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An expert-driven causal model of the rhino poaching problem

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ABSTRACT

A significant challenge in ecological modelling is the lack of complete sets of high-quality data. This is especially true in the rhino poaching problem where data is incomplete. Although there are many poaching attacks, they can be spread over a vast surface area such as in the case of the Kruger National Park in South Africa, which is roughly the size of Israel. Bayesian networks are useful reasoning tools and can utilise expert knowledge when data is insufficient or sparse. Bayesian networks allow the modeller to incorporate data, expert knowledge, or any combination of the two. This flexibility of Bayesian networks makes them ideal for modelling complex ecological problems. In this paper an expert-driven model of the rhino poaching problem is presented. The development as well as the evaluation of the model is performed from an expert perspective. Independent expert evaluation is performed in the form of queries that test different scenarios. Structuring the rhino poaching problem as a causal network yields a framework that can be used to reason about the problem, as well as inform the modeller of the type of data that has to be gathered.

1. Introduction

The rhino poaching problem has reached alarming heights and has remained a challenging problem for the past few years. However, what was once the latest buzzword has now become just another story in the newspaper. The reality is that rhino poaching is still on the rise, with no chance of decreasing any time soon.

At the end of 2008 the poaching count stood at 83 rhinos and rapidly increased until a total of 1175 rhinos were poached in 2015. The biggest problem is in the Kruger National Park (KNP), which is home to the largest concentration of rhinos in South Africa (Emslie and Brooks, 1999). The KNP is situated on the border between South Africa, Zimbabwe and Mozambique, which makes it more difficult to deter and apprehend poachers.

Different approaches have been followed to mitigate the rhino poaching problem, but without much success. Most approaches are reactive in the sense that they are only used (or feasible) after a rhino has been poached. If a shot is heard the location of the shot can be triangulated, but by then it is too late. If a poacher is caught with a rhino horn he is incarcerated, but it is too late for the rhino. The approach presented in this paper is proactive instead of reactive: rangers wish to know that a poaching event is likely to occur well before it does. A causal model is developed to predict the area where a next poaching event might occur. Utilising a reduced patrol surface area as informed by the model results in rangers and other resources being allocated more effectively. Extending the previous work by the authors in Koen et al. (2014), a current perspective predictive model of the rhino poaching problem is extended by a team of domain experts. This effort further serves to develop the only expert-driven causal model of which the authors are aware of that applies to wildlife crime. This is also the only known predictive model for the rhino poaching problem.

At the start of the project, data was scarce and an expert approach was a pragmatic method to define and understand the problem, as well as to make predictions. Fortunately for the modeller, but unfortunately for the rhinos, the number of recorded poaching attacks have increased to such an extent that there exists data for a couple of thousand poaching attacks over several years. However, the expert-driven model remains useful in understanding the rhino poaching problem, as well as reasoning about it. Another complication associated with the data is that poaching attacks are scattered over an area roughly the size of Israel. The data sparsity problem remains if the park is divided into one square

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kilometre cells for the purposes of prediction, as is the case in this study. However, as more data becomes available, a model based on data will increasingly be preferred over an expert model to inform predictions. This paper describes the development of the expert model, as well as exploring the very realistic possibility of not having data in a wildlife crime problem in countries or parks with limited resources to record data.

1.1. Literature review

Initially very little was known about the rhino poaching problem and the drivers influencing it. Numerous papers have been published concerning alternative management strategies to cope with the continuously rising cost of rhino poaching (Kahler and Gore, 2012; Duffy and St John, 2013; Biggs et al., 2013; Ferreira et al., 2014), but almost none on modelling the rhino poaching problem. The paper by Ferreira et al. (2015) uses poaching records as well as growth rates for both black and white rhinos from 2008 and 2010 to predict the population sizes and the growth rates of rhinos in the KNP in 2013. A similar paper is presented by Haas and Ferreira (2015) where the same type of information is used to predict when the rhino populations will start to decrease rapidly. This is calculated by using a special form of individual-based model (IBM) called the "agent/individual-based economic-ecological model" (Haas and Ferreira, 2015). The study by Burn et al. (2011) analyses the trends and patterns concerning illegal elephant killings, but they use Bayesian hierarchical modelling in contrast with our causal Bayesian network.

Recently, two papers have been published that model and analyse facets of rhino poaching by following different approaches. The paper by Park et al. (2015) presents a special case of spatio-temporal optimisation problems (an anti-poaching engine) where both poacher and rhino behaviour models are supplied to the engine as input. In the paper by Critchlow et al. (2015), the spatial patterns of various illegal types of wildlife activities are investigated.

