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Assessing trends and seasonal changes in elephant poaching risk at the small area level using spatio-temporal Bayesian modeling

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ABSTRACT

Knowledge about changes in wildlife poaching risk at fine spatial scale can provide essential background intelligence for law enforcement and crime prevention. We assessed interannual trends and seasonal changes in elephant poaching risk for Kenya's Greater Tsavo ecosystem for 2002 to 2012 using spatio-temporal Bayesian modeling. Poaching data were obtained from the Kenya Wildlife Service's database on elephant mortality. The novelty of our paper is (1) combining space and time when defining poaching risk for elephant; (2) the inclusion of environmental risk factors to improve the accuracy of the spatio-temporal Bayesian model; and (3) the separate analysis of dry and wet seasons to understand season-dependent poaching patterns. Although Tsavo's overall poaching level increased over time, the risk of poaching differed significantly across space. Three of the 34 spatial units had a consistently high poaching risk regardless of whether models included environmental risk factors. Adding risk factors enhanced the model's predictive power. We found that highest poaching risk areas differed between the wet and dry season. The findings improve our understanding of elephant poaching and highlight high risk areas within Tsavo where action to reduce elephant poaching is required.

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Spatio-temporal variations; spatial random effects; mean trend; poaching analysis; environmental risk factors

1. Introduction

In the past decade, there has been an increase in African elephant (*Loxodonta africana*) poaching, especially for ivory (Douglas-Hamilton 2009, Wittemyer *et al*. 2014, Nyirenda *et al*. 2015). Estimates suggest that between 2011 and 2013, more than 100,000 African elephants were poached (White 2013, Wasser *et al*. 2015), corresponding to 21% of the total population. Kenya, like many other African countries, is suffering from a continuous year-to-year increase in the proportion of illegally killed elephants since 2003 (Douglas-Hamilton 2009, Maingi *et al*. 2012).

Insufficient human and financial resources, combined with the large areal extent to be monitored, pose major challenges for anti-poaching activities in Kenya (Maingi *et al*.

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Supplemental data for this article can be accessed here.

2012, Rashidi *et al*. 2015). Because of high conservation costs, Kenya cannot offer adequate protection of wildlife from poaching within national parks and reserves (Maingi *et al*. 2012). The Kenya Wildlife Service (KWS) is understaffed with less than one ranger per 100 km^2 of wildlife reserve (Maingi *et al*. 2012). Therefore, assessment of trends and seasonal changes in wildlife crime on a small spatial scale allows for targeting specific locations where crime may be concentrated and assists in the setting of conservation priorities and the concentration of management resources (Maingi *et al*. 2012).

Poaching is a dominant wildlife crime, but it is unevenly distributed over space and time (Burn *et al*. 2011). Poaching data have a covert nature, which makes it difficult to estimate poaching trends (Burn *et al*. 2011) in small spatial units. We therefore need models that can take scarcity of poaching data or incomplete data into account (Gelman and Price 1999). Spatio-temporal Bayesian models are particularly useful when working with fine scale data (DiMaggio 2015) as they can consider poaching risk in areas with zero counts by borrowing information from neighboring areas (Sun *et al*. 2000). This helps to overcome problems of unstable poaching estimates related to a lack of data (Gelman and Price 1999) as a result of low incident counts in small areas and large variations in sampling (Bernardinelli *et al*. 1995, Congdon 2000).

The assessment of trends in wildlife poaching using Bayesian models has been limited to large-scale studies at countrywide levels (Burn *et al*. 2011). Critchlow *et al*. (2015) used ranger-collected data from 1999 to 2012 to identify spatio-temporal trends in general illegal activities in a Ugandan national park. The illegal activities included infringing upon nature reserves for plant harvesting, cultivation, animal grazing, or poaching. Although the above studies used Bayesian models to monitor the spatio-temporal variation in trends within a unified framework, they did not incorporate expert knowledge for the selection of ecological covariates or for prior probabilities. Prior probabilities are represented by probability distributions indicating known effects of the ecological covariates on illegal activities. Moreover, they also did not investigate seasonal changes in areas highly at risk of illegal activity. Rashidi *et al*. (2015) addressed the problem of limited data in small geographic units (blocks) using expert knowledge and Bayesian modeling but focused on spatial variations. Here we incorporate a temporal element into the analysis. Space-time analyses have extra benefits to purely spatial analyses, since they permit the simultaneous study of mean trends and unusual local trends (Richardson *et al*. 2006). This is important because patterns of illegal activities can vary over time and space (Critchlow *et al*. 2015).

In this paper, we assess interannual trends and seasonal changes in elephant poaching risk for Kenya's Greater Tsavo ecosystem for an 11-year period, from 2002 to 2012, using spatio-temporal Bayesian modeling. This study has three specific objectives, i.e. (1) to identify the presence of space–time interactions, by ascertaining if temporal trends in poaching risk differ between areas of the Greater Tsavo ecosystem; (2) to investigate if the accuracy of poaching prediction can be improved by adding environmental risk factors to the spatio-temporal Bayesian model; and (3) to assess whether locations of the highest elephant poaching risk differ between wet and dry seasons.

