A Bayesian Decision Network Approach for Salinity Management in the Little River Catchment, NSW

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Abstract: Salinisation is a major environmental problem affecting land and water systems in Australia. This paper outlines a study currently being undertaken to provide a new tool to manage salinity from environmental and socioeconomic perspectives. In this study, biophysical and socio-economic aspects of the Little River Catchment and their relevance to salinity management will be investigated using a Bayesian Decision Network (BDN) approach. The Little River Catchment is located in the upper Macquarie River Basin in central western NSW. Salinity has been nominated by the catchment community as the main environmental problem. The focus of this study is on exploring the economic and biophysical impacts of scenarios for salinity management, consistent with salinity strategies both in NSW and the Murray Darling Basin. This will involve developing a modelling system to assist decision makers in formulating alternatives, analysing the impacts of these alternatives on salinity, water supply and the farming community, and interpreting and suggesting appropriate options for implementation in the catchment. The BDN approach has been selected because of its ability to represent the dryland salinity problem graphically and to model complex interactions between system variables. Additional reasons for selecting this approach are the ability of BDNs to integrate qualitative information and knowledge with quantitative information, and its capacity to deal with uncertainty.

Keywords: *salinity management; Bayesian decision network; conditional probability distribution*

1. INTRODUCTION

Land and water salinity is increasing in Australia (National Land & Water Resources Audit, 2001) and has serious negative effects on the environmental and socio-economic health of catchment systems. Addressing such a crucial environmental problem, at both large and small scales, requires an integrated catchment modelling approach, in which key biophysical and socioeconomic drivers, processes and impacts are all considered. This paper provides an overview of a Bayesian decision network approach being developed for the Little River Catchment (LRC) for such integrated management of dryland salinity.

2. CASE STUDY: THE LITTLE RIVER CATCHMENT

2.1 Catchment overview

The Little River Catchment (2388 km^2) is located in the Cabonne and Wellington council areas in the Macquarie River Basin in NSW (see Figure 1). The majority of the catchment is under dryland cropping and improved native pasture. The average annual precipitation in the LRC ranges from about 560 mm in the west to 700 mm in Molong in the south (IVEY&DPMS 2001). In terms of salt load contribution to the Macquarie River, the Talbragar and Little River contribute the greatest salt loads of any tributary. Approximately 12% of the salt load of the Macquarie River at Dubbo is from the Little River. There are severe salinity outbreaks in some parts of the catchment (IVEY& DPMS, 2001: 6.6). In 1988, 0.41% of the catchment was affected by dryland salinity. In 1998, this area was estimated to have increased fourfold to at least 4408 hectares (DLWC, 2000 cited in IVEY& DPMS, 2000). These figures indicate the increasing trend of salinisation in this catchment. "Total costs of dryland salinity are currently estimated as $1.67 million per year in the Little River Catchment" (IVEY& DPMS: iv).

IVEY & DPMS (2000) in Stage 2 of the Mid-Macquarie Regional Plan undertook a multi-criteria analysis (MCA) to find priorities for issues of concern among the catchment community. This study found that dryland salinity and high water tables in both rural and urban areas were of the highest concern.

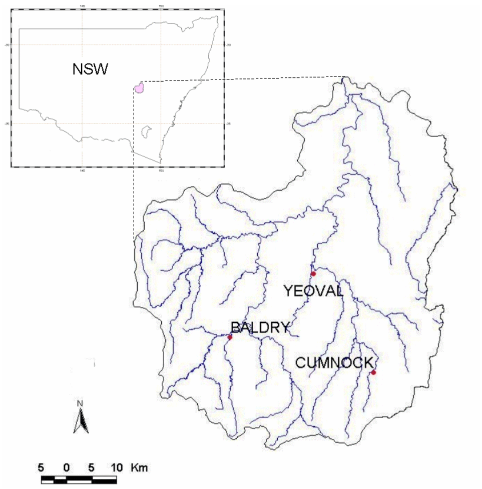

Figure 1. Little River Catchment

2.2 Salinity management in the Little River Catchment

Different Land Management Units (LMU) correspond with varying strategies for salinity management. LMUs are parcels of land identified by similar characteristics including topography, geology and soils. In addition, in every LMU the action needs to be focused on the areas that are already affected by outbreaks of salinity (IVEY and DPMS, 2001). Since dryland salinity has off-site impacts, an effective strategy should engage all land managers. The Stage Two Report of Mid-Macquarie Regional Plan (IVEY and DPMS, 2000) outlines the general principles for managing and preventing dryland salinity as:

- Decreasing discharge by increasing water use in recharge areas;
- Increasing water use in discharge areas;
- Considering more suitable land management strategies;
- Improving irrigation efficiency to reduce the potential risk of irrigation-induced salinity;
- Using water- balance models and monitoring water tables in cropping areas.

Water use in recharge areas could be increased by either using surface water in high transmission-loss streams, or by using rainfall over the recharge areas. The use of groundwater in non-saline or slightly saline aquifers could lead to discharge reduction. In discharge areas, increasing the usage of surface water could be effective in salinity control.

Preventative practices for salinity which have been recommended for the LRC are:

- Matching land use to land capability - by considering the water holding capacity and permeability of the soils;
- Reducing fallow duration and increasing crop frequency - by applying companion farming, response/opportunity cropping and delaying removal of deep rooted species until mid-summer;
- Using crop–pasture rotation (phase cropping);
- Applying fertilisers and/or ameliorants - in particular application of liming products is recommended to reduce acidification in some parts of the catchment;
- Practicing conservation farming - in order to improve ground cover and litter retention and to reduce soil compaction;
- Growing perennial mixed pastures;
- Applying strategic grazing - encouraging perennial vegetation, increasing plant regrowth;
- Implementing strategic tree planting - tree planting in appropriate areas brings the best results in terms of salinity control. Areas of high elevation have the highest priority. Also tree planting in areas where the groundwater is close to the surface is recommended;
- Conserving remnant vegetation - by re-establishing understorey, planting buffers around remnants, and linking remnants with corridors of native vegetation; and
- Monitoring - by establishing shallow and deep piezometer networks, and soil testing (IVEY and DPMS).

Where salinity outbreaks have already occurred and prevention is no longer an option, the use of best management practices can reduce salt discharge to stream and minimise other associated environmental problems such as erosion. These practices include:

- Strategic grazing - by fencing off the problem areas, and periodic grazing in suitable areas;
- Revegetation - by applying salt tolerant species, preferably a composition of grass, forb, and saltbush;
- Strategic tree planting - by applying fast growing and salt tolerant trees; and
- Engineering practices - by applying drainage systems, pumps, and using saline water where justified in terms of technical and economical issues (IVEY and DPMS).

Overall management options for dryland salinity in the catchment can be summarised as in Table 1.

Table 1. Management options for dryland salinity (adapted from Hall, 2002).

Practice	Process	Impact
Conservation farming Farm forestry Intercropping trails Native pasture Perennial pasture	Percolation	Reduce recharge and runoff
Remnant vegetation conservation	Percolation	Reduce discharge areas, recharge and runoff
Riparian corridor conservation	Groundwater interception, Reduce saline runoff to stream	Reduce discharge areas, recharge and runoff
Saline agro-forestry Saline pastures and Pumping	Pumping to reduce groundwater level	Reduce discharge areas
Drainage	Draining	Discharge areas

