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Elephant poaching risk assessed using spatial and non-spatial Bayesian models

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ABSTRACT

Bayesian statistical methods are being used increasingly in crime research because they overcome data quality problems that arise due to the covert nature of crime, but the use of such methods is still in its infancy in the field of wildlife poaching—a specific form of crime. We analyzed poaching risk for African elephant (*Loxodonta africana*) by comparing spatial and non-spatial Bayesian models. Reports on elephant poaching in the Tsavo ecosystem were obtained for 2002–2012 from the Kenya Wildlife Service. The ecosystem was divided into 34 spatial units for which poaching data were aggregated and served as the base units for analysis. Spatial and non-spatial Bayesian models were fed with expert knowledge obtained through survey responses from 30 experts. The predictive accuracy of both models was assessed using the Deviance Information Criterion (DIC). Our results indicated that spatial Bayesian modeling improved the model fit for mapping elephant poaching risk compared to using non-spatial Bayesian models (DIC value of 193.05 vs 199.03). The results further showed that the seasonal timing of elephant poaching (i.e., in dry and wet seasons), density of waterholes, livestock density and elephant population density were factors significantly influencing the spatial patterns of elephant poaching risk in the Tsavo ecosystem for both models. Although there were similarities in the high risk areas for elephant poaching recognized in both models, risk probability values per spatial unit could differ. Furthermore, spatial Bayesian modeling also identified areas of high poaching risk that were not predicted by the non-spatial model. These findings provide vital information for identifying priority areas for combating elephant poaching and for informing conservation management decisions. The model we present here can be applied to poaching data for other threatened species.

1. Introduction

Widespread illegal hunting and the bush meat trade occur more frequently and with greater impact on wildlife populations in the Southern and Eastern savannas of Africa than previously thought (Lindsey et al., 2012). For example, in 2011 alone, about 40,000 elephants were poached for their ivory in Africa—equivalent to a species loss of about 3% (Wittemyer et al., 2014). A better understanding of where and when poaching is likely to occur would enable more effective law enforcement and possibly decrease the decline of wildlife due to poaching (Critchlow et al., 2015). Given the covert nature of poaching (Burn et al., 2011) that makes it difficult to record detailed spatial and temporal information on all poaching events, methods are needed that can deal with data scarcity (Gelman and Price, 1999). Not accounting for such scarcity can lead to unstable estimations of poaching patterns (Bernardinelli et al., 1995; Congdon, 2000).

With the ability to incorporate expert knowledge to help inform estimates for poorly sampled areas, Bayesian methods are becoming an increasingly common tool for ecological and disease mapping (Gelman and Price, 1999). In Bayesian statistical methods, crime data is regarded as a fixed quantity, whereas model parameters are considered to be random quantities when the measurement uncertainty is determined. Bayes' theorem combines information

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contained in the data (recorded crime) with prior knowledge to obtain posterior probabilities of crime risk, including risks for those areas that have a crime incidence count of zero (Law and Chan, 2012). The advent of recently developed Bayesian statistical approaches enables associations between crime occurrence and potential risk factors to be analyzed (Law and Chan, 2012; Law and Haining, 2004; Law et al., 2006; Law and Quick, 2013). Although in some situations non-spatial regression models can be carefully implemented to examine such associations (MacNab, 2004), these methods are limited in their ability to handle spatial data in which unmeasured confounders and spatial autocorrelation are evident (Einhorn et al., 1977; MacNab, 2004).

Crime research is increasingly using spatial methods because geocoded crime data and crime-related spatial data are becoming more available, and spatial methods for analyzing crime data at the local level are being developed (Law and Chan, 2012). Spatial analysis at the local level typically takes the form of exploratory spatial analysis such as cluster detection (e.g., hot spot identification) (Rashidi et al., 2015), or confirmatory spatial regression (e.g., risk factor identification) (Law and Quick, 2013).

The spatial association between crime occurrence and potential risk factors has traditionally been modeled using a frequentist (classical) statistical approach in the form of logistic regression (Haines et al., 2012; Nielsen et al., 2004). However, such an approach does not satisfactorily account for local risk factors (i.e., existing in one unit but not in neighboring ones) that remain unknown and are not captured in the model (Law and Chan, 2012). As a result, spatial autocorrelation remains a problem in traditional approaches even if the covariates are adjusted for it (Law and Chan, 2012). Moreover, developing accurate models requires large datasets; this can be a problem in crime research where observational data are scarce, costly to obtain, or subject to design and quality concerns.

