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Water Quality & natural resource management on military training lands in Central Texas: Improved decision support via Bayesian Networks

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A B S T R A C T

The conservation and management of military training lands has long evolved around the unique criteria for maintaining a viable fighting force. In lieu of this primary mission, landscapes have often experienced accelerated degradation and loss of structural and functional capabilities for providing desired ecosystem services (including the basic training mission). In an effort to aid military land managers as well as anyone who makes and implements decisions for natural resource management; we support an innovative approach towards the integration of evidence and the application of diagnosis and prognosis for the decision-making process through the use of Bayesian Networks. Illustrated below is an example for utilizing Bayesian Networks in the decision support process. We utilized data and experience from ongoing efforts at the Fort Hood Military Installation to build the initial network; then integrate expert input from authors and engineers in propagating the node relationships. Through this approach, we demonstrate how military land managers can integrate varying streams of evidence, including empirical, model generated or expert opinion, into a network for decision support. The example below is developed based upon land management issues within the U.S. Army, but the process can be adapted and implemented across most all ecosystems under some form of land management.

1. Introduction

The integration across evidence empirically derived, model generated, and through expert opinion can provide a powerful tool in decision support for managing socio-ecological systems. However, bringing together these disparate sources of information is often a daunting effort, and unless this science can be brought to society through meaningful translations, it will continue to see degradation of landscapes (Schlesinger, 2010) and decision-making with less than optimal information. We propose that socio-ecological land managers can benefit from the utilization of Bayesian Networks in bringing together data, model predictions, and experts' beliefs, for informed decision-making as they progress towards "transdisciplinary" land management (Daily and Ehrlich, 1999). The implementation of BNs for decision making purposes has been discussed by Medina-Cetina and Nadim (2008) as a suitable tool to combine different sources of evidence such as monitoring data, theoretical models and expert's educated beliefs. The integration of this type of multi-level evidence through a probabilistic

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approach allows BNs to embody the causal dependencies between the variables involved in the modeling process, while accounting for the uncertainties associated to their belief. An early approach to study land management using BN was successfully implemented by Bacon et al. (2002), where a simple belief network was designed considering current and proposed land cover changes classified according to their relative financial, social and environmental estimated consequences. Pollino et al. (2007) explored an approach to parameterize BNs for environmental risk management based on expert's beliefs and real data that resulted in a robust and adaptive approach that allows decision makers to improve management practices for dynamic systems. A study that stands out for its applicability on environmentally friendly decision making evaluation protocol for oil and gas site developments was conducted by Yu et al. (2012). This work included a BN with the ability to select a specific type of available technology to analyze its potential environmental, economic and social consequences, and scaled their work to a web-based platform that allows the user to replicate their approach. The use of Bayesian networks are becoming increasingly popular as a means for "reasoning" under uncertainty (Nicholson and Flores, 2011) and have been utilized for predicting water quality management (Reckhow, 1999) and water resource planning (Bromley et al., 2005). The aim of this paper is to illustrate a framework for using Bayesian Networks to improve decision support systems that can influence water quality, and to illustrate this process through an example of real-world land management issues for managing military training lands in a rangeland setting.

Rangelands and their complexity provide a unique and often quite challenging backdrop to the art and science of natural resource management especially when military training is the primary use of the land system. Unsustainable management of rangeland systems leads to the degradation of both the resource base and the value of the commodities and benefits generated from these systems (National Research Council, 1994; Whisenant, 1999). Often times, the complexity and interactions of functions and processes in rangeland systems are overlooked, resulting in old prescriptions covered in new terminology; ultimately yielding the same outcomes from past management decisions (Stacey et al., 2000). The end of the 20th century was marked with the maturation of concepts associated with ecosystem management and adaptive approaches towards sustainability of rangeland resources. Science-based concepts from population to landscape ecology built upon the interrelatedness of ecosystem function and process across spatial and temporal scales and guided research in land management and ecological science into a new era of understanding. However, use of scientific and technological resources alone does not necessarily lead to successful management of natural resources. While the aspects provide evidence (i.e. experimental observations, model predictions and expert's beliefs) to guide decision-making, land managers may also consider socioeconomic and institutional components that may condition, and ultimately drive, the decision-making process (Meffe et al., 2012). In addition, land managers are faced with having to make decisions with less than full information available and are typically trying to manage effectively while minimizing unintended consequences (Bosch et al., 2007). For natural resource managers, this presents two issues; 1) how can good, science-based management decisions be made and 2) how can the manager best acquire the data needed to improve their understanding (McCann et al., 2006).

Holling et al. (2002) proposed that the issues associated with sustainable development and the complexities of ecosystems are not wholly limited to any single discipline, but are instead integrated across social, ecological and economic paradigms. Past challenges have often been addressed by devising solutions to complex issues through isolating the challenge from the wider context, ultimately leading to unintended consequences (van der Leeuw et al., 2011). Fox et al. (2009) visualized this through the use of a conceptual framework to evaluate the effectiveness of criteria and indicators for assessing sustainability on rangeland systems at regional and national scales. This framework was the basis for understanding the interactions across biophysical and human subsystems, and how those interactions can be tracked via indicators. Herein, the land manager is faced with varying amounts and types of evidence that must be translated into an 'optimal' decision-making process for implementation on the ground (e.g. empirical vs. theoretically driven models, maps with varying resolutions, field 'point' sampling, spatial clustering of data, varying frequency of monitoring, etc.). Land managers are also challenged with trying to apply "science" that has been developed and distributed through traditional peer-reviewed means and often are tested through "remote scenarios;" reductionist approaches (Bosch et al., 2007). Taken, piece-meal, these sources of guidance may cause the land manager to continue addressing symptoms of the issue without actually addressing the underlying causes. Resource management requires making difficult decisions within the realm of complexity, uncertainty and variability often resulting in decisions that are "imprecise" (McCann et al., 2006) In reality, it has been argued, conservation programs have had mixed success due to a lack of standardization or unrelated assessment/monitoring systems, leading to a loss of reliability and acceptance from the public (Müssner and Plachter, 2002). Moreover, although both the theory and practice of conservation has increased in acceptance, gaps remain between theoretical models and implementation of conservation actions (Pullin and Knight, 2001). Pickett et al. (1997) has suggested that there are two consistent problems in conservation biology: (1) "converting scientific knowledge into conservation practice," and (2) a "lack of monitoring and evaluation of conservation actions, particularly management plans." Pullin and Knight (2001) argue that in the absence of evidence to the contrary, managers will ultimately revert to "traditional" conservation practices and personal experience in determining what will be implemented. Through the use of Bayesian approaches, mental models based upon scientific evidence can be user defined and tested; thus providing a more effective approach to bridging the gap between science and management (Bosch et al. 2003; Bosch et al., 2007).

Progression from "experiential-based" decision-making to "effectiveness-based" decision-making requires the ability to integrate available sources of evidence, and to be able to trace quantitatively any changes on the state of evidence (e.g. increasing model complexity or expanding the data collection). One approach to this would be to integration of empirically generated data with output from computer simulation models and expert opinion of land managers. This paradigm shift requires a framework for which these different types of data can be integrated into a system that informs decision-makers and land managers of the risk associated with "potential" options and provides output upon which decisions can be made based on a wide range of information. Francis and Hamm (2011) discuss how the preparation of "regional land use plans requires the formulation of value statements and decisions about the future." They go on to discuss the important cultural and ecological values that must be protected; including the economic objectives and resulting benefits that may be achieved, the risk decision makers are prepared to accept, and whether the decisions result in unacceptable risks to stated cultural and/or ecological values. The use of Bayesian techniques has components that make the process useful in assessing "real-life" data analysis and management questions (Uusitalo, 2007). Utilizing Bayesian approaches provides a means for efficiently handling limited data, provides the ability to integrate a combination of information sources, and allows learning related to causal relationships (Heckerman and Wellman, 1995). Bayesian approaches can provide relatively good prediction accuracy with relatively small sample sizes (Kontkanen et al., 1997), and they are conducive to combining decision-support tools to assist in management (Kuikka et al., 1999; Marcot et al., 2001).