2. Materials and methods

2.1. *Study area*

The Greater Tsavo ecosystem covers 38,128 km^2 in south-east Kenya (Figure 1). Our study area was composed of the Tsavo East National Parks North (north of the Galana River) and South (south of the Galana River), as well as the Tsavo West National Park, with the remaining areas being covered by private ranches (Figure 1). The rivers and streams of the Tsavo ecosystem include the Tsavo, Tiva, Galana, Athirivers and Voi (Maingi *et al*. 2012). *Commiphora* savanna is the prevailing vegetation community in the study area (Cobb 1976). The area's climate shows clear seasonality and also displays a large geographic variation. The long wet season takes place between March and May. Rainfall amount during the wet season is largest between the Taita Hills and the Kilimanjaro area. The short rainy season occurs in November and December when rainfall is concentrated mostly in the eastern and northern parts of the area (Smith and Kasiki 2000, Ngene *et al*. 2013). The Tsavo ecosystem is home to the largest population of Kenya's elephants but also experiences the largest number of elephant poaching incidents in Kenya (Maingi *et al*. 2012, Rashidi *et al*. 2015). It is also one of four sites for 'Monitoring of Illegal Killing of Elephants' (MIKE program) in Kenya (Shaffer and Bishop 2016).

To quantify local differences in elephant poaching trends, the Greater Tsavo ecosystem was subdivided into 37 blocks, which were initially designed for the aerial counting of the elephant population in the Tsavo-Mkomazi ecosystem (Ngene *et al*. 2013). Block boundaries

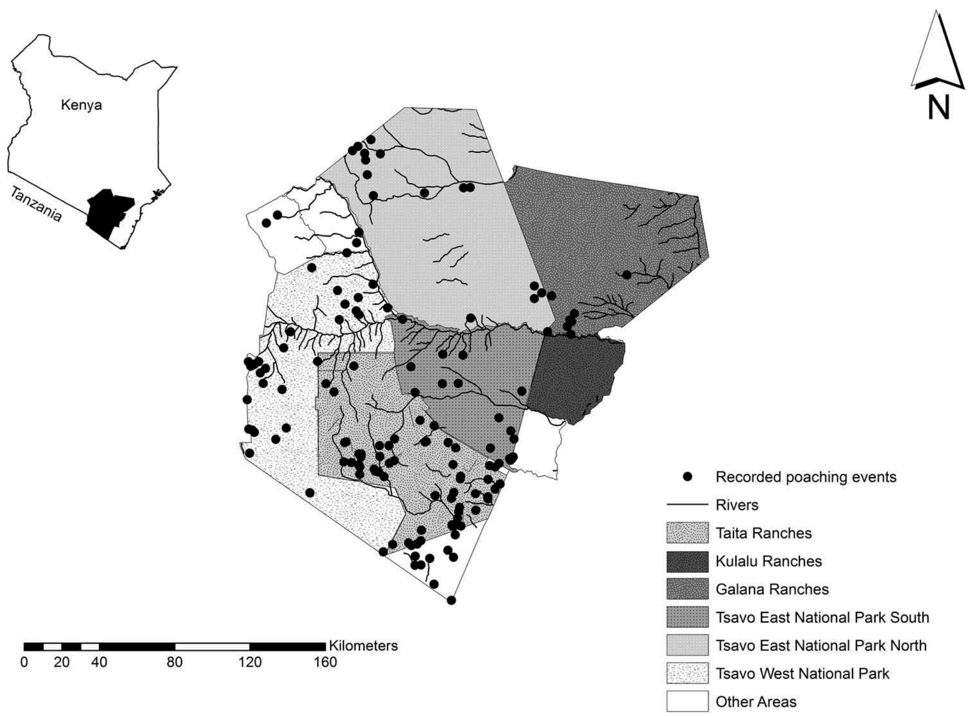

Figure 1. Location of the Greater Tsavo ecosystem in Kenya. The points (151) indicate the recorded sites of elephant poaching and the colors show the different ranches and sections of the Greater Tsavo ecosystem (2002–2012).

