relying on differential equations in order to build a qualitative model for a fishery. This model based on timed-automata, was successfully used for scenarios testing and possible futures querying. In fact, aquatic systems have been repeatedly modeled and analyzed in a qualitative manner, with various approaches including loop analysis (Dambacher et al., 2003), (Dambacher et al., 2009).

In our paper, we focus on qualitative models within decision-aid contexts, dealing with trends rather than precise output values.

1.4. From causal maps to Bayesian networks

Causal maps (known also as Cognitive Maps, CMs for short) have often been used to model influences between heterogeneous elements of a given system. They have been used for ecosystem management (Hobbs et al., 2002), (Özesmi, 2004), agro-systems (Papageorgiou et al., 2009), coastal fishing management (Prigent et al., 2008) or farmers' risk assessment (Winsena et al., 2013).

Causal maps, displayed as directed graphs, are generally defined as the beliefs of a person, for a particular domain (Axelrod, 1976). They represent variables and causal relations among variables within a decision problem, which enables to describe and capture a certain knowledge in a more comprehensive and less time-consuming manner than other methods (Sucheta et al., 2004). The graphical construction of causal maps is usually easy, even when working with actors not familiarized with such approaches. Even people reluctant to any mathematical formalism can express their views in a qualitative manner.

However, our study's main goal is to provide tools to facilitate decision making processes. Drawing inferences in CMs (i.e. obtaining new facts or conclusions from other information) is not an easy task (Laukkanen, 1996). Simple CMs allow a deductive reasoning that predicts an effect from a given cause. Thus, we can get responses about the effects of a given cause, try different scenarios and simulate their effects (Eden et al., 1992). However, the task becomes very difficult when a CM contains loops, feedbacks or multiple paths. Moreover, even if deductive reasoning can be achieved, we cannot answer why an observed effect is produced. A second limitation in CMs comes from the impossibility to model the uncertainty within the variables.

Bayesian networks (BNs) are a well-established method for reasoning under uncertainty and making inferences (Pearl, 1988) and (Pearl, 2009). They allow to compute the probability of any variable given the state of some observed ones. They can be used either to perform abductive reasoning (i.e. diagnosing a cause given an effect), or for deductive reasoning (i.e. predicting an effect given a cause). Hence, they provide an efficient tool, used within a wide range of subjects, from ecological forecasting (Borsuk et al., 2003) to criminal scenarios testing (Vlek et al., 2013). However, the elicitation of the structure and parameters of a network in complex domains can be a tedious and time-consuming task.

Despite the limitations of each model (BN and CM), their combination called Bayesian Causal Map (BCM) offers a powerful tool (Shenoy and Nadkarni, 2001). This approach uses the initial CM in order to construct the structure of the BCM, but still defines local probabilities from experts' knowledge. This might be impractical, because the notion of probability would not be well understood by domain experts.

For the structure of the BCM, we follow the procedure described in (Shenoy and Nadkarni, 2001). Concerning the parameters of the BCM, we propose an automatic procedure, relying on the causal values associated to the relations in the CM.

After a short description of the modeling formalisms used in our study and a presentation of the detailed procedure (from fishers' interviews to BCM construction), we will then display our results for this specific study. Finally, we will discuss this approach by emphasizing some of its advantages and drawbacks.

2. Modeling formalism

2.1. Cognitive maps

Cognitive or causal maps (CMs) are directed graphs representing experts' knowledge. A map expresses individual judgments, thinking or beliefs about a given situation. It is displayed by a network of causalities or influences among concepts (Chaib-draa, 2002) and (Eden, 1988), (Fig. 1).

Three different components constitute a CM:

1. Concepts: In a cognitive map, a node represents a concept corresponding to a variable of the studied problem.

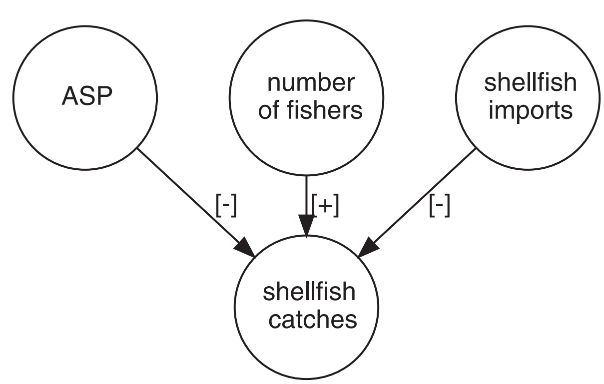

Fig. 1. Example of a simple causal map related to our study (three relations between four concepts).