This paper demonstrates the use of Bayesian Networks (BN) to serve as a framework for integrating available sources of evidence that land managers and scientists alike can use to generate likely management scenarios derived from identified triggering events or control variables in a military training land management scenario. The Bayesian Network (BN) is a probabilistic causal graphical model representing the likely relationships of a set of events or random variables, related via a directed acyclic graph (DAG) (Korb and Nicholson, 2004). Events or random variables are represented as nodes, and their conditional dependencies are represented in directed edges. A probability function of the variable is assigned in each node. Using the dependency relationship, BN provides diagnostic (bottom-up, "symptoms to cause") and prognostic (top-down, "new information about causes to new beliefs about effects") probabilistic inference. In summary, the aim for using BN in natural resource management is to 1) assess the influence of available evidence, 2) to introduce the effect of causal relationships between the participating events/variables defined in the decision-making process (BN model), 3) to assess the inherent uncertainty associated to each participating event, and 4) to formulate a systematic and reproducible approach that allows for propagating and updating the state of evidence as the decision-making process starts and new evidence is collected.

To illustrate the benefits and limitations of the proposed approach, a synthetic case-study is presented that is built based upon land management challenges faced by military land managers in Central Texas, with the nodes being populated through expert opinion. Experts were two rangeland ecologists who have a long term working knowledge with natural resource management on the selected military installation, and two engineers who have extensive knowledge in utilizing process models to test aspects of data generated from the selected military installation. This problem is formulated using a simple conceptual model depicting the interactions between military training with mechanized vehicles and maintenance of water quality in local riparian areas that feed a drinking water reservoir. Water quality is considered the target variable, since training exercises have the potential for significant impact on downstream parameters. Bayesian Networks have been utilized across a broad swath of ecological questions from issues dealing with fisheries (Kuikka et al., 1999; Borsuk et al., 2002; Little et al., 2004); to impacts of climate change on crop production. From a water resources perspective, Batchelor and Cain (1999) utilized these approaches in the impact of farming systems by irrigated or rainfed approaches. This work outlines the potential capabilities of the approach with the objectives of: 1) illustrating the benefits and limitations of using BN as a tool in decision support for land managers, 2) providing a mathematical review of the process in support of the concept of an integrated approach for analyzing natural resource management options, and 3) testing of the concepts through a simplified case-study.

The added value of this work to natural resource management is to further demonstrate the ability and flexibility to assimilate available evidence into optimal-decision making under extreme land management constraints. During the evidence assimilation process, a decision-making model is generated, which is fundamental to generate likely scenarios upon changes of the system of interest. Therefore, this paper is not about the review of existing practice of rangeland management, nor about the development of a theoretical decision-making framework, but rather, about an integration of these two to improve current natural resource management in a military land management system.

2. Theory/calculation: water quality model development

2.1. Model formulation

An expert-based Water Quality BN model was constructed as part of the process to assimilate key variables defining water quality at the site of interest. The resulting model included eight variables: Climate (C), Water Storage (W), Management (M), Vegetation (V), Carbon Pools (CP), Runoff Erosion (RE), Production Traditional (PT), and finally Water Quality (WQ) (Fig. 1). The model depicts how the control variables and their relationships can influence the quality of water in the given area. This is not unique, but the authors' consensus is that it can serve as a first approach to define the corresponding natural resource management options.

The synthetic model represents the simplest interactions between the control variables taking place in the natural resource management program, balancing resulting variables CP, WQ and PT. The definitions of each of these random variables are as follows:

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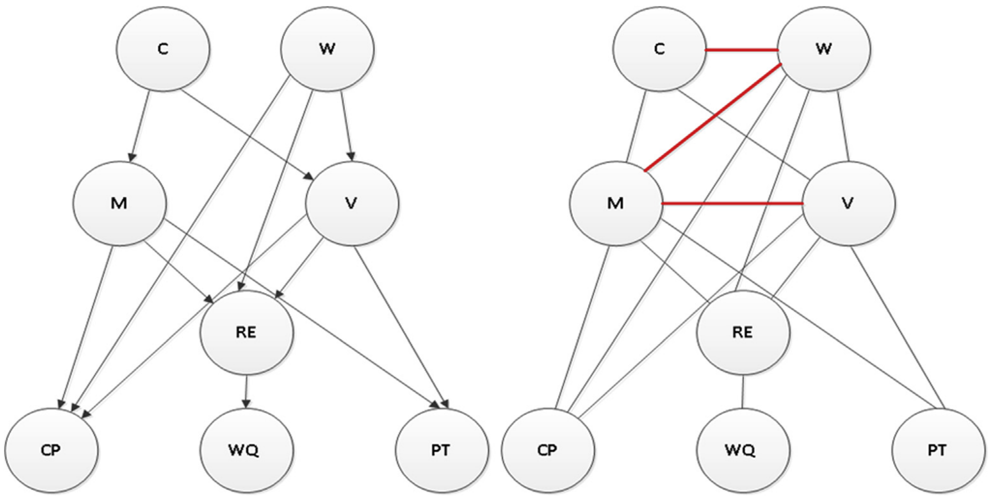

Fig. 1. The *Water Quality* Bayesian Network Model: *C* = Climate; *W* = Water Storage; *M* = Management; *V* = Vegetation; *CP* = Carbon Pools; *RE* = Runoff Erosion; *PT* = Production Traditional; *WQ* = Water Quality. Edges denote the conditional dependencies between variables. Unconnected nodes are conditionally independent. For example, biomass of the vegetation in the area has direct influence on the amount of runoff erosion, but not directly related to the management type.

- Climate (C) – defined an integration of temperature and precipitation relative to the long term average for the location.
- Water Storage (WS) – the ability of the system to retain water within the region due to soil texture, bulk density, and water holding capacity
- Management (M) – the land management choices made to support military mission.
- Vegetation (V) – the vegetation cover, biomass, and plant litter for a given site and growth form.
- *Carbon Pools (CP)* – above and belowground organic carbon that can be lost or sequestered.
- Runoff Erosion (RE) – the amount of water and soil loss from water runoff events
- Production Traditional (PT) – site productivity with regard to biomass yield and economic potential
- Water Quality (WC) – defined as the divergence from accepted water quality standards set forth for managing federal lands with regard to sediment load and nutrients,

In order to have a preliminary assessment on the influence of these variables in the definition of Water Quality, it is proposed to use qualitative descriptors (e.g. low, medium, and high), for which probability values representing their current state are assigned based on experts' opinion Tables 1-8. This can be easily updated once data and either empirical of physical based models become available, anticipating the corresponding uncertainty reduction in the predictions of the BN model. From here, we introduce the mathematical definition of the proposed model for illustrating its computational implementation.

2.2. Computational implementation

A Bayesian Network (BN) facilitates the generation of causal and evidence-based inferences as the state of each participating variable changes. This allows the user to measure the impact of likely interventions on the assessment of water qual-

Table 1
Climate Variable, P(C).

C1	0.01	Wet
C2	0.05	Average
C3	0.68	Dry
C4	0.27	Extra-Dry

Table 2
Water Storage Variable, P(W).

W1	0.05	Low
W2	0.7	Medium
W3	0.25	High

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Table 3
Management Variable, P(M|C).

	C1	C2	C3	C4	
M1	0.1	0.15	0.2	0.3	Minimum
M2	0.6	0.7	0.4	0.2	Moderate
M3	0.3	0.15	0.4	0.5	Intensive

Table 4
Vegetation Variable, P(V|C,W).

	W1				W2				W3				
	C1	C2	C3	C4	C1	C2	C3	C4	C1	C2	C3	C4	
V1	0	0.4	0.7	0.8	0	0.1	0.4	0.45	0	0	0.1	0.1	Low Biomass
V2	0.3	0.3	0.3	0.2	0.2	0.5	0.4	0.4	0.1	0.4	0.6	0.5	Medium Biomass
V3	0.7	0.3	0	0	0.8	0.4	0.2	0.15	0.9	0.6	0.3	0.4	High Biomass

ity (prognosis); or to define a target state of water quality, for identifying the triggering scenarios of the upper level variables that would allow for a certain level of quality to be reached (diagnosis).

The inference mechanism can be made through the message passing algorithm such as Kim and Pearl's, which is used most frequently for belief propagation, but works only on polytrees or singly-connected networks (Korb and Nicholson, 2004). However, a BN usually has a directly acyclic graph structure, as in the case of the proposed Water Quality model (Fig. 1), where two nodes are connected by more than one path. The connection between node W (Water Storage) and R (Runoff Erosion) Fig. 1 is an example of the multi-path connection, which has both direct (W-R) and indirect (W-V-R) connections (Fig. 1). Such cases are not handled by the message passing algorithm, and a method called 'clustering' is developed to transform a graph into a probabilistically equivalent polytree. A clustering algorithm merges multiple nodes to remove the multiple paths between two nodes (i.e., joint-clustering algorithm, Korb and Nicholson 2004). This algorithm consists of 3 main steps (Korb and Nicholson, 2004):

i. Moralization – connecting all parents and removing connective arrows.
ii. Triangulation – adding connective arrows to guarantee the formation of a triangulated graph.
iii. Junction Tree – identifies maximal 'cliques' (a set of nodes that are pairwise linked) to create 'supernodes'.

The first step, moralization is based in 'marrying' the parents of a child node. Triangulation is conducted for ensuring that the joint probability terms are functions of the existing dependencies between nodes containing a complete acyclic graph.

After the Water Quality model was translated into a polytree, it was possible to examine the computational implementation of Kim and Pearl's message passing algorithm for updating the nodes' beliefs. Herein, the total strength of belief was defined as the product of the causal support ($\pi(X)$) from parent and the diagnostic support ($\lambda(X)$) from descendants:

$$BEL(X) = \alpha\lambda(X)\pi \tag{1}$$

where α is a normalizing constant that makes $\sum_X BEL(X) = 1$. From the original model in Fig. 1, $P(C)$, $P(W)$, $P(M|C)$, $P(V|C,W)$, $P(CP|M,V,W)$, $P(RE|M,V,W)$, $P(PT|V,W)$, and $P(WQ|RE)$ were given. These represent the current state of information for each variable, and defines the passing of information on both diagnosis and prognosis analysis.

For the prognosis analysis, or top-down message passing, calculating the belief starts from root node (Z_1 in the example), and propagates to the leaves as depicted in Fig. 2 which shows the two steps that the top-down messages travel. Conventionally, $\pi_Y(X)$ denotes a top-down message from node X to Y. The probability of the initial top-down messages is given by:

$$\pi(Z_1) = \pi_{Z_2}(Z_1) = \pi_{Z_4}(Z_1) = P(Z_1) = P(C,M,V,W) = P(C)P(M|C)P(V|C,W)P(W) \tag{2}$$

Eq. (2) stands for the 108-component vector shown as $\pi(Z_1)$. Because the default bottom-up messages (λ's) were unit vectors, therefore $BEL(Z) = \pi(Z_1)$. Before passing $\pi(Z_1)$ to Z1's children, the marginal probabilities of nodes M and V were computed by simply summing up the appropriate rows. Thus, the computation of marginal probability $P(M)$ was:

$$\begin{cases} P(M=m_1) = \sum_{id=1}^{9} row_{id} + \sum_{id=28}^{36} row_{id} + \sum_{id=55}^{63} row_{id} + \sum_{id=82}^{90} row_{id} = 0.16 \\ P(M=m_2) = \sum_{id=10}^{18} row_{id} + \sum_{id=37}^{45} row_{id} + \sum_{id=64}^{72} row_{id} + \sum_{id=91}^{99} row_{id} = 0.58 \\ P(M=m_3) = \sum_{id=19}^{27} row_{id} + \sum_{id=46}^{54} row_{id} + \sum_{id=73}^{81} row_{id} + \sum_{id=100}^{108} row_{id} = 0.26 \end{cases} \tag{3}$$

Table 5
Carbon Pool Variables, P(CP|M,V,W).

	M1									M2									M3									
	W1			W2			W3			W1			W2			W3			W1			W2			W3			
	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	
CP1	0.8	0.7	0.6	0.8	0.2	0.1	0.8	0.1	0.1	0.8	0.6	0.3	0.8	0.1	0.05	0.8	0.05	0	0.8	0.5	0.2	0.8	0.1	0.05	0.8	0	0	Low
CP2	0.2	0.25	0.3	0.2	0.3	0.3	0.2	0.3	0.2	0.2	0.3	0.4	0.2	0.2	0.15	0.2	0.25	0.15	0.2	0.3	0.5	0.2	0.3	0.25	0.2	0.2	0.1	Medium
CP3	0	0.05	0.1	0	0.5	0.6	0	0.6	0.7	0	0.1	0.3	0	0.7	0.8	0	0.7	0.85	0	0.2	0.3	0	0.6	0.7	0	0.8	0.9	High

Table 6
Runoff Erosion Variable, P(RE|M,V,W).

	M1									M2									M3									
	W1			W2			W3			W1			W2			W3			W1			W2			W3			
	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	V1	V2	V3	
RE1	0.5	0.3	0.5	0.35	0.35	0.6	0.1	0.4	0.85	0.5	0.4	0.65	0.25	0.45	0.75	0.1	0.5	0.85	0.5	0.5	0.8	0.2	0.55	0.8	0.1	0.6	0.9	Low
RE2	0.3	0.4	0.4	0.25	0.4	0.3	0.2	0.4	0.1	0.35	0.35	0.25	0.3	0.35	0.15	0.25	0.35	0.1	0.35	0.35	0.15	0.3	0.35	0.15	0.3	0.3	0.1	Medium
RE3	0.2	0.3	0.1	0.4	0.25	0.1	0.7	0.2	0.05	0.15	0.25	0.1	0.45	0.2	0.1	0.65	0.15	0.05	0.15	0.15	0.05	0.5	0.1	0.05	0.6	0.1	0.1	High

Table 7
Production Traditional, P(PT|V,W).

	M1			M2			M3			
	V1	V2	V3	V1	V2	V3	V1	V2	V3	
PT1	0.7	0.35	0	0.5	0.25	0	0.3	0.15	0	Unsustainable
PT2	0.3	0.45	0.6	0.5	0.5	0.45	0.7	0.5	0.3	Sustainable
PT3	0	0.2	0.4	0	0.25	0.55	0	0.35	0.7	Maximized

Table 8
Water Quality Variable, P(WQ|RE).

	RE1	RE2	RE3	
WQ1	0.1	0.6	0.7	Low
WQ2	0.2	0.2	0.2	Medium
WQ3	0.7	0.2	0.1	High

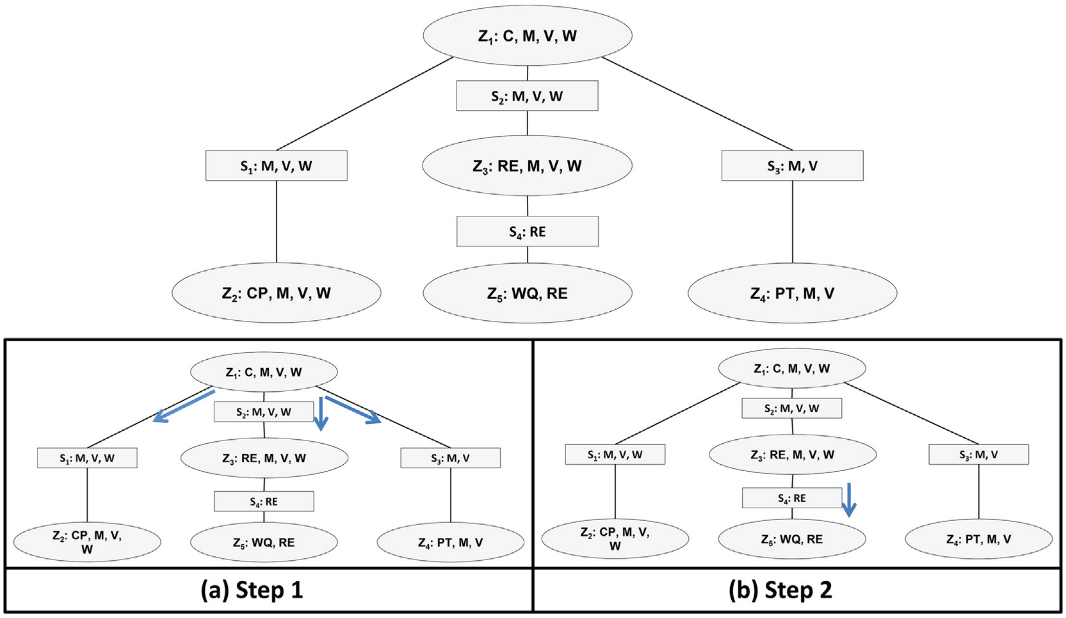

Fig. 2. Top-Down Message Propagation. (a) Root node (Z_1) initiates the message to its children ($\pi(Z_1) = \pi_{Z_2}(Z_1) = \pi_{Z_3}(Z_1) = \pi_{Z_4}(Z_1)$). (b) Then, Z3 sends a message to the leaf node ($\pi_{Z_5}(Z_3)$).

We then considered $\pi_{Z_2}(Z_1)$. The interdependencies between Z_1 and Z_2 were from the shared variable $Z_1 \cap_2^Z$. That is:

$$S1 : P(Z_2|Z_1) = P(Z_2|Z_1 \cap_2^Z) = P(CP, M, V, W|M, V, W) = P(CP|M, V, W) \tag{4}$$

As was the case of Z_1, the top-down message that Z_2 generates was the same as the prior probability of $Z2$. Using Eq. (4):

$$\pi(Z_2) = P(Z_2) = \sum_{Z_1} P(Z_2|Z_1)P(Z_1) = \sum_{C} P(CP|M, V, W)P(C, M, V, W) = P(CP|M, V, W)P(M, V, W) \tag{5}$$

which means that the π-message from node Z_j receiving message from Z_i through a separator S_k can be calculated by multiplying the interdependency defined by S_k ($P(CP|M, V, W)$) (Eq. (5)), and the joint probability of the variables in the S_k ($P(M, V, W)$ (Eq. (5)). Estimates of $P(CP|M, V, W)$ and $P(M, V, W)$ were then obtained and $\pi(Z_2)$ established in the form of 81-component vectors. Summing up the rows, the marginal probability of CP was computed. Top-down messages $\pi(Z_3)$ and $\pi(Z_4)$ and the marginal probabilities $P(RE)$ and $P(PT)$ were calculated in a similar way (Eqs. (6) and (7)):

$$\pi(Z_3) = P(Z_3) = P(RE|M, V, W)P(M, V, W) \tag{6}$$

$$\pi(Z_4) = P(Z_4) = P(PT|M, V)P(M, V) \tag{7}$$

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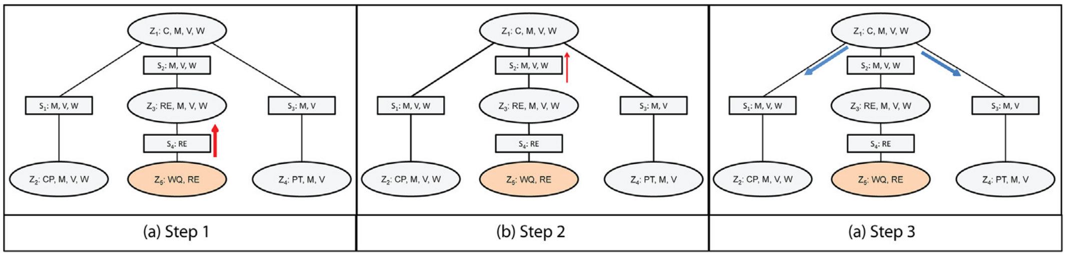

Fig. 3. Bottom-Up Message Propagation. (a) Evidence is entered to node Z_4 to initiate the message to its parent ($\lambda_{Z_3}(Z_5)$). (b) Then, Z_3 sends a message to the root node ($\lambda_{Z_1}(Z_3)$). (c) To deliver the effect of the evidence to the nodes Z_2 and Z_4, Z_1 produces top-down messages ($\pi_{Z_2}(Z_1)$ and $\pi_{Z_4}(Z_1)$).

Then, as in Fig. 2(b), Z3 was able to send a π-message down to Z_5. Next $\pi(Z_5)$ was calculated using Eq. (8) and $P(WQ)$ was then calculated by summing up appropriate variables.

$$\pi(Z_5) = P(WQ|RE)P(RE) \tag{8}$$

For the diagnosis analysis or the bottom-up message passing example, evidence was entered at $WQ = wq_3$ (high). Back-propagation of information started at Z_5 (Fig. 3), and continued up to the root. Fig. 3 shows the three steps where the bottom-up messages and their by-product top-down messages travel. As shown in Fig. 3(c), bottom-up belief propagation sometimes can produce top-down messages to convey the effect of the evidence to the entire tree. Conventionally, $\lambda_X(Y)$ denotes a bottom-up message from node Y to X:

$$\lambda(Z_5) = \begin{cases} 1 & if\ WQ = wq_3 \\ 0 & otherwise \end{cases} \tag{9}$$

and this message prompts Z_5 to generate a corresponding λ-message for Z_3

$$\lambda_{Z_3}(Z_5) = Dependency(S_4) * \lambda(Z_5) = P(WQ = wq_3|RE) = \{0.7, 0.2, 0.1\} \tag{10}$$

which in turn generates new belief of Z_3.

For the new $BEL(Z_3)$, Eq. (1) was used with the $\pi(Z_3)$ given from the above top-down process. Note that the normalizing constant α in Eq. (1) was not 0 this time. With the new $BEL(Z_3)$, the marginal probability $P(RE)$ was calculated.

Next, $\lambda(Z_3)$ was obtained from the bottom-up message Z_3. This is further illustrated in Eq. (11), for obtaining $\lambda_{Z_1}(Z_3)$:

$$\lambda_{Z_1}(Z_3) = Dependency(S_2) * \lambda(Z_3) = \begin{cases} P(RE = re_1|M, V, W) \\ P(RE = re_2|M, V, W) \\ P(RE = re_3|M, V, W) \end{cases} \tag{11}$$

After computing $\lambda(Z_1) = \lambda_{Z_1}(Z_3)$, $BEL(Z_1)$ was re-calculated using Eq. (1). With the updated $BEL(Z_1)$, new $P(C)$, $P(M)$, $P(V)$, and $P(W)$ values were calculated.