Bayesian statistics have been used to fit spatial models in several crime studies (Haining and Law, 2007; Law and Chan, 2012; Law and Haining, 2004; Law et al., 2006; Law and Quick, 2013; Porter and Brown, 2007). However, to our knowledge, few studies have utilized spatial Bayesian methods to explore relationships between wildlife poaching (a specific form of crime) and potential risk factors. One example is Burn et al. (2011), who studied global trends and factors associated with the illegal killing of elephants in Africa and Asia between 2002 and 2009. They used a Bayesian hierarchical modeling approach to estimate the trend and the effects of site- and country-level factors associated with the poaching. At a country level, key determinants for elephant poaching were poor governance and low levels of human development; whereas at a site level they were low human population density and forest cover. Although Burn et al. (2011) explored spatial Bayesian modeling in their analysis, they did not incorporate any informative prior knowledge (expert knowledge) in the model.

Expert knowledge can provide information about model parameters and help characterize uncertainty in models, and it can be useful when data are limited or are not available (Kuhnert, 2011). For example, Murray et al. (2009) used expert judgments to fill information gaps related with species occupancy in unreachable sites. Expert knowledge has also been used to assess the impacts of grazing levels on bird density in woodland habitats (Martin et al., 2005). Furthermore, expert knowledge was used to create Bayesian networks for criminal profiling from limited data (Baumgartner et al., 2008).

Bayesian methods can incorporate expert knowledge through priors (prior knowledge), using probability distributions representing what is known about the effect of the factor on what is being modeled (Gelman et al., 2014; Kuhnert et al., 2010; Stigler, 1986). The priors reflect the knowledge available on model parameters before observing the current data (Schoot et al., 2014; Stigler, 1986). Non-informative priors can be specified if one does not want to impose any prior knowledge on a model. The use of non-informative priors is referred to as objective Bayesian statistics since only the data determine the posterior results (Clarke, 1996; Press, 2009; Schoot et al., 2014). In contrast, informative priors convey information on prior preference for certain parameter values. Methods using informative priors are referred to as subjective Bayesian statistics (Akaike, 1977; Clarke, 1996; De Finetti et al., 1990; Press, 2009; Schoot et al., 2014). Subjective priors are beneficial because findings from previous research and expert knowledge can be incorporated into the analyses (Akaike, 1977; Clarke, 1996; Press, 2009; Schoot et al., 2014). For example, after several studies on the relationship between elephant poaching and risk factors, we may be able to provide a fairly accurate prior distribution of the parameters that measure this relationship. Prior information can also be obtained from expert knowledge gained from extensive experience. Different points of view might represent different priors for parameters, however, it has been shown that Bayesian expert systems are robust with respect to the absolute difference in priors (McCarthy, 2007). For example, Crome et al. (1996) used Bayesian methods to study effects of logging on mammals and birds. They were mainly interested in investigating real differences of opinion, which were elicited from experts. Differences of opinion were represented in the different priors for the impact of logging on mammals and birds. They revealed that these differences of opinion could reach consensus for various species (McCarthy, 2007).

In a previous study, we analyzed elephant poaching hotspots from poaching incidence data using clustering techniques (Rashidi et al., 2015). However, we did not incorporate any knowledge about risk factors nor did we account for the possibility of missing poaching data in the records. In the present study, we propose to use expert knowledge as prior information on risk factors.

A key feature of the spatial Bayesian modeling approach is the specification of the spatial random effect term to the Bayesian non-spatial model; this term can account for unidentified or unexplained sources of spatial autocorrelation. The spatial random effect term includes a spatially unstructured random variable and a spatially structured variable. Spatially unstructured random variables ignore the geographical location of the analysis units, whereas spatially structured random variables assume that geographically proximate spatial units tend to have similar risks (Law and Chan, 2012). Another advantage of the Bayesian spatial model is its capability to account for missing data, where, due to data limitations, the analyst is concerned about the effects of important covariates that are missing (Law and Haining, 2004; Law and Quick, 2013).

Our study aimed to address four questions: (1) Is the Bayesian spatial model more effective for mapping elephant poaching risk than the non-spatial model? (2) What are the key factors influencing elephant poaching risk as determined by Bayesian spatial and non-spatial models? (3) Where are the high risk areas for elephant poaching in the Tsavo ecosystem based on both models? (4) Where are areas of high risk unexplained by the covariates?

2. Materials and methods

2.1. Study area

The Tsavo ecosystem consists of an area of about 38,128 km^2 in south-east Kenya (Fig. 1). It lies between 2 and 4°S, and 37.5–39.5°E. The Tsavo ecosystem has the highest population of elephants in Kenya, and also the highest number of reported elephant poaching incidents (Maingi et al., 2012; Rashidi et al., 2015). The anti-poaching activities in the Tsavo ecosystem face challenges of insufficient human and financial resources, and the extensive area to be covered (Maingi et al., 2012; Rashidi et al., 2015). Several rivers cross the ecosystem, including the Tsavo, Tiva, Galana, Athirivers,