Critchlow et al. (2015) focus on identifying drivers of different types of illegal activities, whereas this study only focuses on the poaching of white rhinos. Park et al. (2015) also attempt to safeguard rhinos, but they do not differentiate between black and white rhinos. The behaviour, vegetation preference, and population numbers of white rhinos are very different to that of black rhinos, thus it would not make sense to simply group the two subspecies together under the common heading of "rhinos".

Another similarity between this study and Park et al. (2015) is that both investigate ways to mitigate rhino poaching attacks through prediction for the safeguarding of the rhino population. Both this study and that of Critchlow et al. (2015) understand that the patterns of illegal activities are important in solving the poaching problem, and that the drivers of poaching are poorly understood and documented.

The maps of the game reserves or parks in all three studies are divided into grids with square cells of equal size. For this study a grid size of 5 km × 5 km was used initially, but later on it was changed to 1 km × 1 km for evaluation purposes, whereas in Park et al. (2015) a grid size of 400 m × 400 m is used. The focus of this study is on the KNP situated in the north of South Africa, spanning an area of 19,485 km^2 (Ferreira et al., 2015), whereas the park used in the study of Park et al. (2015) is Olifants West in South Africa, spanning an area of about 14 km × 10 km. Critchlow et al. (2015) focus on the Queen Elizabeth Conservation Area in Uganda which at 1978 km^2 is roughly 10 times smaller than the KNP. They divide the map of the Queen Elizabeth Conservation Area into 500 m × 500 m. Both this study and the study by Critchlow et al. (2015) identify areas of greatest risk in terms of animal poaching, although this study focuses on rhino poaching. The grid sizes of all three studies are in line with the size of the corresponding game reserves or parks.

Further similarities between Park et al. (2015) and this study are the assumptions that poaching attacks usually occur during twilight and at night. The belief that rhinos avoid busy areas is also shared by both studies. Both studies calculate the probability of a cell being under attack by a poacher and utilise models which have both spatial and temporal components. Park et al. (2015) divide their temporal dimension into hourly intervals and use a different spatio-temporal graph for each agent, whereas this study uses a different instantiation of the causal model for each cell.

The biggest difference between the three studies is in terms of the approaches used. Park et al. (2015) use a special case of spatio-temporal optimisation problems combined with behavioural models, as well as multi-variate regression, whereas this study uses a Bayesian Network (BN). Critchlow et al. (2015) explicitly model ranger patrol effort, whereas this study predicts the probability of poaching events.

Park et al. (2015) also rely on certain assumptions that decrease the study's likelihood to yield usable results in a different environment. Firstly, the authors know where the rhinos in Olifants West are, because 20 of the rhinos in question are collared and have been tracked by Global Positioning System (GPS) for two years. In our study, the location of the rhinos is unknown as the area is immense and the rhinos are not collared, thereby adding an extra layer of difficulty to the problem.

Another difference between the studies is that Park et al. (2015) use drones in combination with rangers for patrolling. If the study is to be adapted and used in other environments, it is thus assumed that drones are permitted in those parks. The authors state that in the Olifants West study they had one drone per ranger. One drone can cover a relatively small area, but even for a park as small as Olifants West six drones were needed. If their study is to be adapted to the KNP, for example, there will be significant challenges such as obtaining approval for flying the drones, buying enough drones for the entire park (drones are very expensive), maintaining all the drones, *etcetera*.

Although it seems that BNs are not used in other wildlife crime applications, BNs have been used for urban crime applications. The paper by Gholami et al. (2015) presents a dynamic BN (DBN) that can be used to assign optimal patrol routes to patrol units, be it community policing or the police force. Urban crime is, according to the authors, opportunistic, and the criminals learn the movements of the patrol unit and use it to their advantage. The authors state that "...the criminals can adapt their strategy by seeking crime opportunity in less effectively patrolled locations." It is thus important that the criminals do not know the whereabouts of the patrol unit, just as is the case with the rhino poaching problem. The authors of (Gholami et al., 2015) generate optimal patrol strategies by modelling the relationships between the patrol unit and the criminals as a DBN.

1.2. The process

A systems engineering process called a "spiral process" (Boehm, 1988) was followed in constructing and evaluating the causal model. Our take on the spiral process is illustrated in Fig. 1 and it is called such because of its continuous nature of structuring, analysing, and synthesising, while moving ever closer to a desired solution.

According to Korb and Nicholson (2010), the spiral model for knowledge engineering with BNs (KEBN) starts off with a requirements analysis, then proceeds to the design phase, and is then implemented after which it is validated and tested. The process repeats itself until some stopping criteria is reached. This study loosely follows this process except for the implementation phase: