A framework for inferring predictive distributions of rhino poaching events through causal modelling

Hildegarde Koen*†, JP de Villiers*†, Gregor Pavlin§, Alta de Waal‡, Patrick de Oude§, Franck Mignet§
*Council for Scientific and Industrial Research (CSIR), Pretoria, South Africa
†Electrical, Electronic, and Computer Engineering, University of Pretoria, Pretoria, South Africa
Email: hkoen@csir.co.za, jdvilliers1@csir.co.za
‡Department of Statistics, Faculty of Natural and Agricultural Sciences, University of Pretoria, Pretoria, South Africa
Email: alta.dewaal@gmail.com
§D-CIS Lab / Thales Research & Technology Netherlands, Delft, The Netherlands
Email: gregor.pavlin@d-cis.nl, patrick.deoude@d-cis.nl, franck.mignet@d-cis.nl

***Abstract*—Rhino poaching in South Africa is leading to a catastrophic reduction in the rhino population. In this paper a Bayesian network causal model is proposed to model the underlying (causal) relationships that lead to rhino poaching events. The model may be used to fuse a collection of heterogeneous information sources. If a game reserve is partitioned into several geographical areas or cells, the model may perform inference for each of these cells separately, and give a relative predictive distribution of poaching events over the game reserve. After an overview of the current problem definition and a brief overview of similar modelling approaches, the Bayesian network model is presented. The developed Bayesian network based model is an initial attempt at proposing a sensible modelling approach for this problem. Some of the complexities of the approach are discussed, before considering how the model may be validated at a later stage.**

I. Introduction

Statistics show a startling increase in the number of rhino poaching attacks since 2008. There were 83 rhinos poached in 2008, and the number has grown to 1004 in 2013 [1], [2]. Thus far, 376 rhinos have been poached in South Africa between 1 January 2014 and 15 May 2014 [2]. The increase in poaching attacks in recent years can be seen in Figure 1.

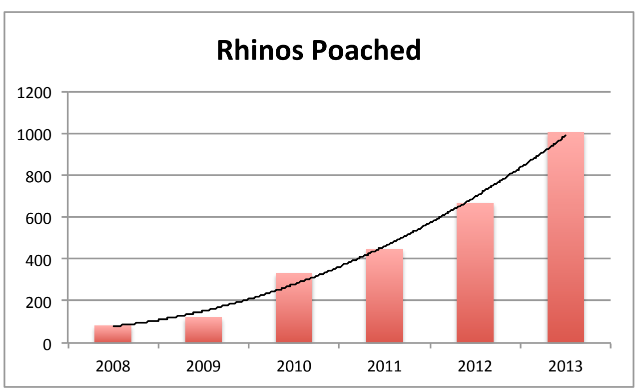

Fig. 1. Rhinos Poached between 2008 and 2013

The Kruger National Park (KNP) is home to the largest number of white rhinos, and second largest number of black rhinos, in the world [3], and has been hit the hardest by poaching attacks as shown in Figure 2. During 2012 and 2013 the KNP suffered approximately 60% of the annual rhino poaching losses (calculated from numbers obtained from [2]). Another reason for the high poaching incidence in the KNP is the fact that it is located on the border between South Africa, Zimbabwe, and Mozambique. The Great Limpopo Transfrontier Park is being established which connects all the large game reserves meeting at the borders of South Africa, Zimbabwe, and Mozambique [4]. Parts of the fence already came down a decade ago, giving the animals free reign to roam the fields that were once closed to them [4]. However, there still exists political boundaries which the rangers are not allowed to cross.

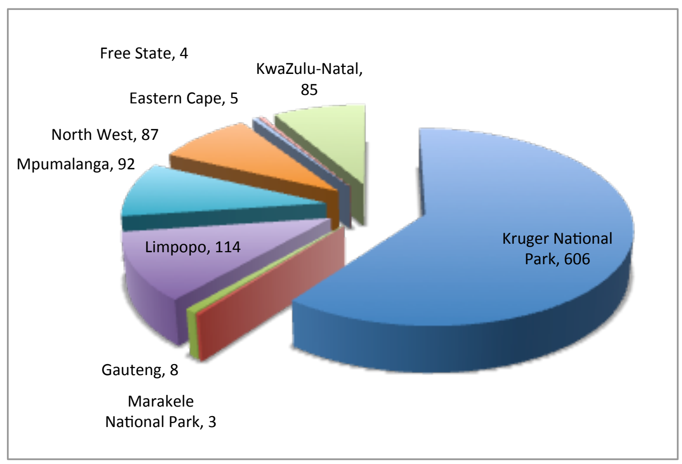

Fig. 2. Distribution of poached rhinos in 2013

In many countries, rhino horn is believed to have significant medicinal benefits [5], even though there have been numerous scientific studies proving otherwise [6]. Rhino horn demand increased when stories were aired claiming that ground up rhino horn could cure cancer [5]. Rhino horn is seen as a commodity, and exporting it has become a lucrative business. Many of the poachers (the so-called “foot soldiers”) come from poverty, and even a single rhino poaching success could elevate their status in the community to that of middle class [7], [8].

Another reason for the boom in rhino poaching is the fact that it is not seen as a serious crime [8]. A poacher is arrested and then usually given a fine before being released. In more recent cases poachers started receiving heavy jail sentences, but in most cases they only spend the night in prison and are then let go with a fine. Rhino poaching is, for the most part, a low-danger high-reward crime.

By current calculations and poaching trends, it is estimated that the rhino population in the wild will be extinct by 2026. The year 2014 might also be the year that rhino poaching exceeds rhino births. The time to combat this problem is now.

Game reserves and agencies have tried various methods to mitigate the situation ranging from injecting rhino horns with a substance that makes the consumer very ill [9], [10]; to employing the military in the park [11]; to spending big sums of money on developing new technology [12], with little success. Wardens and caretakers are considering mathematics, science and technology to assist in the fight against rhino poaching. A framework is presented in this paper that fuses a "current perspective" Bayesian network (BN) model with expert knowledge and historic data to present a rich representation of the rhino poaching problem. To the authors' knowledge, this application is the first of its kind. BN applications in the ecological environment are on the rise [13], [14], and this work investigates the suitability of a causal network framework to mitigate rhino poaching problems.

In Section II a comparison to similar works is given, which is followed by an outline of the fusion framework in Section III that illustrates the novelty of this work. An overview of BNs is given in Section IV, and the model is presented in Section V. Sections VI and VII discuss the challenges, expected difficulties, validation, and evaluation of the model. The paper is concluded with Section VIII.

II. Comparison to Similar Work

Bayesian networks (BNs) are well established and popular as a modelling tool in the context of environmental and resource management with a wide range of documented case studies [15], [16], [17], [18], [19]. BNs are particularly useful for modelling complex and multi-faceted environmental problem areas, and arguments supporting this statement have been documented widely [20], [21], [13]. Düspohl *et al.* [21] argue that in order to understand complex human-environment systems, integration of system, target and transformation knowledge is needed. Generation of these three types of knowledge is often referred to as transdisciplinary science. In order to support transdisciplinary research, a modelling approach should 1) represent and integrate knowledge from the diverse disciplines, 2) explicitly support stakeholder knowledge and perspective through participation in a real-world problem, and 3) handle uncertainty. Given these three requirements, BNs are ideal as an integrative modelling tool (Düspohl *et al.*). Case studies that highlight the approach include [22], [17], [18] and [21] cite no less than 30.

Except for modelling scenarios where the structure and probability tables can be learned from data, models are constructed with stakeholder involvement in one or more of the modelling stages, referred to as "participatory modelling". Bromley [23] identified seven stages of participatory BN modelling. The stages are 1) defining the problem, context and stakeholder engagement, 2) identify variables, actions and indicators, 3) construct the pilot network, 4) collect data, 5) define states of variables, 6) construct conditional probability tables, and 7) test the network, collect feedback from stakeholders, and make final modelling decisions. Johnson *et al.* [15] suggested that during a core process stages 1 – 3 are performed with stakeholder participation and stages 4 – 7 are performed in an iterative process. Processes and frameworks are documented to provide guidance on how to interact with these experts and how to elicit the knowledge in the correct way [24], [14]. Typically, experts and stakeholders are involved in the initial stages of model development which involves the identification of variables and the construction of the pilot network [15], [19], [21].

An important feature of BNs is its ability to combine different information sources [13] such as empirical data, literature information, and expert knowledge, making it an excellent integrative modelling technique. Many examples showcase this integrative capability of BNs. In particular, the combination of Geographic Information System (GIS) data and other data sources are of special interest to us as it displays the model's ability to integrate knowledge on different levels of abstraction [14], [16] in a space and/or time dimension. Johnson *et al.* [24] discuss different techniques to integrate BNs and GIS. They considered four methods: 1) GIS input to BN, 2) GIS input to, and from BN, 3) complex interactions between BN and GIS, and 4) BNs and GIS within a larger framework.

All of the above-mentioned case studies focus on the use of BNs as a decision support system. In other words, potential actions serve as variables somewhere in the network. The network can then be used in several modes: 1) predictive mode (top-down), 2) prescriptive mode (best state of variables if other variables are specified) and 3) diagnostic mode (bottom-up, what-if analysis) [19]. All three these modes are extremely useful in understanding and reasoning about the transdisciplinary system - as Düspohl [21] stated: *An important goal of transdisciplinary research is social learning of the participants of the joint research process*.

The related work discussed here puts our contribution into context in the following way: Firstly, we work in a complex environment with three actors: the rhino (fauna and flora in an environmental context), the poachers (and their resources and techniques), and the rangers (resources). This necessitates the need for a modelling technique that can handle the transdisciplinary character of the problem context, but also integrate different levels of abstraction. Secondly, we deviate from the modelling process in the sense that we involve the stakeholder at a later stage in model development. We already constructed a pilot network internally and will present the pilot network to stakeholders at the first meeting. The reason for this is that, apart from high costs to involve stakeholders, it is almost impossible to get a core group together in a workshop fashion for more than two days. We hope that this approach will be more effective and will report on the lessons learnt in a follow-up article. Thirdly, we introduce a type of mixed-mode Gaussian mixture model (GMM) [25] as a technique to incorporate GIS information in the BN instead of raw GIS information. Finally, we use the model to generate a level of certainty (chance) of a poaching taking place, and we do not consider management intervention. Although reasoning in the three modes is very valuable to understand the human-environment complexities and intervention, the main mode of this network will be predictive.