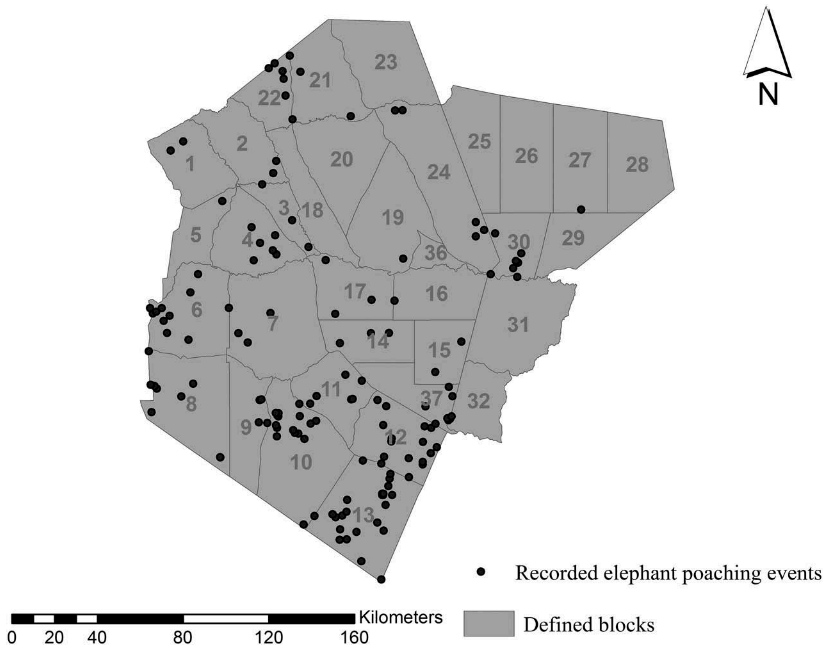

Figure 2. Distribution of recorded elephant poaching incidents between 2002 and 2012 within the defined blocks in the Greater Tsavo ecosystem.

were defined by the KWS according to easily detectable features such as roads, hills, rivers and protected area boundaries. Block sizes ranged from 248 km^2 to 2008 km^2, with and average size of 1098 km^2 (Ngene *et al*. 2013). Block numbers 33–35 were omitted since they were located in Tanzania and poaching data there were not accessible (Rashidi *et al*. 2015). We used the 34 blocks in the Kenyan part of the ecosystem as the geographic units in our analysis. All data, for both the elephant population and elephant poaching incidents, were linked to these geographic units (Figure 2).

2.2. *Data*

2.2.1. *Elephant population and poaching incidence data*

Data on elephant populations and poaching were obtained from the KWS. Aerial surveys were undertaken by the KWS in the Tsavo ecosystem from 7 to 12 February 2011 to record elephant populations (Ngene *et al*. 2013). We assumed that the spatial distribution of the elephant population in 2011 could be used for all blocks and years because there were no significant changes in the population from 2002 till 2012 (Ngene *et al*. 2013). The data set comprised the number of elephants observed per location, the geographic coordinates and names of these locations, and the observation dates (Ngene *et al*. 2013). Aerial patrols and daily ground patrols were executed by the KWS through the MIKE program to record elephant poaching incidents. Consistent patrolling and a wide coverage of the monitored sites belong to the core methods employed by the MIKE program (Burn *et al*. 2011) Rangers used their bush and tracking skills, as well as contacts with the local communities, to recognize poachers and poacher trails (Rashidi *et al*. 2016). They also used visual cues in the field (e.g. the presence of vultures) to identify carcass locations (Rashidi *et al*. 2016) and global positioning system units for recording locations (Cites 2010). Patrol forms and carcass forms were completed by the rangers. The full data set consisted of 151 poaching locations in the study area for the years 2002–2012. The data contained the estimated date of death, location names of where elephant carcasses were found and coordinates of the locations where elephant carcasses were found. The Spatial Join geoprocessing tool in ArcMap 10 was used to link the data on the 151 poaching locations to the 34 blocks (Tables S1, S2 and S3).

2.2.2. *Environmental risk factors*

The selection of environmental risk factors was based on previous studies (Kyale *et al*. 2011, Maingi *et al*. 2012, Rashidi *et al*. 2016). We obtained spatial and spatio-temporal information on these risk factors as per Rashidi *et al*. (2016). The factors included: (1) elephant population density, (2) livestock density, (3) mean normalized difference vegetation index (NDVI), (4) standard deviation of NDVI, (5) elevation, (6) slope, (7) density of waterholes, (8) distance to rivers and streams, (9) distance to roads, (10) distance to international border, (11) distance to settlements and (12) seasonal timing of elephant poaching (i.e. poaching probabilities in the dry and wet seasons).

We used the variance inflation factor (VIF) to evaluate and account for the effects of multicollinearity between variables (Dormann et al. 2013). This is a method based on the calculated VIF statistics, which iteratively selects variables based on the maximum linear correlation found between pairs of variables and excludes the variable that has the larger VIF. This procedure is repeated until there is no variable pair with a high coefficient of correlation left (Naimi 2013). Here, we first selected variable pairs that had a linear correlation coefficient greater than the threshold set to 0.5. For the variable pair with the highest correlation, one of the variables was excluded, that is, the one with the highest VIF. The procedure was repeated until no variable pair with a correlation coefficient above 0.5 remained. Of the selected variables, elephant population density, livestock density, standard deviation (STD) of NDVI, distance to rivers and streams, waterhole density, distance to road, distance to international border and seasonal timing of elephant poaching (i.e. probabilities in dry and wet seasons) remained after accounting for multicollinearity (Table S4).