In the last step, top-down messages were sent from Z_1 to Z_2 and Z_4 ($\lambda_{Z_2}(Z_1)$ and $\lambda_{Z_2}(Z_1)$). $P(M, V, W)$ for $\pi_{Z_2}(Z_1)$ and $P(M, V)$ for $\pi_{Z_4}(Z_1)$ was be calculated. Updated $BEL(Z_2)$ and $BEL(Z_4)$ and new marginal probabilities of CP and PT were then developed.

3. Climate node definition

The Water Quality model contains a Climate variable (node) that was site specific for the proposed analysis. This is defined as a probabilistic distribution of four discrete climate states: Wet, Average, Dry and Extra-Dry. To offer a more realistic interpretation of climate states for this analysis, a climate reference index was chosen for the Fort Hood area that could reflect the node's definition included in the WQ model. The Standardized Precipitation Evapotranspiration Index (SPEI) was chosen for this purpose as it can reflect the climate states based on temperature and precipitation. It is calculated using the monthly (or weekly) difference between precipitation and Potential Evapotranspiration (PET) (Serrano et al., 2008).

The state of climate at Fort Hood was compared to the driest and wettest places in the world to identify the trend of the climate behavior. A representative extreme dry site in the world is the Atacama Desert, Chile, (McKay, 2002), with the lowest annual precipitation records due to the barrier effect of the Andes mountain belt. On the other hand, Mt. Waialeale in Hawaii records more than 1145 cm (451 inches) of annual precipitation, and counts as the wettest spot in the world (USGS, 2012). Relative cumulative frequency curves were plotted to compare, on a global scale, the SPEI patterns from 1950 to 2009 between the wettest and driest places in the world with respect to the Fort Hood area. From the data gathered, four plots were prepared based on 1-, 3-, 6- and 12-month time periods SPEI (Fig. 4 a-d).

The domain of the plots for one month SPEI of the three studied locations allowed for determining the minimum and maximum estimates, which were used to obtain the corresponding quartiles. The readings on the Fort Hood's relative cumulative curve for each quartile defined the state of information for each quarter of the domain, which were translated into the discrete distribution of the climate variable. Extreme values of the climate distribution, the quartiles and the respective read-

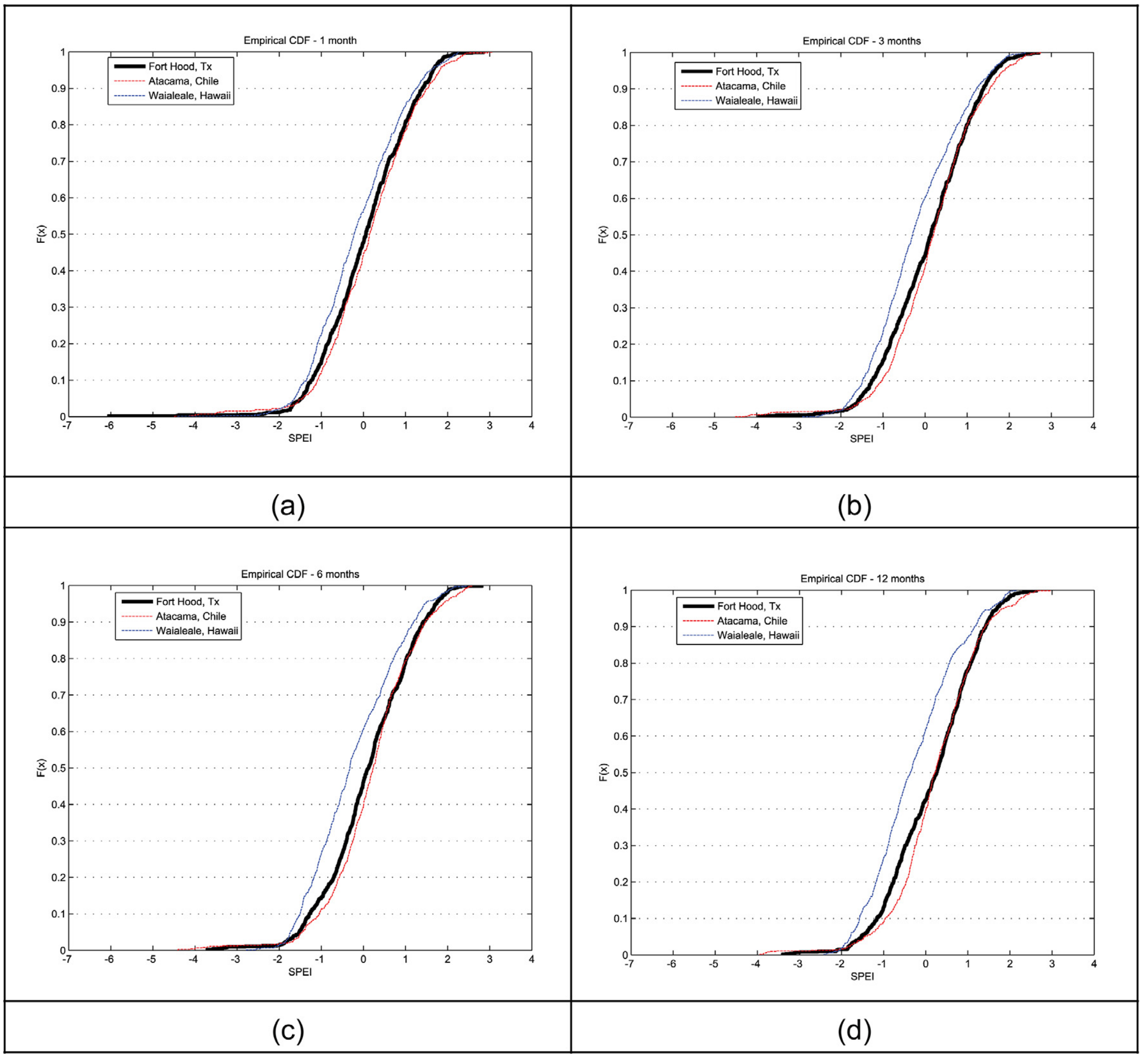

Fig. 4. Relative cumulative frequency curves for SPEI data in Atacama Desert, Chile, Mt. Waialeale, Hawaii, and Fort Hood, Tx. Temporal range of (a) 1 month; (b) 3 months; (c) 6 months and (d) 12 months.

ings in the relative cumulative function of the study area were calculated. The computation of the probability density function of the climate node was made using Eq. (12).

$$P(C_j) = F(Q_i) - F(Q_{i-1}), \mathrm{j} = \{1, 2, 3, 4\} \tag{12}$$

where$P(C_j)$: Probability of a climate state ($i = \{\mathrm{Extra} - -\mathrm{Dry}, \mathrm{Dry}, \mathrm{Average}, \mathrm{Wet}\}$) $\mathrm{F}(Q_i)$: Relative Cumulative Frequency, $i = \{4, 3, 2, 1, 0\}$.

Definition of the remaining nodes was based on expert's opinions. A panel of 3 experts was convened and specific questions were asked to determine node definitions and probability values. These are anticipated to change as new data and/or model predictions become available, reducing the uncertainty on the estimates of the participating variables (i.e. nodes), and consequently providing higher confidence in the decision-making process involving the testing of interventions (e.g. change of management M, water storage W, vegetation V, etc.). The illustrative case introduced below, shows the likely effects of different states of information, when different interventions take place during the process for defining Water Quality at Forth Hood TX, either in prognosis or in diagnosis. Numerical computations were conducted using GeNie software (Loboda et al., 2010).