III. Fusion Framework

One of the main goals of this project is to fuse together different aspects of the rhino poaching problem. Figure 3 shows a simplified view of the fusion framework for this problem.

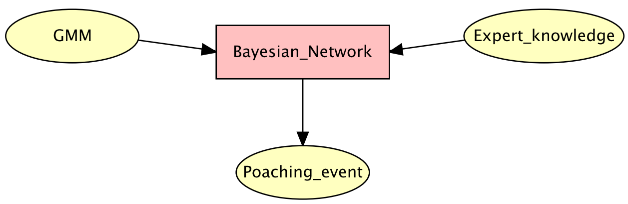

Fig. 3. Fusion Framework

The BN is developed by the researchers and uses GIS map data. The model inputs a mixed-mode GMM [25] as a prior distribution. Expert knowledge is used to populate the BN and to compute the conditional probabilities. The output of the BN is a posterior probability and answers operational questions such as, "What is the possibility of a poaching attack occurring within a specified region?" and "What is the possibility of finding a poacher within a specified region?". A complex model is developed containing everything we know about the problem. This comprehensive model may in future be used to assist with decision support to the safeguarding unit protecting the rhinos.

The motivation behind using BNs is the fact that these types of networks can capture the causal relationships which are inherent to the problem. Continuous GIS data can be converted such that it can be used in a discrete BN. The model can be updated as poaching event reports become available, and BNs can be used effectively using expert knowledge when data is scarce [15], [26].

The modelling process allows for the identification of relevant variables which can be included when future data is captured. Formerly, expert workshops have been attempted with no prior considerations - the "clean slate" approach such as was used in [15]. One of the outcomes of this work will be to assess whether the building of a "current perspective" model beforehand will accelerate the workshop process without biasing the outcome.

The diagram in Figure 4 illustrates the design process of the BN. The researchers start off with a "current perspective" BN based on their own ideas and expertise obtained over the period of working with this problem. The next step is to have a workshop with experts to populate the BN, and even to change the network architecture, in order to have a refined model. After that, data of these newly identified variables will be gathered, and this will further refine the model. The last two steps could actually become a cycle as the researchers can go back and refine the experts' view according to what the data states.

IV. Bayesian Networks

BNs are flexible graphical models that consist of nodes and edges. The nodes depict the variables and the edges depict the

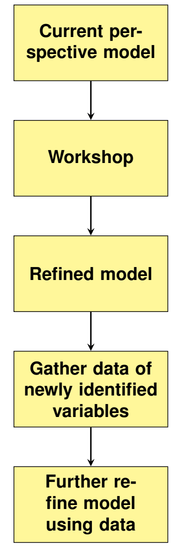

Fig. 4. Diagram of model design

causal links between them. BNs are directed acyclic graphs (DAGs) meaning that the edges have direction, and there are no cycles in the network. The reason BNs were chosen is because of their flexibility and elegance in handling new information, and their ability to fuse expert knowledge, domain knowledge, and data. BNs can also learn with relatively sparse and missing data [16], an attribute that is greatly valued in real-world applications where data is more often than not sporadic and contain missing values.

BNs along with other graphical models, provide researchers with a simple way of planning and constructing models [27]. Inferring model characteristics such as conditional independencies between variables is simplified greatly by reading it off the graph.

1

V. The Model

The likelihood of poaching activities in a specific area can be estimated by considering different types of correlated data, *i.e.* observations of certain events, and phenomena that take place in a certain time interval (*i.e.* time slice). Poaching activities usually cannot be directly observed, but we can observe phenomena that are related to poaching in different ways.

Firstly, some observations provide clues about phenomena that facilitate poaching, such as certain weather conditions, the moon phase, the presence of rhinos, *etcetera*. These phenomena represent the context and the preconditions for poaching. For example, poaching cannot take place at a certain location if the rhinos are not present, but poaching is also unlikely during broad daylight in an area with sparse vegetation.

Secondly, there are observations providing clues about phenomena that are consequences of poaching activities, for example observations of dead animals. Observation of certain type of people or behaviour can provide clues about the presence of poachers, *etcetera*.

This paper discusses an approach that can systematically use the above mentioned types of observations to estimate the

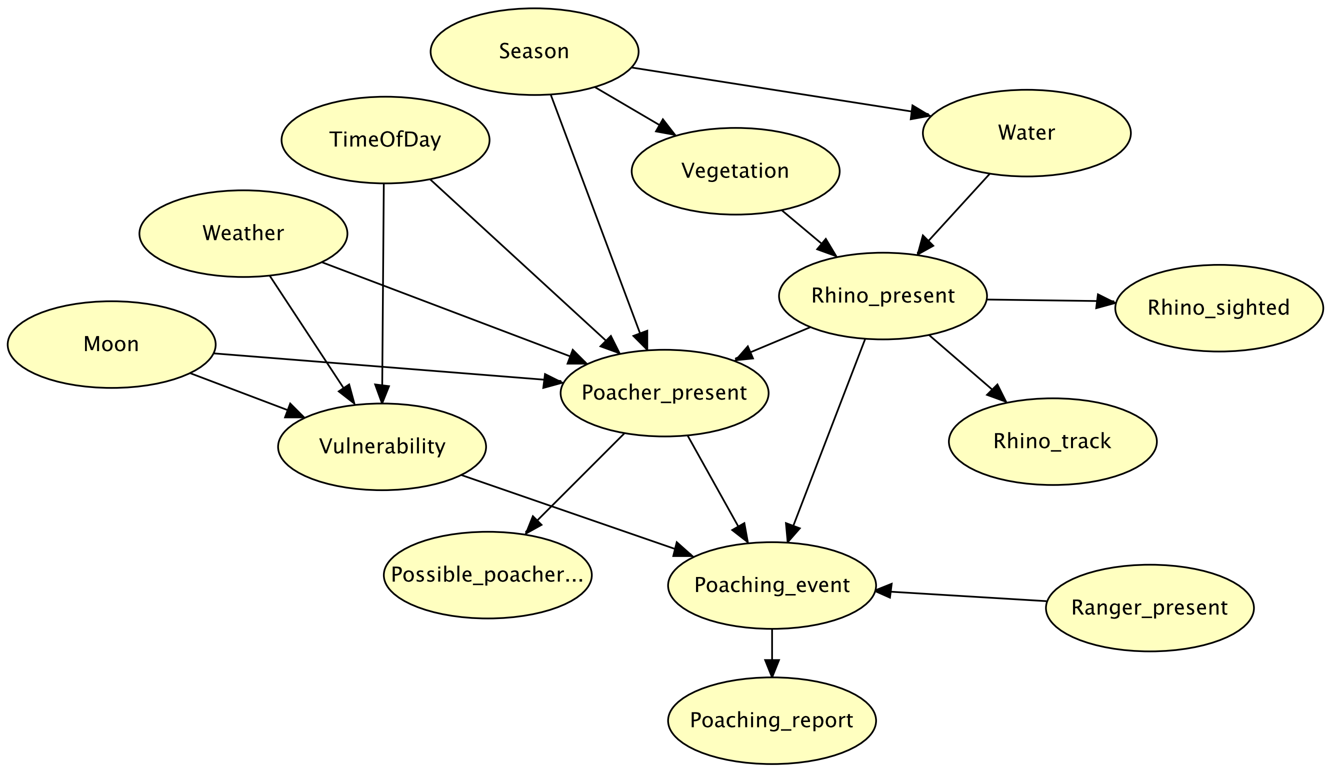

Fig. 5. The Rhino Model

chance of poaching activities, which are events that usually cannot be directly observed. In principle, the likelihood is computed with an inference algorithm that (i) takes as input various observations of related phenomena and (ii) uses a model describing the correlations between these observations and the hidden phenomena of interest.

In the poaching case there exists relatively complex relations between multiple types of phenomena. Such relations can be viewed as causal and stochastic, therefore we develop a causal probabilistic model shown in Figure 5. This model relates to a particular geographically bounded area or cell. Thus consider a map of a reserve or game park partitioned into $i = 1, \ldots, M$ areas where the ith area is denoted by A_i. For each cell A_i, the model contains different variables which are defined as follows:

$Poaching\_event$, a binary variable that takes on value $true$ if poaching takes place at location A_i. This is a hidden variable as it cannot directly be observed.

$Rhino\_present$, a binary variable that takes on value $true$ if a rhino is present at location A_i. This is a hidden variable as it cannot directly be observed.

$Rhino\_track$, a binary variable that takes on value $true$ if a rhino tracking system indicates that tracked rhinos are at location A_i. Moreover, as outputs of tracking systems are usually noisy (associated with uncertainties), the variable is likely to be instantiated with soft evidence, a binary distribution over the states $true$ and $false$.

$Rhino\_sighted$, a binary variable that takes on value $true$ if a rhino is sighted by rangers or other professionals. This is hard evidence, a yes or no answer obtained by asking rangers at location A_i whether the rhinos are present.

$Poacher\_present$, a binary variable that takes on value $true$ if poachers are present at location A_i. This is a hidden variable as it cannot directly be observed.

$Possible\_poacher\_sighted$, a binary variable that in the simplest case takes on value $true$ if we receive reports that potential poachers are present at location A_i. Such feedback might also be a result of a more sophisticated inference system combining various information about the movement of poachers and observations at A_i. The inference would produce an estimate of the poacher presence in the form of a probability distribution over the states $true$ and $false$. In such a case, the input would be soft evidence.

$Ranger\_present$, a binary variable that takes on value $true$ if a ranger is present at location A_i.

$Season$, a discrete variable with four states corresponding to the four seasons.

$Moon$, a discrete variable with four states corresponding to the four major moon phases: *new moon, first quarter, last quarter, full moon.*

$Weather$, a discrete variable with n states corresponding to n weather types.

$Vulnerability$ encodes the knowledge about the vulnerability of rhinos at location A_i. This variable encodes knowledge about the environment, roughly the suitability of A_i for poaching. This knowledge is captured by a mixed-mode GMM extracted from historical data collected via poaching reports.

$Water$, a binary variable that takes on value $true$ if location A_i is close to water. The value can be derived from maps.

$Vegetation$, a binary variable that takes on value $true$ if suitable vegetation for rhinos is present at location A_i. The value can be derived from maps.

$TimeOfDay$, a discrete variable with four states: *morning, day, evening, night*.

$Poaching\_report$, a binary variable that takes on $true$ if a poaching report is generated.

The following relations are captured as conditional probabilities by the presented model:

1) $P(Poaching\_event|Rhino\_present, Poacher\_present, Ranger\_present, Vulnerability)$ is represented by a Conditional Probability Table (CPT). This relation captures the fact that poaching is likely if the poachers and rhinos are present at location A_i. However, if rangers are present, the likelihood is reduced.
2) $P(Poacher\_present|Rhino\_present, Season, TimeOfDay, Weather, Moon)$ is represented by a CPT that describes the fact that the presence of poachers at location A_i depends on multiple factors. Full moon, high tourist season, daylight, and good weather reduce the likelihood of poaching, as it can be observed more easily.
3) $P(Rhino\_present|Vegetation, Water)$ is represented by a CPT that describes the fact that the presence of rhinos at location A_i depends on multiple factors, such as vegetation and water. Lack of suitable vegetation and water makes the presence of rhinos unlikely.
4) $P(Possible\_poacher\_sighted|Poacher\_present)$ is an observation model represented by a CPT that describes the chance of getting a yes or no answer by professionals (*e.g.* rangers) if they are asked, "Do you see people that are potential poachers in area A_i?"
5) $P(Rhinos\_sighted|Rhinos\_present)$ is an observation model represented by a CPT that describes the chance of getting a yes or no answer by professionals (*e.g.* rangers) if they are asked, "Do you see rhinos in area A_i?".

The presented domain model encodes a joint distribution and is used for the computation of the posterior probability distribution $P(Poaching\_event|\epsilon)$, where ϵ denotes the entire evidence (instantiation of observable variables) collected in a specific time interval. The full joint distribution is given by

$$
\begin{aligned}
P(\mathcal{V}) \quad = \quad & P(Season)P(TimeOfDay)P(Weather) \\
\times \quad & P(Moon)P(Ranger\_present) \\
\times \quad & P(Water|Season)P(Vegetation|Season) \\
\times \quad & P(Rhino\_present|Water, Vegetation) \\
\times \quad & P(Rhino\_sighted|Rhino\_present) \\
\times \quad & P(Rhino\_track|Rhino\_present)) \\
\times \quad & P(Poacher\_present|Moon, Weather, \\
\ldots \quad & TimeOfDay, Season, Rhino\_present) \\
\times \quad & P(Possible\_poacher|Poacher\_present) \\
\times \quad & P(Vulnerability|Moon, Weather, \\
\ldots \quad & TimeOfDay) \\
\times \quad & P(Poaching\_report|Poaching\_event) \\
\times \quad & P(Poaching\_event|Vulnerability, \\
\ldots \quad & Poacher\_present, Rhino\_present, \\
\ldots \quad & Ranger\_present),
\end{aligned}
$$

where $\mathcal{V} = \{Season, TimeOfDay, \ldots, Ranger\_present\}$. Variables $Vulnerability$, $Season$, $Moon$, $Weather$, $Water$, and $Vegetation$ are called context variables as they serve as boundary conditions for the estimated processes; these variables describe the conditions in which the processes of interest evolve, such as movement of rhinos, movement of poachers, poaching actions, and the corresponding observations. Thus, the context variables do influence the inferred processes while they are not influenced by these processes.

Variables $Rhino\_sighted$ and $Possible\_poacher\_sighted$, on the other hand, represent the observable phenomena influenced by the hidden phenomena and the context variables. The observations corresponding to the states of these variables are collected at runtime, in a specific time interval and within area A_i.

Moreover, the presented model is limited in that it does not capture the temporal aspects of the problem space explicitly. The model represents snap shots of phenomena that take place within a specific time interval. The dynamics of the processes within such a time slice is not explicitly modelled.

VI. Challenges and Expected Problems

Three tasks are involved in building BNs, namely: (i) determine the relevant variables in the domain and their values, (ii) specify the structure of the model (qualitative knowledge) that captures the conditional independencies between the variables, and (iii) specify the parameters of the model (quantitative knowledge) where for each node in the DAG a conditional probability distribution (CPD) needs to be specified through a conditional probability table (CPT). Considering tasks (ii) and (iii), there are two ways to obtain the structure and/or parameters of a BN, namely through domain expert elicitation [28], [29] or through automated knowledge discovery [30], [31], [32] (or a combination of both). Obtaining the parameters of a BN through domain expert elicitation can be a daunting task [33], whereas obtaining the structure of the model is considered an achievable exercise. Often experts are biased, disagree with each other, and are not proficient in converting their domain expertise into numerical probabilistic knowledge [34]. Several techniques are proposed in the literature that support the elicitation process, such as transcribing probabilities and using a scale with both numerical or verbal anchors for marking assessments [29], [35].

Automated learning of probabilistic models gained much popularity in recent years. However, automated learning of models is only a viable option if enough and relevant data is available. In many domains the amount of data is insufficient, incomplete, or the data is in such a format that it is not easily usable. The data generally needs to be preprocessed before it can be used for automated learning of the model. Preprocessing data generally comes at significant costs with respect to resources.

Considering the domain shown in Figure 5 it is unlikely that data is available for each of the variables shown in the BN model. Considering the dependence between the variables $Poacher\_present$ and $Poaching\_event$, for example, some of the data for these variables can be obtained from poaching reports produced after incidents of poached rhinos, and some from tourist sightings. Since these poaching reports only report what is seen at the time of a carcass being found, it does not suggest anything about poacher presence in general. Reports about poachers' attempts to poach rhinos are far less common, unreliable, or non existing. In other words, generic information about poacher presence might be very difficult to obtain.

Poacher and rhino sightings can be recorded from tourist or ranger sightings, but these sighting reports are sporadic and could be inaccurate. Ranger presence will in most cases be recorded, as they are assigned different locations to patrol.

To guide the parameter elicitation process, sensitivity analysis [36] is an indispensable and valuable method. Given the hypothesis variable and the observation variables, the impact on the posterior of the hypothesis variable can be investigated. By varying one (or more) specific parameters in the model the effect on the posterior probability can be computed. Sensitivity analysis gives the modeller insight into the sensitivity of certain parameters on the hypothesis variable. The elicitation process can be geared towards the most influential parameters when the sensitivity of the parameters on the posterior of the hypothesis variable is known. Sensitivity analysis is also a known BN evaluation technique. Other evaluation considerations are discussed in the next section.

VII. Validation and Evaluation

Many established methods exist to validate and evaluate BNs. The paper by Marcot [37] provides a detailed exposition of such methods. These methods are broadly classified as methods which 1) perform sensitivity analysis, 2) evaluate scenarios, 3) depict complexity, 4) assess prediction performance, and 5) evaluate the uncertainty of model posterior probability distributions. There are current ongoing efforts by the Evaluation of Technologies for Uncertainty Representation Working Group (ETURWG) within the fusion community to capture and organise evaluation methods for fusion systems which perform reasoning tasks in the presence of uncertainty. These efforts are part of a continuous refinement process, and the latest results of these efforts are presented in the Uncertainty Representation and Reasoning Framework (URREF) ontology [38]. This is in light of the distributed nature of several previous efforts to characterise the evaluation of fusion systems [39], [40], [41] and [42]. A paper which has been submitted in parallel to this conference [43] attempts to unify the URREF ontology with traditional BN evaluation methods when used in information fusion. This is performed using an abstraction of the fusion reasoning process which is known as the atomic decision process (ADP) in [44] and [45]. The evaluation of the rhino poaching BN will be performed mainly using the methods of [37] while making sure that the uncertainty representation and the associated reasoning methods are evaluated using the criteria of the URREF ontology.

VIII. Conclusion

Rhino poaching continues to reach alarming levels and the authors turn to causal models to mitigate this problem. BNs are enjoying success as a popular modelling tool in the context of environmental and resource management problems. BNs have the ability to combine different sources of information, and can handle sparse or missing data elegantly. Expert knowledge can also be used to populate the BN when there is a lack of data. Normally, the experts are given a blank slate and have to develop and populate their own BN model. In this case, the authors have already developed the model. BNs also have the ability to work well with GIS data, which is particularly important in environmental applications.

A framework is presented to fuse diverse sources of information into a single causal network. The authors use a mixed-mode GMM to incorporate historic poaching information and fuse this with the obtained expert knowledge in the model.

The authors will face several challenges in obtaining the expert knowledge. Furthermore, converting non-quantitative knowledge to probabilities is also an acknowledged challenge.

The model shown in Figure 5 is a static model, *i.e.* a non-temporal BN. This means that reasoning is performed in a definite time frame. In essence this time frame determines which of the different observations spread over time are fused together to determine the posterior probability. Determining the duration of this time frame is often difficult. To relax this problem somewhat time could be considered explicitly in the model by using a temporal probabilistic model, such as dynamic BNs [46]. In such models the posterior for poaching locations can be computed over time.

Acknowledgment

The authors would like to extend their gratitude to Dr. Henk Roodt for his review and insights into the paper.

References

[1] Unknown, "Rhino poaching statistics," *Department of Environmental Affairs*. Available: https://www.environment.gov.za/sites/default/files/docs/rhinopoaching_statistics.pdf [Last accessed: 22 May 2014].