2.3. *Modeling strategy and analysis*

We fitted two different sets of spatio-temporal Bayesian models (Table 1). The first set was used to assess local trends of elephant poaching from 2002 to 2012 in the Greater Tsavo ecosystem and includes two models. Model 1.1 did not account for the potential risk factors that vary geographically across the blocks, while Model 1.2 added risk variables to the model to test whether the ‘risk’ covariates enhanced the prediction of poaching (Table 1). Expert knowledge, based on survey responses from 30 experts, was input to Model 1.2 (Rashidi *et al*. 2016). We used this expert knowledge for the selection of environmental risk factors and also incorporated expert knowledge through priors (prior knowledge), based on probability distributions representing what is known about the effect of the environmental risk factor on elephant poaching risk. The second spatio-

Table 1. Model structure for the two different model sets used in this paper.

Model	Types	Data
Set 1	$\log(e_{ij}) + \alpha + u_i + s_i + (y + \delta_i)t_j$	Data include wet and dry season data
1.1	$\log(e_{ij}) + \alpha + u_i + s_i + (y + \delta_i)t_j + \beta_1 x_{1i} + \ldots + \beta_{kx} k_i$	Data include wet and dry season data
1.2		
Set 2	$\log(e_{ij}) + \alpha + u_i + s_i + (y + \delta_i)t_j$	Data include only wet season data
2.1	$\log(e_{ij}) + \alpha + u_i + s_i + (y + \delta_i)t_j$	Data include only dry season data
2.2		

temporal Bayesian model set was used to investigate seasonal changes in elephant poaching risk. The second set also includes two models, one fitted for the wet and one for the dry season (Table 1). Data were divided into seasonal categories (wet and dry) based on rainfall distribution in the study area. Model 2.1 was used to determine risk areas for elephant poaching during the wet season, and Model 2.2 was used to determine risk areas for elephant poaching in the dry season (Table 1).

For all models, we used Poisson regression with the log link function, as this function accounts for rare incidences (McCullagh and Nelder 1989, Torabi and Rosychuk 2012, Li *et al*. 2014). Bayesian approaches combine observed data (i.e. elephant poaching incidents) and prior knowledge (e.g. neighborhood structure, information from adjacent blocks or experts) to estimate posterior distributions of unknown parameters (e.g. local differential trends in elephant poaching) (Luan *et al*. 2015). The prior data reflect the knowledge available on model parameters before observing the current data (Stigler 1986, Schoot *et al*. 2014). The prior distribution is used to model data dependence between neighboring areas (Law and Chan 2012) since it contains information about how the poaching risks are related to one another.

The poaching cases (Y_{ij}) for area $i = 1, \ldots, I$, and time period $j = 1, \ldots, T$ can be modeled as a

$Y_{ij} \sim$ Poison (lambda$_{ij}$).

where the parameter lambda$_{ij}$ of the Poisson distribution (P) is the expected value of Y_{ij}, exp $[Y_{ij}]$.

exp $[Y_{ij,}]$ = lambda$_{ij} = \theta_{ij*}\, e_{ij}$

Using a log link function, unknown risk (θ_{ij}) is split into parameters measuring purely spatial variation, purely temporal variation and spatio-temporal interaction:

$\log(\theta_{ij}) = \alpha + u_i + s_i + (y + \delta_i)t_j$

Log (lambda $_{IJ}$) = $\log(e_{ij}) + \alpha + u_i + s_i + (y + \delta_i)t_j$

where e_{ij} is the corresponding number of expected elephant poaching cases for area $i = 1, \ldots, I$, and time period $j = 1, \ldots, T$. The purely spatial variation is represented by an intercept α (average elephant poaching for the study region), u_i (unstructured random effects) and s_i (spatially structured random effects). These terms accommodate any over-dispersion that may arise when modeling count data at the areal level (Luan *et al*. 2015). Regional temporal variation of elephant poaching for the study region is captured by y. We assumed a linear regional trend over all areas in the study region, which depends on the nature of the data set (the observed elephant poaching incidents data) (Torabi and Rosychuk 2012). δ_i is the interaction between the spatial and temporal effects. To explore the geographic variation of the local trends, we mapped the posterior probability (PP) of a local differential trend (δ_i) that was greater than the mean trend (Law *et al*. 2014, 2015). PP can be viewed as the Bayesian equivalent of the p-value (Meng and

Dempster 1987). It represents the degree that each spatial unit is greater than the mean trend, which accounts for the variance of area-specific trends. High PP_i values indicate that area-specific trends have a high probability of differing from the mean trend, whereas low PP_i values indicate that area-specific trends have a low probability of differing from the mean trend.

To capture the number of elephant poaching incidences expected, we used an indirect standardization method (utilizing the average trend and elephant population) (Law *et al*. 2015). Indirect standardization utilizes the risk estimates in the reference population (total population in the study region as a whole) to calculate the expected number of incidents in the study population (Yuan 2013). The expected number of elephants poached was calculated for each block, season and year. For example, in 2011 block no. 3 had an elephant population of 27 and 5 poaching incidents. Given that from 2002 to 2012 the overall increase in incidents in the study region was 246, and in 2011 the total elephant population in the study region was 1370, the expected number of incidents for block 3 in 2011 was 9.59 (= 5 + (27 × 246/1370)), where 246/1370 is the average trend of elephant poaching in the whole study region.