4. Discussion

Once the climate node was defined for the Fort Hood, TX area a prognosis analysis was conducted using the proposed Ecosystem Services Model (Fig. 5). The message provided by the parent Climate shown as predominantly Dry and Extra

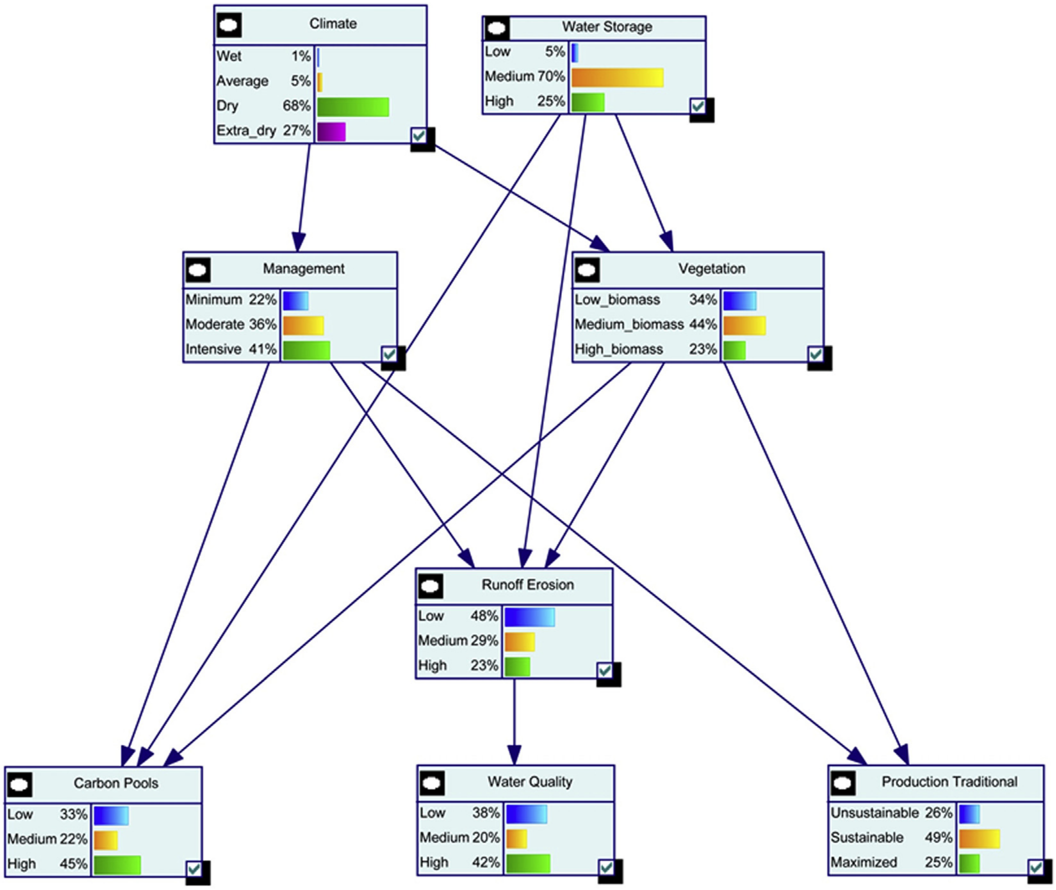

Fig. 5. Water Quality Model for Prognosis.

Dry, with an 70% probability of a medium Water Storage capacity, and the conditional probability tables (CPTs) defined by the intermediate nodes M, V and RE, yielded ambivalent or extreme and practically symmetric type of distributions for Carbon Pools and Water Quality levels (u-shaped, with extreme probabilities of low plus high about exceeding 80%), while Production Traditional showed a bell-shape type of behavior with about 50% probability of 'sustainable'. This analysis represents the expected state system response for an annual estimate of Water Quality at Fort Hood under drought conditions.

From the climate state standpoint, the prognosis results for Water Quality indicate potentials for higher marginal probabilities of low water quality (0.38) and high water quality (0.42) when compared to moderate water quality (0.20) (Fig. 5). These results appear to be driven by effects of the Dry and Extra Dry Climate States which influence vegetation cover. Low water quality in the network is driven by the run-off erosion variable. Conditions that were conducive to higher probabilities of high runoff were low Vegetation conditions with high Water Storage. At Fort Hood, a likely scenario for these conditions could be training areas that, at the beginning of drought conditions, have had vegetation removal during military training when soil water storage was high. Any rainfall received would have higher potential for runoff and erosion due to lack of vegetation cover and higher soil moisture status. Conditions that were conducive to higher probabilities of low runoff and erosion (and therefore higher water quality) were low, medium, and high Water Storage with high Vegetation amounts. Management intensity also increased probability of low runoff erosion for the high Vegetation states. A scenario such as this at Fort Hood would be sites where adequate vegetation biomass is maintained or vegetation has been allowed to recover after a disturbance.

The Carbon Pools variable responded similar to the Water Quality variable with regard to probability for low and high amounts (Fig. 5). Conditions that led to high Carbon Pools were associated with conditions of higher Water Storage and higher Vegetation biomass. Low Carbon pools were driven by the drier climate and water storage impacts on vegetation biomass which resulted in higher probabilities of low carbon storage.

A set of diagnosis or bottom-up message propagation analyses were formulated for six cases with extreme conditions for the variables at the lowermost side of the Ecosystem Services model (Carbon Pools: low and high; Water Quality: low and high; and Production Traditional: unsustainable and maximized). These six conditions are described, and likely interventions are discussed that could help to improve the understanding on the impact these interventions may have, if implemented.

For the diagnosis analysis for Carbon Pools, we used 100% probability estimates for either high or low carbon pools as our target, and then assessed the impacts on the responding nodes of the network (Fig. 6). Under this diagnosis scenario, we would predict significant impacts on the water storage, vegetation, runoff/erosion and production nodes. For low carbon pools, reduced water storage capacity from the "low" and "medium" capacity categories were seen as sensitive variables for low carbon pools (Fig. 6a). As would be expected, the Vegetation variable exhibited one of the strongest responses with percentage of low vegetation biomass (83%) resulting in the low carbon pools. In addition, the runoff/erosion node shows an increase in the "high" category from 12% to 39% while the "unsustainable" production node increases from 14% to 42% due to the strong influence of the low vegetation biomass nodes on these variables. Under the 100% high Carbon Pools diagnosis, vegetation biomass exhibited large shifts in the vegetation biomass probabilities with medium biomass and high biomass having 61% and 39% probability, respectively while the low biomass in the Vegetation node went down to zero. The Water Storage node also exhibited shifts with a greater percentage of high Water Storage needed to have Carbon Pools at 100% high. Lastly, the Management and Climate nodes show less sensitivity than the other variables for the Carbon Pool extremes.

For the second diagnosis analysis, two Water Quality extremes were evaluated to allow examination of how a hypothetical land manager could use this to assess factors that influence what is acceptable (regulated) regarding the quality of water that departs the installation's landscape. For this analysis, low quality water and high quality water as set at 100% probability and the diagnosis analysis was performed. If the manager were willing to accept 100% low quality water, the impacts are quite significant on the contributing factors. Perhaps most obvious is the significant increase in runoff erosion predicted from 6% under high water quality to 43% under low water quality (Fig. 7a). This result is driven by higher probabilities of low biomass in the vegetation node which also results in a diminished storage in the carbon pool under this scenario. For the other Water Quality extreme (100% high Water Quality), the opposite occurs where higher probabilities of high vegetation biomass would be needed to reduce Runoff Erosion and shift Carbon Pools to medium and high (Fig. 7b).