[2] A. Modise, "Media release: Rhino poaching update," *South African National Parks*, 15 May 2014. Available: http://www.sanparks.co.za/about/news/default.php?id=56069 [Last accessed: 16 May 2014].

[3] R. Duffy, R. Emslie, and M. Knight, "Rhino poaching: How do we respond?" Evidence on Demand, Report, 2013.

[4] Unknown, "Great Limpopo Transfrontier Park could be fenced once again," *Times LIVE*, 28 May 2013. Available: http://www.timeslive.co.za/scitech/2013/05/28/great-limpopo-transfrontier-park-could-be-fenced-once-again [Last accessed: 25 February 2014].

[5] R. Ellis, *Tiger Bone & Rhino Horn: The Destruction of Wildlife for Traditional Chinese Medicine*. Island Press, 2005.

[6] "Yemen acts to halt rhino horn daggers; scientific tests fail to show rhino horn effective as medicine," *Environmentalist*, vol. 3, no. 2, pp. 153–153, 1983. [Online]. Available: http://dx.doi.org/10.1007/BF02240165

[7] M. Eustace, "Rhino poaching: what is the solution?" *Business Day Live*, 8 August 2012. Available: www.businessday.co.za/articles/Content.aspx?id=162979 [Last accessed: 5 February 2014].

[8] C. Eloff, "Rhino poaching in South Africa – is it a losing battle?" *PositionIT*, pp. 57–62, 2012.

[9] D. Smith, “South African game reserve poisons rhino’s horns to prevent poaching,” *The Guardian*, 4 April 2013. Available: http://www.theguardian.com/environment/2013/apr/04/rhino-horns-poisoned-poachers-protect [Last accessed: 25 February 2014].

[10] M. Gosling, “Poison the rhino horn,” *Cape Times*, 30 November 2012. Available: http://www.iol.co.za/capetimes/poison-the-rhino-horn-1.1433583 [Last accessed: 25 February 2014].

[11] S. Mouton, “SANParks takes fight to poachers,” *Times LIVE*, 13 December 2012. Available: http://www.timeslive.co.za/thetimes/2012/12/13/sanparks-takes-fight-to-poachers [Last accessed: 22 January 2014].

[12] S. Kings, “Rhino conservation gets record-breaking R232m boost,” *Mail & Guardian*, 5 February 2014. Available: http://http://mg.co.za/article/2014-02-05-r232-million-for-rhino-conservation [Last accessed: 26 February 2014].

[13] L. Uusitalo, “Advantages and challenges of Bayesian networks in environmental modelling,” *Ecological Modelling*, vol. 203, no. 3-4, pp. 312 – 318, 2007. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0304380006006089

[14] S. Johnson, S. Low-Choy, and K. Mengersen, “Integrating Bayesian networks and geographic information systems: Good practice examples,” *Integrated environmental assessment and management*, vol. 8, no. 3, pp. 473–479, 2012.

[15] S. Johnson, K. Mengersen, A. de Waal, K. Marnewick, D. Cilliers, A. M. Houser, and L. Boast, “Modelling cheetah relocation success in southern Africa using an Iterative Bayesian Network Development Cycle,” *Ecological Modelling*, vol. 221, no. 4, pp. 641–651, 2010.

[16] D. Pullar and T. Phan, “Using a Bayesian Network in a GIS to model relationships and threats to koala populations close to urban environments,” in *MODSIM 2007: Land, water and environmental management: Integrated systems for sustainability.*, L. Oxley and D. Kulasiri, Eds., 2007, pp. 1370–1375.

[17] M. E. Borsuk, C. A. Stow, and K. H. Reckhow, “A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis,” *Ecological Modelling*, vol. 173, no. 2, pp. 219–239, 2004.

[18] M. E. Borsuk, P. Reichert, A. Peter, E. Schager, and P. Burkhardt-Holm, “Assessing the decline of brown trout $salmotrutta$ in Swiss rivers using a Bayesian probability network,” *Ecological Modelling*, vol. 192, no. 1, pp. 224–244, 2006.

[19] A. De Waal and T. Ritchey, “Combining Morphological Analysis and Bayesian Networks for Strategic Decision Support,” *ORiON*, vol. 23, no. 2, pp. 105–121, 2007.

[20] D. N. Barton, S. Kuikka, O. Varis, L. Uusitalo, H. J. Henriksen, M. Borsuk, A. de la Hera, R. Farmani, S. Johnson, and J. D. Linnell, “Bayesian networks in environmental and resource management,” *Integrated environmental assessment and management*, vol. 8, no. 3, pp. 418–429, 2012.

[21] M. Düspohl, S. Frank, and P. Doell, “A Review of Bayesian Networks as a Participatory Modeling Approach in Support of Sustainable Environmental Management,” *Journal of Sustainable Development*, vol. 5, no. 12, 2012. [Online]. Available: http://www.ccsenet.org/journal/index.php/jsd/article/view/20071

[22] S. Johnson, F. Fielding, G. Hamilton, and K. Mengersen, “An Integrated Bayesian network approach to Lyngbya majuscula bloom initiation,” *Mar Environ Res*, vol. 69, pp. 27–37, 2010.

