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Combining state and transition models with dynamic Bayesian networks☆

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ABSTRACT

Bashari et al. (2009) propose combining state and transition models (STMs) with Bayesian networks for decision support tools where the focus is on modelling the system dynamics. There is already an extension of Bayesian networks – so-called dynamic Bayesian networks (DBNs) – for explicitly modelling systems that change over time, that has also been applied in ecological modelling. In this paper we propose a combination of STMs and DBNs that overcome some of the limitations of Bashari et al.'s approach including providing an explicit representation of the next state, while retaining its advantages, such an the explicit representation of transitions. We then show that the new model can be applied iteratively to predict into the future consistently with different time frames. We use Bashari et al.'s rangeland management problem as an illustrative case study. We present a comparative complexity analysis of the different approaches, based on the structure inherent in the problem being modelled. This analysis showed that any models that explicitly represent all the transitions only remain tractable when there are natural constraints in the domain. Thus we recommend modellers should analyse these aspects of their problem before deciding whether to use the framework.

1. Introduction

Environmental management involves making decisions that will impact on the ecological system. Examples include whether to control exotic flora or fauna, restrict farming or forestry practices, or change the landscape to alter water flow or usage. Any useful environmental decision support tool must model changes in the ecological system over time, particularly those that are the result of human activities.

The so-called *state-and-transition model* (STM) has been used to model such changes over time in systems that have clear transitions between distinct states of a physical environment, in particular rangeland vegetation (Stringham et al., 2003; Bestelmeyer et al., 2003; Sadler et al., 2010), but also other ecological and environmental domains (e.g., Saatkamp et al., 1996). The STM framework facilitates the organisation of information for management purposes. STMs are mainly based on the state/transition/threshold relationships determined by the resilience and resistance of the ecosystems' primary ecological processes. They combine the graphical depiction of transitions and their causal factors with tables of qualitative descriptions of the transitions.

Bayesian networks (BNs) are an increasingly popular paradigm for reasoning under uncertainty. A Bayesian network (Pearl, 1988; Jensen and Nielsen, 2007) is a directed, acyclic graph whose nodes represent the random variables in the problem. A set of directed edges connect pairs of vertices, representing the direct dependencies (which are often causal connections) between variables. The set of nodes pointing to X are called its parents, and is denoted $pa(X)$. The relationship between variables is quantified by conditional probability tables (CPTs) associated with each node, namely $P(X|pa(X))$. The CPTs together compactly represent the full joint distribution. Users can set the values of any combination of nodes in the network that they have observed. This evidence, e, propagates through 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 for performing this probabilistic updating, providing a powerful combination of predictive, diagnostic and explanatory reasoning.

Fig. 1 gives an example BN for a simple artificial ecological problem, to illustrate the components (structure and the CPTs) together with several reasoning scenarios, using screenshots from the Netica BN software (Norsys, 1994–2010).

The complexity of a BN model is naturally the number of parameters, typically the size of the CPTs. However, often there is so-called "local structure" in the relationship between parent and

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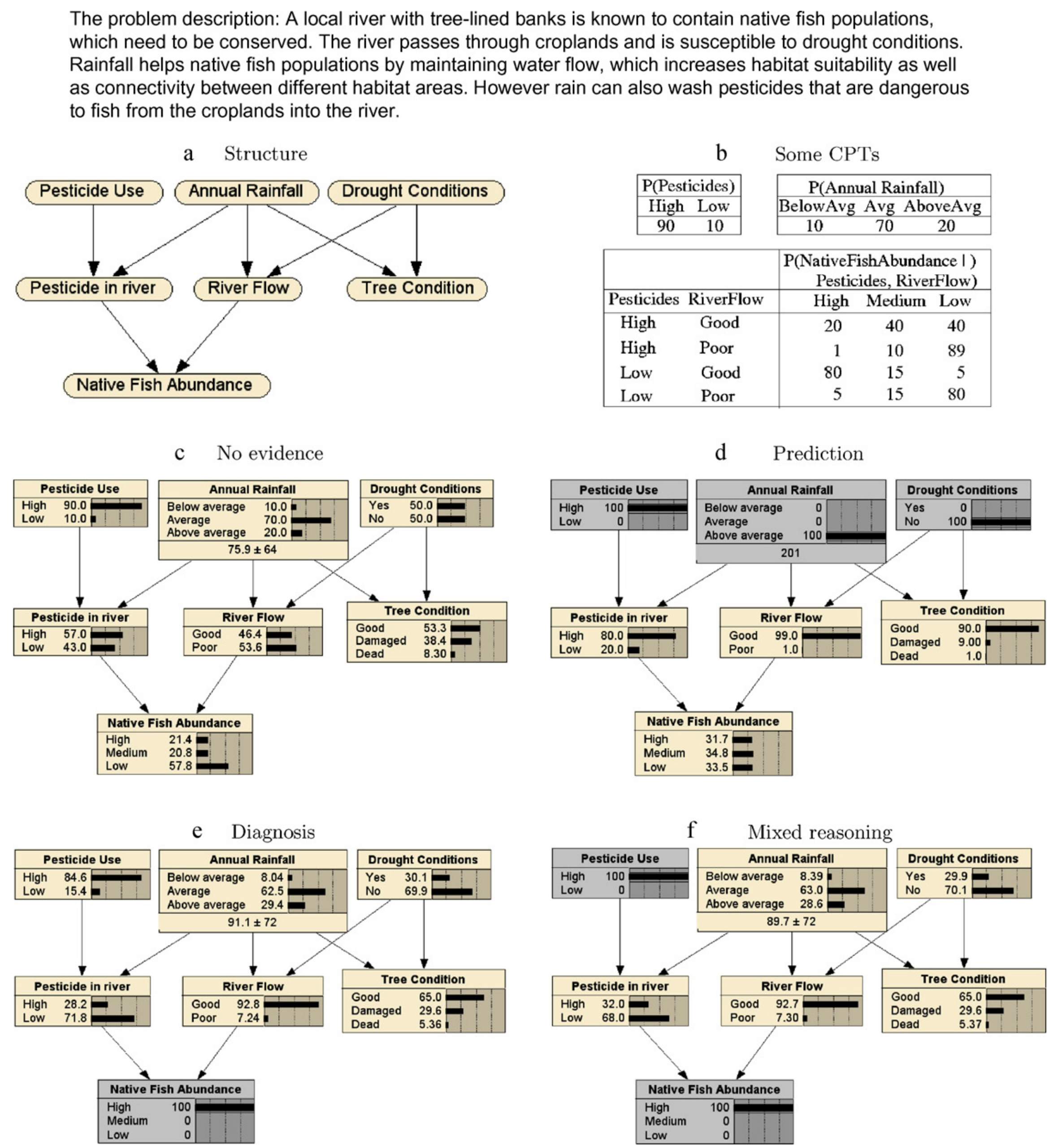

Fig. 1. BN example—"Native Fish" (Nicholson and Woodberry, 2010).

child nodes, so the full CPT does not need to be specified, instead more compact "context sensitive" representations can be used (e.g., Boutilier et al., 1996). In addition, the most efficient inference algorithms do not work directly on the BN graph, but instead compile it into a so-called junction tree. The complexity of the inference then depends on the structure and size of this compiled form.

Over the past 10 years, BNs have been widely used in ecological modelling (see Section 5.2.3 in Korb and Nicholson, 2010 for a survey), with a number of modelling guidelines published (e.g., Varis and Kuikka, 1999; Borsuk et al., 2004; Renken and Mumby, 2009), while Uusitalo (2007) reviews their features and use in modelling environmental applications.

Bashari et al. (2009) suggested combining STMs and BNs to obtain the advantages of both, namely the STM's graphical depiction of transitions with the BN's quantitative representation of the uncertainty using probabilities. They describe an approach to rangeland management decision support that combines a state and transition model with a Bayesian network to provide a relatively simple and updatable rangeland dynamics model that can accommodate uncertainty and be used for scenario, diagnostic, and sensitivity analysis. In this paper we begin with a detailed analysis of Bashari et al.'s framework, then formalise and modify it to overcome most of the limitations identified (Section 2).

The crucial weakness in their framework, however, is that it does not explicitly model the "next" state of the system, a key component in any dynamic modelling framework. We then show how an existing variant of Bayesian networks – so-called *dynamic Bayesian networks* (DBNs) – can be used to overcome this problem (Section 3). DBNs are a long-established extension to ordinary BNs that allow explicit modelling of changes over time (e.g., Dean and Kanazawa, 1989; Kjærulff, 1992; Nicholson, 1992). They have been used in a range of applications such as robot monitoring (Forbes et al., 1995; Dean and Wellman, 1991; Nicholson and Brady, 1992),