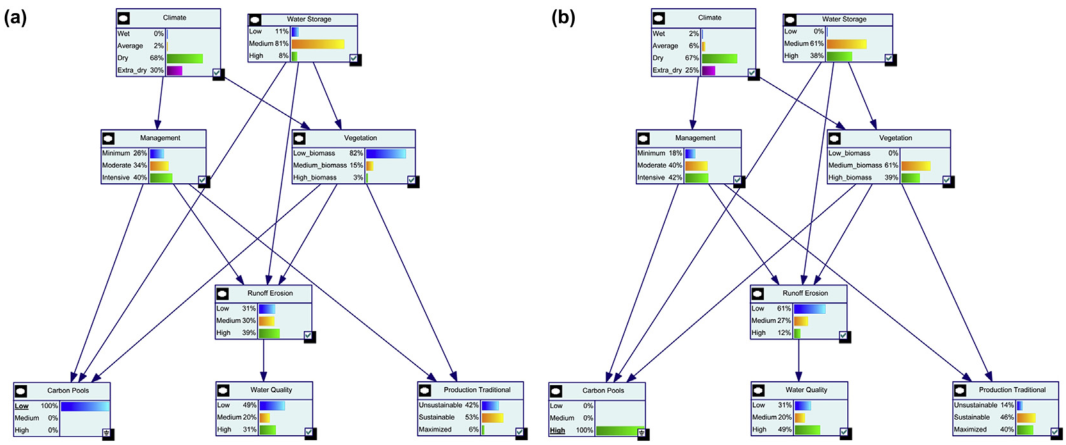

Fig. 6. Water Quality Model for Diagnosis after setting known values of Carbon Pools in extreme conditions. a) 100% Low; b) 100% High.

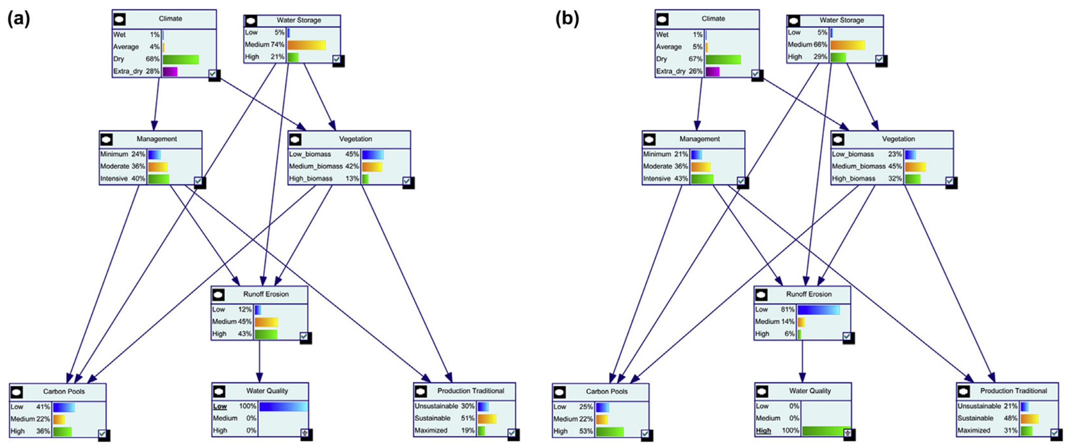

Fig. 7. Water Quality Model for Diagnosis after setting known values of Water Quality: a) 100% Low; b) 100% High.

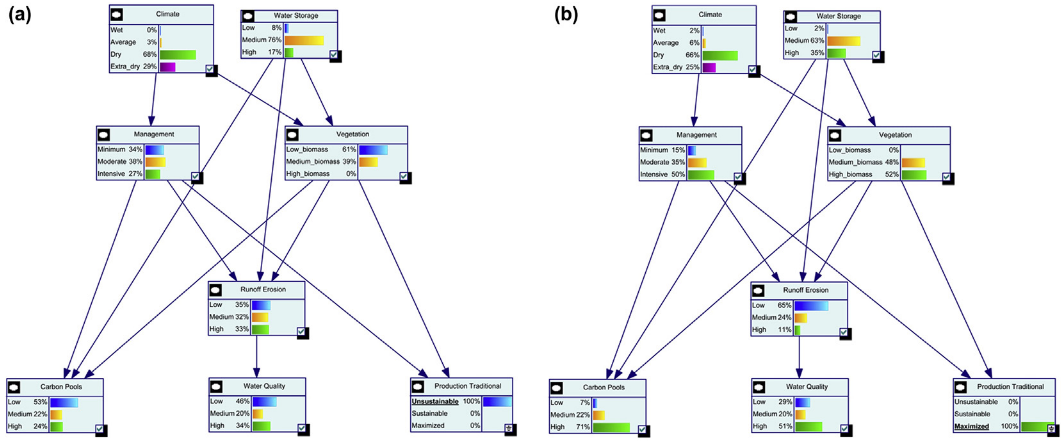

Fig. 8. Water Quality Model for Diagnosis after setting known values of Production Traditional extremes: a) 100% Unsustainable; b) 100% Maximized.

Finally, Fig. 8 shows the likely scenarios when back-propagating the extreme conditions of Production Traditional. When the diagnosis is set to obtain a 100% unsustainable Production Traditional, a non-informative distribution was seen for both the Runoff Erosion and Management nodes. The Vegetation node appeared to be the most sensitive and was characterized by a predominant low to medium biomass probabilities (Fig. 8a). On the other hand, when anticipating 100% of maximized Production Traditional, the Runoff Erosion exhibited a higher probability of having low RE (Fig. 8b). In this scenario, Management was a sensitive variable with higher probabilities of mid to intense Management practices required to achieve maximized production. The updated state of the Vegetation variable, given a maximized Production Traditional, favored 100% mid to high biomass. The sensitivity of the Climate and Water Storage given extremes conditions for PT does not appear to be as sensitive as the other variables (Fig. 8b). An interesting point regarding these production extremes is the minimal difference between "unsustainable" and "maximized" production on the Water Quality node. There is a slight difference between "low" and "high" water quality under the two scenarios, but perhaps not as much of a difference as might be expected by the land manager.

For the purposes of this paper, the diagnostic analysis illustrated only single interventions; however, the flexibility of the Bayesian approach allows for simultaneous interventions to be analyzed as well. The single interventions were presented to show the potential of starting with expert's opinions to build a model that can recreate the complexity of dynamic processes. The proposed model is introduced as a tool to generate approximate scenarios based on causal probabilistic reasoning, which can be further refined after introducing simulation modeling or field collected data. Moreover, the proposed model can be calibrated once additional evidence becomes available, thus, requiring only the 'updating' of the state of nature it represents.

5. Conclusions

This paper uses probabilistic causal inference as applied to natural resource management for ecosystem services. This framework provides an opportunity for military installations, such as Fort Hood, to implement this integrated framework for evaluation of climate, management, and environmental variables that impact ecosystem services which could alter sustainability of training and the natural resource base. Details about its computational implementation is discussed, as well as preliminary investigations on prognosis and diagnosis analyses are presented for extreme control conditions, as a way to present changes on the state of information in the proposed control variables. It is anticipated that the uncertainty for the different variables included in the model will be reduced, as additional evidence is introduced into the model (e.g. simulation model predictions and field data). This would allow for the model calibration and refinement, and a later implementation that would require the model updating. The BN framework also provides opportunities for informed adaptive management (Bashari et al. 2008; Rumpff et al. 2011). As simulation modeling and field data collection systems are put in place and allowed to update nodes in the BN, managers can adapt to the changing conditions to more effectively manage the installation services.

The Bayesian Network presented here allows opportunities for examining ecosystem services in a prognostic and diagnostic way to assess uncertainties and sensitive variables. Bashari et al. (2008), in an evaluation of a Bayesian network for a state and transition model of subtropical grasslands in Australia, stated that the Bayesian network provided opportunities to incorporate expert knowledge and accommodate uncertainty and variability within the modeling approach.

Results from the different prognosis and diagnoses scenarios, showed a consistent behavior with previous data and models developed for most traditional grassland dominated systems; thus indicating that the original BN functions within the realm of reality for these landscapes. With the process in place, work can continue with a more defined effort for the military landscape for which the illustration was prepared. In the future, the framework can be expanded to accommodate additional nodes that could influence ecosystems services and training sustainability at military installations. Haines-Young (2011) point out that BNs provide capabilities to capture stakeholder opinions in order to evaluate, compare and analyze different stakeholder perspectives. These capabilities could potentially enhance management and training decisions to optimize trade-offs and reduced impacts to ecosystem services and military training.