[23] J. Bromley, N. Jackson, O. Clymer, A. Giacomello, and F. Jensen, “The use of Hugin®to develop Bayesian networks as aid to integrated water resource planning.” *Environ. Model. Software*, pp. 231 – 242, 2005.

[24] S. Johnson and K. Mengersen, “Integrated Bayesian network framework for modeling complex ecological issues,” *Integrated environmental assessment and management*, vol. 8, no. 3, pp. 480–490, 2012.

[25] C. Lawrence and W. Krzanowski, “Mixture separation for mixed-mode data,” *Statistics and Computing*, vol. 6, no. 1, pp. 85–92, 1996.

[26] S. L. Rinderknecht, M. E. Borsuk, and P. Reichert, “Bridging uncertain and ambiguous knowledge with imprecise probabilities,” *Environmental Modelling & Software*, vol. 36, pp. 122 – 130, 2012, Thematic issue on Expert Opinion in Environmental Modelling and Management.

[27] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics)*, 1st ed. Springer, Oct. 2007.

[28] F. V. Jensen, *Bayesian Networks and Decision Graphs*. Springer-Verlag, 2001.

[29] L. C. Van Der Gaag, S. Renooij, C.L.M.Witteman, B. M. P. Aleman, and B. G. Taal, “How to elicit many probabilities,” in *Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence*. Morgan Kaufmann Publishers, 1999, pp. 647–654.

[30] G. F. Cooper, E. Herskovits, and T. Dietterich, “A Bayesian method for the induction of probabilistic networks from data,” in *Machine Learning*, 1992, pp. 309–347.

[31] P. Spirtes, C. Glymour, and R. Scheines, *Causation, Prediction, and Search*, 2nd ed. Cambridge, MA, USA: The MIT Press, Jan. 2001.

[32] W. Buntine, “A guide to the literature on learning probabilistic networks from data,” 1996.

[33] M. J. Druzdzel and L. C. van der Gaag, “Building probabilistic networks: ”Where do the numbers come from?” Guest editors’ introduction,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 12, no. 4, pp. 481–486, 2000.

[34] G. Gigerenzer and A. Edwards, “Simple tools for understanding risks: from innumeracy to insight,” *BMJ*, vol. 327, no. 7417, pp. 741–744, 9 2003.

[35] M. Kruger and L. Ziegler, “User-oriented Bayesian identification and its configuration,” in *Information Fusion, 2008 11th International Conference on*, June 2008, pp. 1–8.

[36] E. Castillo, J. M. Gutiérrez, and A. S. Hadi, “Sensitivity analysis in discrete Bayesian Networks,” *IEEE Transactions on Systems, Man, and Cybernetics. Part A: Systems and Humans*, vol. 27, pp. 412–423, 1997.

[37] B. G. Marcot, “Metrics for evaluating performance and uncertainty of Bayesian network models,” *Ecological Modelling*, vol. 230, pp. 50 – 62, 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0304380012000245

[38] P. Costa, “URREF Ontology - version 2.0,” *Evaluation of Technologies for Uncertainty Representation Working Group (ETURWG)*. Available: http://eturwg.c4i.gmu.edu/?q=node/43 [Last accessed: 18 March 2014].

[39] E. Waltz and J. Llinas, *Multisensor Data Fusion Systems*. Artech House, 1990, ch. System modelling and performance evaluation.

[40] R. DeWitt, “Principles for testing a data fusion system,” PSR (Pacific Sierra Research, Inc), Internal report, March 1998.

[41] H. D. Liggins M.E. and J. Llinas, *Handbook of Multisensor Data Fusion*, 2nd ed. CRC Press, 2009, ch. Assessing the performance of multisensor fusion processes, pp. 655–675.

[42] E. Blasch, P. Valin, and . Boss, “Measures of effectiveness for high-level fusion.” in *FUSION*. IEEE, 2010, pp. 1–8.

[43] J. de Villiers, G. Pavlin, P. Costa, K. Laskey, and A. Jousselme, “A URREF interpretation of Bayesian network information fusion,” in *Submitted to Information Fusion (FUSION), 2014 17th International Conference on*. ISIF, July 2014.

[44] A. Jousselme and P. Maupin, “A brief survey of comparative elements for uncertainty calculi and decision procedures assessment,” in *Proc. of the 15th Int. Conf. on Information Fusion*, 2012, panel Uncertainty Evaluation: Current Status and Major Challenges.

[45] A. L. Jousselme, “Objects under evaluation (evaluation subjects),” *Evaluation of Technologies for Uncertainty Representation Working Group (ETURWG)*. Available: http://eturwg.c4i.gmu.edu/?q=t8 [Last accessed: 18 March 2014].

[46] K. Murphy, “Dynamic Bayesian networks: Representation, inference and learning,” Ph.D. dissertation, UC Berkeley, Computer Science Division, Jul. 2002.