2.4. *Computational details*

An improper uniform prior U ($-\infty$, $+\infty$) was defined for the intercept α (Luan *et al*. 2015). A normal distribution prior with mean 0 and variance σ_s^2 was specified for u_i (Law *et al*. 2015). The prior for the regional time trend (γ) was a vague prior normal distribution with mean equal to zero and variance of 1000 (Law *et al*. 2014). An Intrinsic Conditional Autoregressive Gaussian distribution (ICAR) was used to specify priors for spatial random effect s_i and spatio-temporal interaction δ_i (Torabi and Rosychuk 2012, Law *et al*. 2014, 2015, Li *et al*. 2014, Luan *et al*. 2015). Under the ICAR specification, the means of s_i and δ_i for one block depend on the s_i and δ_i, respectively, of the neighboring blocks' distribution, where adjacency is defined as areas that have common borders (Torabi and Rosychuk 2012, Luan *et al*. 2015). The amount of variation of s_i and δ_i is controlled by hyperparameters σ_s^2 and σ_δ^2, respectively, and is contrariwise related to the number of neighbors of the *i*th block (Torabi and Rosychuk 2012, Law *et al*. 2014, 2015, Li *et al*. 2014, Luan *et al*. 2015). In Bayesian approaches, priors assigned to hyperparameters (i.e. the parameters of priors) are called hyperpriors (Luan *et al*. 2015). We conducted analysis using a uniform hyperprior distribution of (0.5, 0.0005) for σ_u, σ_s and σ_δ. This gamma distribution is a prior that offers a reasonable range for relative risk (Elliot *et al*. 2000).

Spatio-temporal modeling was conducted using the statistical software WinBUGS, version 1.4.3 (McCarthy 2007). Models were specified textually via the BUGS language in WinBUGS, in which the model likelihood and the prior distribution are defined (Figure S1) (McCarthy 2007). WinBUGS uses 'Markov Chain Monte Carlo' (MCMC) algorithms to estimate posterior distributions of the model parameters (McCarthy 2007). MCMC methods create random samples from the posterior distribution: the value of each step is conditional on the previous step (Kéry 2010), and after enough iterations, the algorithm converges to the required posterior value (Law *et al*. 2006). With a sufficient number of simulated observations, this iterative procedure leads to an accurate estimation of the distribution (Kim 2011).

To assess trends and seasonal changes in the elephant poaching risk in the Greater Tsavo ecosystem from 2002 till 2012, we fitted the spatio-temporal Bayesian models using WinBUGS software with two parallel chains thinned by 10 to reduce auto-correlation (Luan *et al*. 2015). For each model, to obtain 20,000 samples from the posterior distribution, MCMC chains comprising 10,000 iterations with a burn-in of 1000 were found to be sufficient to achieve convergence. Convergence was assessed by Brook–Gelman–Rubin Diagnostic, history plots, visually examining trace plots and Monte Carlo standard error (<5 % of the sample posterior standard deviation) (Law *et al*. 2014, Luan *et al*. 2015).

To assess the model fit, we used the Deviance Information Criterion (DIC) (Spiegelhalter *et al*. 2002). The DIC can be considered as Bayesian equivalent of the Akaike Information Criterion (AIC), and it utilizes the number of effective parameters (defined as the posterior expectation of the deviance minus the deviance evaluated at the posterior mean of the parameter (King *et al*. 2009)) instead of the actual number of parameters used by the AIC (Ntzoufras 2011). The advantage of DIC is that it can be directly computed from an MCMC output, and moreover it can be applied in a larger variety of models (Ntzoufras 2011). Lower values for the DIC indicate that the model fit is closer to the data. A difference in DIC values between two models should be at least 5 to conclude that one of the models fits the data better, because of Monte Carlo sampling errors inherent in the calculation of the DIC (Law *et al*. 2014).

3. Results

Figure 3 shows the probability that local elephant poaching trends were greater than the mean trend (Table 2) using two different models (Table 1). Variation in area-specific elephant poaching trends was statistically significant at the 95% credible interval (Table S4). Blocks with the highest probability were areas that have experienced relatively higher risks of elephant poaching over the 11 years and showed a steeper, increasing trend in poaching compared with the mean trend (Figure 3). In both models, the largest positive trends (probability that elephant poaching risk is above mean trend > 0.9) were located in specific blocks (blocks 9, 26 and 29) in the Tsavo West National Park, Tita ranch and Galana ranch (Figure 3).

Our results indicate that while similar blocks with the highest poaching trend were found by both models (Model 1.1 and Model 1.2), some blocks displayed different probability classes (blocks 1, 2, 5, 6, 10, 14, 17, 19, 20, 22, 24, 25, 27 and 31) (Figure 3). Moreover, Model 1.2, which accounts for potential risk factors, had a smaller value for the DIC (Table 2) which indicates a more accurate model fit for Model 1.2 than Model 1.1.

Based on our modeling results, we could map elephant poaching incidences (Figure 2) and estimate poaching trend over time (Figure 3). A large spatial variability can be observed both in observed poaching incidence and estimated risk.

Further, the results indicate that among the selected factors that remained after accounting for multicollinearity, livestock density, distance to road, seasonal timing of elephant poaching, density of waterholes and distance to international border were significant at the 95% credible interval (Table S4). Inclusion of zero values within the 95% Bayesian credible intervals implies the insignificance of the estimates (Jianmei

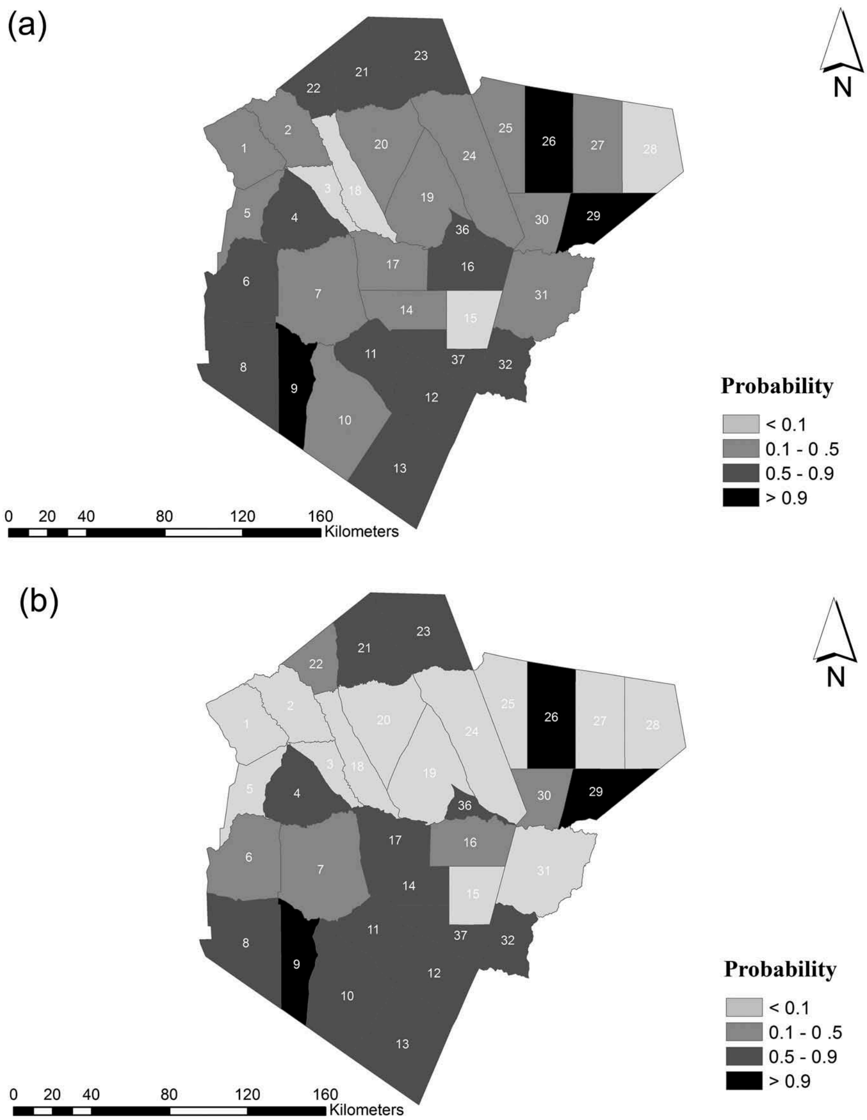

Figure 3. Probability that local elephant poaching risks were greater than the mean temporal trend: (a) Model 1.1: spatio-temporal Bayesian model without accounting for the potential risk factors and (b) Model 1.2: spatio-temporal Bayesian model which includes potential risk factors.

Table 2. The results of model fitting for Models 1.1 and 1.2.

	Model 1.1	Model 1.2
γ: overall time trend (credible interval: 2.5%, 97.5%)	0. 27 (0.4,0.61)	0.76 (0.1,1)
DIC: deviance information criteria	14,870	14,725
P_D: effective number of parameters	276	250

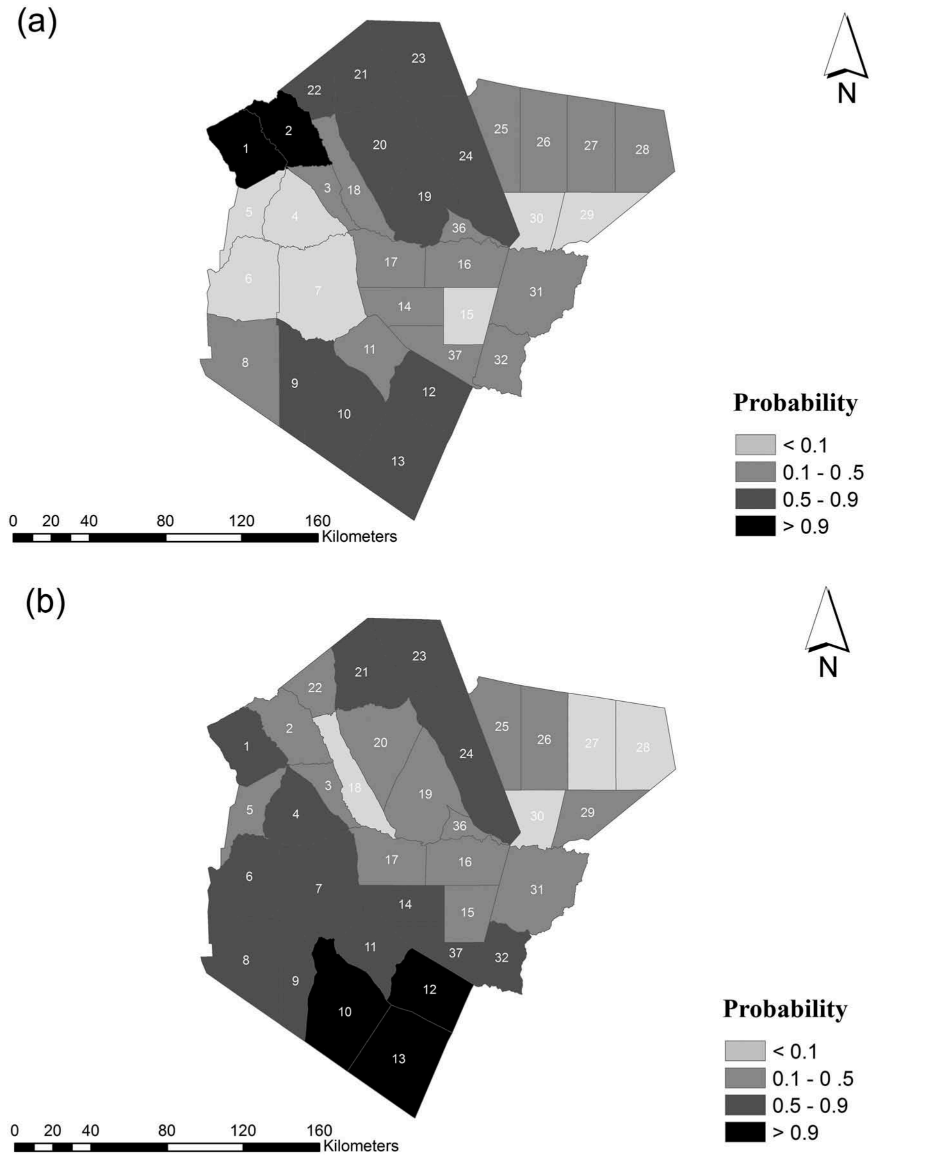

Figure 4. Seasonal changes in high risk areas for elephant poaching in Tsavo ecosystem (2002–2012) using the spatio-temporal Bayesian model: (a) Model 2.1: wet season and (b) Model 2.2: dry season.

2014). In other words, if the credible interval for estimated parameters covers zero, then that would be considered as lack of evidence for different variances (Kéry 2010).

Figure 4 shows that the highest risk areas for elephant poaching differ between the wet and dry seasons.

4. Discussion

The ability to detect areas with increasing elephant poaching can aid decision-making regarding conservation priorities, by prompting the need for further management attention, such as increased ranger/patrol activities in areas with higher poaching risk (Figure 3). For example, for the Tsavo, blocks no. 26 and no. 29 in the Galana ranch and no. 9 in the Tsavo West National Park and Tita ranch should be prioritized for preventive actions.

These three blocks are all located in areas with human settlements in and around them. Therefore, the result can be partly explained by human–elephant conflict over resources (space, water and forage) in these areas (Ngene 2010). Another reason could be possible collaboration of local people with poachers or their indifference toward elephant poaching (Maingi *et al*. 2012). The findings thus indicate the need for strategies such as local community conservation programs (Maingi *et al*. 2012) to obtain community support. And priority should be given to security patrols in these areas to mitigate elephant poaching risks.

The highest risk areas for elephant poaching determined by this study differ from those identified in the previous study (Rashidi *et al*. 2016), which focused only on the spatial variation observed in elephant poaching in the Tsavo ecosystem without investigating the interaction between time and space. Spatio-temporal methods may therefore detect relatively subtle changes in elephant poaching risk in specific blocks over time that would not have been detected by spatial analyses alone (Critchlow *et al*. 2015). However, there were also blocks (blocks 6, 10, 16 and 21), which did display similar probability classes in both studies.

Furthermore, we found that block no. 9 was consistently identified as a hot spot with a high poaching risk, as Rashidi *et al*. (2015) had also observed, when using spatial as well as spatiotemporal clustering methods (Figure 3). However, in the current study, some new areas showing a significantly increasing trend were detected (Figure 3) and we further demonstrated the probability that each block would show a differential trend from the mean elephant poaching trend in the Tsavo ecosystem (Figure 3). By explicitly stating the probability of observed poaching risk in a particular block, we detected high-risk areas where this risk is unlikely to be due to chance (DiMaggio 2015). This allowed us to be more specific about high risk area locations rather than having to resort to reporting clusters of areas (as typically recognized by SaTScan). For example, Rashidi *et al*. (2015) found that blocks no. 8, no. 9 and no. 10 were hotspots, irrespective of the clustering method used. However, they did not detect probabilities regarding elephant poaching risk for these areas. In the current study, we detected that the elephant poaching risk probability differed between these three blocks (Figure 3).

The fact that some areas show significantly different trends in poaching could be due to potential risk factors that vary geographically across the blocks. Therefore, we set Model 1.2 to consider the effect of adding these variables to the Model 1.1 (Table 1) and to test whether the covariates enhanced the prediction of the model. We found that density of waterholes, livestock density, seasonal timing of elephant poaching, distance to roads and distance to international border significantly contributed to the estimation of temporal trends in elephant poaching in Kenya's Greater Tsavo ecosystem (Table S4). Rashidi *et al*. (2016) also found the first three risk factors to be covariates, while the latter two were new in the present study. The fact that some variables like elephant density and distance to rivers have been deemed important by experts but were not significant in our models could be due to theoretical knowledge rather than personal and local experience (Doswald *et al*. 2007). Such variables may be collinear with other covariates responsible for elephant poaching and therefore make scoring difficult (Doswald *et al*. 2007). Although expert opinion is useful for collecting general knowledge on elephant poaching, combined expert and field data enhanced the posterior estimates and further improved elephant poaching models. Our results also indicated that selected variables were useful predictors, because Model 1.2 provided an improved model fit through a lower DIC. This result is in contrast with the results of Critchlow *et al*. (2015), who found that their selected ecological covariates were not useful predictors for incidences of illegal activities. One reason for this contrast could be the selection of potential risk factors in our study, which were based on expert knowledge. This supports the idea that combining expert opinion with empirical data improves model performance (Murray *et al*. 2009).

Furthermore, the results obtained from Models 2.1 and 2.2 demonstrated that the highest risk areas for elephant poaching differed between the wet and dry seasons. This finding supports the idea from the previous study (Rashidi *et al*. 2016) that elephant poaching is more likely to occur in different locations in the dry season than in the wet season. This could be explained by seasonal preferences for specific land cover by elephant (Shaffer and Bishop 2016) as well as seasonal variations in surface water availability. It may be expected that elephants move to other areas where water and food supplies are plenty, but conservation security there might be lower (Sibanda *et al*. 2016).

A limitation when studying elephant poaching trends lies in the collection of poaching data, which may be underreported or misreported by rangers (Maingi *et al*. 2012). It is possible that the elephant poaching data that we used for this study only represent a proportion of the total poaching that occurred between 2002 and 2012. However, we mitigated this problem by utilizing a spatio-temporal Bayesian model, which provides a flexible framework for borrowing information over space and time from adjacent blocks by using spatial and temporal random effects (Li *et al*. 2014). For example, the recorded elephant poaching incidences (Figure 2) and estimated poaching trend over time (Figure 3) are very different in blocks no. 26 and no. 29 in the Galana ranch. Our study demonstrates that the spatio-temporal Bayesian model is a valuable approach when recorded elephant poaching incidents are scarce or incomplete, as it allowed the discerning of elephant poaching trends in some blocks that could not be ascertained from a visual analysis of the poaching data alone. With improvements to the observation effort and the recording of patrol data and associated contextual information, and with the development of appropriate models, predictions of poaching could be further improved (Keane *et al*. 2011).

A linear regional trend over an 11-year period was assumed in this study, which is appropriate for the data on observed elephant poaching incidents. When using poaching data that cover multiple time periods rather than subsequent years, a non-linear trend analysis may further reduce error in the model, thereby providing additional insight into poaching change over time.

5. Conclusions

We examined spatial variation in trends and seasonal changes in elephant poaching risk from 2002 to 2012 in Kenya's Greater Tsavo ecosystem, using spatio-temporal Bayesian modeling. We also tested the hypothesis concerning whether risk factors enhanced the prediction of the model. This modeling framework has been shown to effectively account for inconsistent results due to limited and/or missing data. Our results indicate that the mean trend in elephant poaching is increasing in the Tsavo ecosystem over time. Assessment of spatio-temporal poaching trends in small areas showed that blocks with the strongest positive trends in elephant poaching are situated in the Tsavo West National Park, Tita ranch and Galana ranch. Our results also indicate that adding risk factors enhances model fit. Furthermore, our results indicate that areas with the highest poaching risk differ between dry and wet seasons.

Obtained results have several practical implications. The KWS can benefit from our results by allocating their financial and human resources more effectively to prevent or reduce poaching activity in areas with relatively strongly increasing poaching trends. Our results also provide vital information for decision-making and management regarding setting conservation priorities. Moreover, the models we present here may also be adjusted and applied to poaching data for other threatened species and in other areas.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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