References

Bacon, P.J., Cain, J.D., Howard, D.C., 2002. Belief network models of land manager decisions and land use change. J. Environ. Manage. 65 (1), 1–23.
Bashari, H., Smith, C., Bosch, O.J.H., 2008. Developing decision support tools for rangeland management by combining state and transition models and Bayesian belief networks. Agric. Syst. 99 (1), 23–34.
Batchelor, C., Cain, J., 1999. Application of belief networks to water management studies. Agric. Water Manage. 40 (1), 51–57.
Borsuk, M.E., Stow, C.A., Reckhow, K.H., 2002. Predicting the frequency of water quality standard violations: A probabilistic approach for TMDL development. Environ. Sci. Technol. 2109–2115.
Bosch, O.J.H., Ross, A.H., Beeton, R.J.S., 2003. Integrating science and management through collaborative learning and better information management. Syst. Res. Behav. Sci. 20, 107–118.
Bosch, O.J.H., King, C.A., Herbohn, J.L., Russell, I.W., Smith, C.S., 2007. Getting the big picture in natural resource management – systems thinking as a "method" for scientists, policy makers and other stakeholders. Syst. Res. Behav. Sci. 24, 217–232.
Bromley, J., Jackson, N.A., Clymer, O.J., Giacomello, A.M., Jensen, F.V., 2005. The use of Hugin® to develop Bayesian networks as an aid to integrated water resource planning. Environ. Model. Softw. 20, 231–242.
Daily, G.C., Ehrlich, P.R., 1999. Managing Earth's ecosystems: an interdisciplinary challenge. Ecosystems 2, 277–280.
Fox, W.E., McCollum, D.W., Mitchell, J.E., Swanson, L.E., Kreuter, U.P., Tanaka, J.A., Evans, G.R., Heintz, H.T., Breckenridge, R.P., Geissler, P.H., 2009. An integrated social, economic, and ecologic concept (ISEEC) framework for considering rangeland sustainability. Soc. Nat. Resour. 22, 593–606.
Francis, S.R., Hamm, J., 2011. Looking forward: using scenario modeling to support regional land use planning in Northern Yukon, Canada. Ecol. Soc. 16 (4), 18. http://dx.doi.org/10.5751/ES-04532-160418.
Heckerman, D., Wellman, M.P., 1995. Bayesian networks. Commun. ACM 38 (3), 27–30.
Holling, C.S., Gunderson, L.H., Ludwig, D., 2002. In quest of a theory of adaptive change. In: Gunderson, L.H., Holling, C.S. (Eds.), Panarchy: Understanding Transformations in Human and Natural Systems. Island Press, Washington, D.C..
Haines-Young, R., 2011. Exploring ecosystem service issues across diverse knowledge domains using Bayesian Belief Networks. Prog. Phys. Geogr. 35 (5), 681–699.
Kontkanen, P., Myllymaki, P., Silander, T., Tirri, H., 1997. Comparing predictive inference methods for discrete domains. In: Proceedings of the sixth Internationa Workshop on Artificial Intelligence & Statistics. Ft. Lauderdale, FL pp. 311-318.
Korb, K.B., Nicholson, A.E., 2004. Bayesian Artificial Intelligence. Chapman and Hall, Boca Raton, Florida, US.
Kuikka, S., Hilden, M., Gislason, H., Hansson, S., Sparholt, H., Varis, O., 1999. Modeling environmentally driven uncertainties in Baltic cod (*Gadus morhua*) management by Bayesian influence diagrams. Canad. J. Fish. Aq. Sci. 56, 629–641.
Little, L.R., Kuikka, S., Punt, A.E., Pantus, F., Davies, C.R., Mapstone, B.D., 2004. Information flow among fishing vessels modelled using a Bayesian network. Environ. Modell. Software 19 (1), 27–34.
Loboda, T., Voortman, M., 2010. GeNIe. (Version 2.0) [Computer Software]. Decision System Laboratory. University of Pittsburg. Retrieved February 2011. Available from http://genie.sis.pitt.edu/.
Marcot, B.G., Holthausen, R.S., Raphael, M.G., Rowland, M.M., Wisdom, M.J., 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. For. Ecol. Manage. 153 (1), 29–42.
McCann, R.K., Marcot, B.G., Ellis, R., 2006. Bayesian belief networks: applications in ecology and natural resource management. Can. J. For. Res. 36, 3053–3062.
McKay, Christopher P., 2002. Two Dry for Life: The Atacama Desert and Mars. NASA Ames Research Center.
Medina-Cetina, Z., Nadim, F., 2008. Stochastic design of an early warning system. Georisk 2 (4), 223–236.
Meffe, G., Nielsen, L., Knight, R.L., Schenborn, D., 2012. Ecosystem Management: Adaptive. Island Press, Community-Based Conservation.
Müssner, R., Plachter, H., 2002. Methodological standards for nature conservation: case-study landscape planning. J. Nat. Conserv. 10, 2–23.
National Research Council, 1994. Rangeland Health: New Methods to Classify, Inventory and Monitor Rangelands. National Academy Press, Washington, D.C..
Nicholson, A.E., Flores, M.J., 2011. Combining state and transition models with dynamic Bayesian networks. Ecol. Model. 222, 555–566.
Pickett, S.T.A., Ostfeld, R.S., Shachak, M., Likens, G.E. (Eds.), 1997. The Ecological Basis of Conservation. Chapman & Hall, New York.
Pollino, C.A., Woodberry, O., Nicholson, A., Korb, K., Hart, B.T., 2007. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. Environ. Model. Softw. 22 (8), 1140–1152.
Pullin, A.S., Knight, T.M., 2001. Effectiveness in conservation practice: pointers from medicine and public health. Conserv. Biol. 15 (1), 50–54.
Reckhow, K.H., 1999. Water quality prediction and probability network models. Can. J. Fish. Aq. Sci. 56, 1150–1158.
Rumpff, L., Duncan, D.H., Vesk, P.A., Keith, D.A., Wintle, B.A., 2011. State-and-transition modelling for Adaptive Management of native woodlands. Biol. Conserv. 144 (4), 1224–1236.
Schlesinger, W.H., 2010. Editorial: "Translational Ecology". Science 329, 609.
Serrano, V., Beguería, S., López-Moreno, J., 2008. A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. J. Clim. 23, 1696–1718.
Stacey, R.D., Griffin, D., Shaw, P., 2000. Complexity and Management: Fad or Radical Challenge to Systems Thinking? Routledge, New York, NY.
USGS, 2012. Rain: a valuable resource Retrieved from http://ga.water.usgs.gov/edu/earthrain.html.
Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. modell. 203 (3), 312–318.
Leeuw, S., Costanza, R., Aulenbach, S., Brewer, S., Burek, M., Cornell, S., Crumley, C., Dearing, J.A., Downy, C., Graumlich, L.J., Heckbert, S., Hegmon, M., Hibbard, K., Jackson, S.T., Kubiszewski, I., Sinclair, P., Sőrlin, S., Steffen, W., 2011. Toward an integrated history to guide the future. Ecol. Soc. 16 (4), 2. doi: 10.5751/ES-04341-160402.
Whisenant, S.G., 1999. Repairing damaged wildlands: A process-oriented, landscape scale approach. Cambridge University Press.
Yu, O.Y., Medina-Cetina, Z., Guikema, S.D., Briaud, J.L., Burnett, D., 2012. Integrated approach for the optimal selection of environmentally friendly drilling systems. Int. J. Energy Environ. Eng. 3 (1), 25.