3. BAYESIAN NETWORKS

The previous section described the problem of dryland salinity in the LRC and discussed recommended management options for this problem. This section outlines a Bayesian Network approach which will be implemented for considering these management options in the catchment. Bayesian Networks (BNs) are capable of representing and considering uncertainty in system knowledge. "The basic concept in the Bayesian treatment of uncertainties in causal networks is conditional probability" (Krieg, 2001:10). Bayesian Networks use probability theory to manage uncertainty by explicitly representing the conditional dependencies between the different knowledge components (Varis and Kuikka, 1999). Bayesian methods provide a formalism for reasoning about partial beliefs under conditions of uncertainty (Pearl, 1988). "Bayesian networks are direct acyclic graphs (DAGs) in which the nodes represent variables, the arcs signify the existence of direct causal influences between the linked variables, and the strengths of these influences are expressed by forward conditional probabilities" (Pearl, 1988: 117). A direct acyclic graph is a graph that has directed arcs and no cycles. Each node or variable may take one of a number of possible states or values. "In BNs, Bayesian calculus is used to calculate probabilities of various outcomes, because it is known to have a strong theoretical basis and to provide a unified approach to statistical and deterministic theories" (Howson and Urbach, 1991cited in Varis, 2002:177).

Bayesian networks have only recently begun to be applied (Varis, 1997). However there are a significant number of applications in natural resources management, mostly completed recently (see for example Varis, 1997; Ames and Neilson, 2002; Ames, 2002; Varis and Kuikka, 1999).

There are several advantages of using BNs. One of the advantages in implementing Bayesian networks is the possibility of using either observed data, results from model simulations, or even expert knowledge in order to calculate the conditional probability between variables (see for example Ames, 2002; Pearl, 1988; Varis, 2002). This is potentially valuable in the area of natural resources management particularly in those situations where either the availability or reliability of the data connected to natural resources are limited. BNs allow integration of qualitative information and knowledge with the types of quantitative information generally included in integrated models. For example qualitative social information such as on farmers' attitudes towards adoption of best management practices is more readily integrated into BN than into other quantitative models. The uncertainties relating to this information can also be incorporated. Bayesian networks are an appropriate method to deal with uncertainty, which is a key issue in natural systems. A BN is particularly useful for communicating risk and uncertainty and providing a framework for analysing cause and effect relationships in natural systems (Ames, 2002). According to Krieg (2001) any change in the likelihood of a state of a variable in the BN is propagated through the network. In this way, the state of the entire system can be estimated given changes in any part of it (Ames, 2002). This ability makes BNs similar to neural networks, although BNs are more appropriate to modelling decision processes and causal reasoning than neural networks (Pearl, 1999 cited in Ames, 2002).

Ames (2002) categorises Bayesian networks into two main groups:

1) Bayesian Belief Networks (BBN)

In a BBN, marginal and conditional probabilities are estimated from both observed data as well as from expert knowledge, stakeholder opinion, and other subjective information sources (Ames, 2002). A BBN is most suited to issues where observed data are inadequate, but other sources of information are extensive. This is the case in many natural resource problems. According to Ames (2002) the challenge is to combine this subjective information with observed data to model the problems in natural resources management as closely as possible.

2) Bayesian Decision Networks (BDN)

BDNs are defined as Bayesian networks that have been modified to include decision (management option) variables and utility (benefit-cost) variables. BDNs can be considered as a useful tool for putting the decision process into diagrammatic form, for holding relationships between variables, and for analysing the expected effects of management decisions while accounting for the associated uncertainties (Ames and Neilson, 2001).

The next section outlines a preliminary conceptual framework of a BN for considering the issue of salinity management in the Little River Catchment. This framework represents a network of state nodes as well as management and utility nodes.

4. A CONCEPTUAL MODEL FOR SALINITY MANAGEMENT IN THE LITTLE RIVER CATCHMENT

The key variables in most integrated watershed management problems can be classified as:

A. State variables (S)- these are the variables that describe the condition of the system.

B. Decision variables (D)- these are sets of mutually exclusive management options.

C. Exogenous (E) - these are variables that can not be managed and are not affected by management actions.

D. Utility variables (U) - these are outcomes that can be measured in either economic or other terms that can be used to assess the success or failure of a decision (Ames, 2002).

4.1. Preliminary Bayesian decision network

Figure 2 begins to establish natural network connectivity and cause and effect relationships with respect to dryland salinity in the LRC. A preliminary BDN is constituted based on the expert judgment of the modelers. As various sources of information are employed to populate the BDN with conditional probability distributions, the model can be modified. This may occur when new data show that the current model of relationships in the network does not have a major effect in the system or when the data and information exploration reveal model relationships that were not previously considered in the BDN graph (Ames, 2002). Management issues are incorporated through belief propagation in the tree-structured causal networks. The outputs of the BDN include outcomes from various management scenarios using a scenario-based approach. In Table 2 key variables related to dryland salinity have been presented.

Table 2. Key variables grouped by location (recharge areas =R, discharge areas=D, in-stream =I).

Name of variable	Type	Location
Precipitation	E	R, D
Temperature	E	R, D
Lithology	E	R, D
Vegetation mosaic	D	R, D
Engineering practices	D	D
Recharge	S	R
Agricultural income	S	R
Groundwater level	S	D
Extent of discharge areas	S	D
Soil erosion	S	D
Wash off	S	D
Preferences	S	R, D
Evapotranspiration	S	R, D
Runoff	S	R, D
Biodiversity	S	R, D
Baseflow	S	I
Salt load in stream	S	I
Flow discharge in stream	S	I
Drinking water	S	I
Recreational use	S	I
Infrastructure	S	D, I
Cost of vegetation management	U	R, D
Cost of engineering practices	U	D
Revenue from agricultural income	U	R
Benefits from improving drinking water	U	I
Benefits from soil conservation	U	D
Benefits from recreational use	U	I
Benefits to infrastructure management	U	D,I

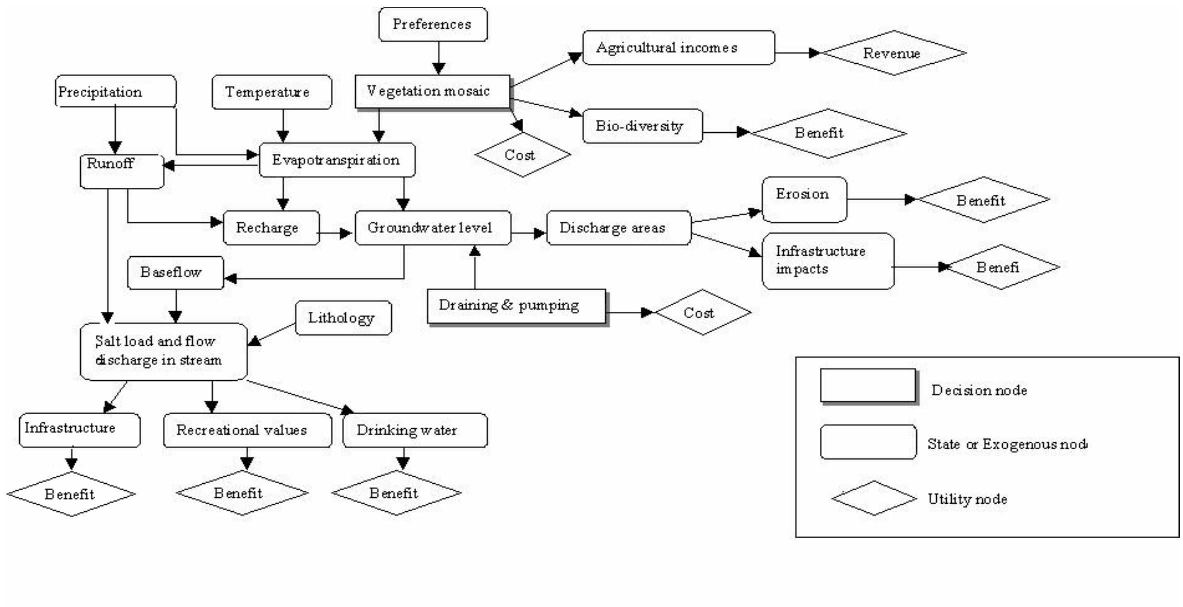

Figure 2. Preliminary Bayesian Decision Network for the Little River Catchment.

The variables of vegatation mosaic and engineering practices are directly influenced by the management alternatives at the recharge and discharge areas. The cost associated with the management options are shown as utility nodes in the diagram. The vegetation management options are effective on groundwater level through recharge, on the extent of discharge areas and eventually on salt load in the stream. Also engineering practices consisting of pumping and draining can change the groundwater level. Consequently, baseflow and salt load in the stream can be effected by the engineering practices to some extent. The crucial endpoint variables in this BDN are salt load in stream and discharge area extent.

In a completed Bayesian decision network, the connection between management options and endpoints can be made by a chain of any number of intermediate variables. However, it is preferable to choose the minimum number of intermediate nodes necessary to define the connections between management options and endpoints while capturing all of the variables needed for decision makers and stakeholders (Ames, 2002). The intermediate nodes should be informative and significant for estimating the endpoints values.

The above BDN will be used as a framework to address the dryland salinity problem in the Little River Catchment. In the following section, data sources and information availability are discussed.

4.2. Data and information sources

For practical purposes and ease of computation, conditional probability distributions will be defined through categorical conditional probability tables (CPTs). In a Bayesian decision network, CPTs can be generated from a variety of information sources including observed data, model simulation results, expert judgement, and economic analyses or stakeholders surveys (Ames, 2002).

In this study the main difficulty with developing CPTs is lack of data. In order to overcome this difficulty, a well-calibrated model will be used. This model has been developed (Carlile *et al.*, in prep.) in the LRC in order to investigate the effects of different land uses on recharge within each hydrological response unit (HRU), and on baseflow and runoff in each subcatchment. The model will also predict salt load contribution to the stream from each HRU and subsequent routing to the outlet point for each sub-catchment (Carlile *et al.*, in prep.). Salt load for each HRU is determined from soil, geology and saline discharge mapping. Conditional probabilities will be determined from the model using a Monte Carlo approach. These will become fully integrated with other elements of the BDN including costs and benefits of different management options. Cost of the management options for both vegetation alternatives and engineering practices in the BDN will be defined through a utility table. A utility table represents the utility of every combination of states of its parent node (Ames, 2002). Although extent of discharge areas and salt load in stream are the main endpoints in this research, considering additional endpoints, such as infrastructure, drinking water, recreational values, soil erosion and biodiversity, allows analysis of the social and economic impacts of management alternatives. In this way, other environmental impacts of salinity management can also be evaluated. Lack of data and difficulty in measuring or defining some attributes are the main obstacles for generating the conditional probability tables for some of the additional variables in the Little River Catchment. Economic analyses, professional judgement and stakeholder surveys are useful information sources to define the prior conditional distribution in study focus area. Given more data and information, these CPTs can be improved to indicate more precisely the probabilistic relationships between variables.

5. DISCUSSION

The Bayesian decision network methodology described in this paper attempts to provide a simple and effective representation of the complicated relationships between variables that are most significant to the natural resources management process. In this methodology, instead of pursuing a detailed model of small-scale processes, the focus is on information in its various forms and how one uses it to comprehend a large, complicated management problem in the context of causes and effects in a system (Ames, 2002). In this study, the emphasis is on defining the problem of dryland salinity in the Little River Catchment (outcomes of interest, available management options and essential intermediate variables) as well as the probabilistic relationships between these variables. One of the advantages of the BDN analysis is that the procedure decomposes a complicated problem into simple components that can be addressed separately. The other advantage of this methodology is the capability of using and integrating different sources of information in order to derive the conditional probability distribution between variables and thereby reducing data constraints. Future work will include: evaluation of the actual application of the BDN for dryland salinity management in the Little River Catchment; and analysing issues associated with updating the model with new data and information in terms of both model structure and conditional probability tables.

6. ACKNOWLEDGMENTS

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