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Contributed Paper

A spatial approach to combatting wildlife crime

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Abstract: *Poaching can have devastating impacts on animal and plant numbers, and in many countries has reached crisis levels, with illegal hunters employing increasingly sophisticated techniques. We used data from an 8-year study in Savé Valley Conservancy, Zimbabwe, to show how geographic profiling—a mathematical technique originally developed in criminology and recently applied to animal foraging and epidemiology—can be adapted for use in investigations of wildlife crime. The data set contained information on over 10,000 incidents of illegal hunting and the deaths of 6,454 wild animals. We used a subset of data for which the illegal hunters' identities were known. Our model identified the illegal hunters' home villages based on the spatial locations of the hunting incidences (e.g., snares). Identification of the villages was improved by manipulating the probability surface inside the conservancy to reflect the fact that although the illegal hunters mostly live outside the conservancy, the majority of hunting occurs inside the conservancy (in criminology terms, commuter crime). These results combined with rigorous simulations showed for the first time how geographic profiling can be combined with GIS data and applied to situations with more complex spatial patterns, for example, where landscape heterogeneity means some parts of the study area are less likely to be used (e.g., aquatic areas for terrestrial animals) or where landscape permeability differs (e.g., forest bats tend not to fly over open areas). More broadly, these results show how geographic profiling can be used to target antipoaching interventions more effectively and more efficiently and to develop management strategies and conservation plans in a range of conservation scenarios.*

Keywords: Bayesian models, bushmeat, geographic profiling, ivory, rhino horn, snaring, spatial analysis

Resumen: *Una Estrategia Espacial para Combatir el Crimen de Vida Silvestre*
La caza furtiva puede tener impactos devastadores sobre el número total de plantas y animales, y en muchos países ha alcanzado niveles críticos ya que los cazadores ilegales utilizan técnicas cada vez más sofisticadas. Utilizamos datos de un estudio de ocho años en la Reserva del Valle de Savé, Zimbabue, para mostrar cómo el perfil geográfico – una técnica matemática desarrollada originalmente para la Criminología y que se aplica recientemente en la búsqueda de alimentos y en la epidemiología animal – puede adaptarse para su uso en la investigación de los crímenes faunísticos. El conjunto de datos contenía información sobre más de 10, 000 incidentes de caza ilegal y la muerte de 6, 454 animales silvestres. Utilizamos un subconjunto de datos en el que se conocía la identidad de los cazadores ilegales. Nuestro modelo identificó la aldea local de cada cazador ilegal con base en las localidades espaciales de los incidentes de caza (p. ej.: trampas). La identificación de las aldeas mejoró con la manipulación de la superficie de probabilidad dentro de la reserva para reflejar el hecho de que, aunque los cazadores ilegales viven en su mayoría fuera de la reserva, la mayoría de los incidentes de caza ocurren dentro de la reserva (en términos de criminalística, crimen de cercanía). Estos resultados, combinados con simulaciones rigurosas, mostraron por primera vez cómo el perfil geográfico puede combinarse con datos SIG y aplicarse a situaciones con patrones espaciales más complejos, por ejemplo, en donde la heterogeneidad del paisaje implica que algunas partes del área de estudio tienen una menor probabilidad de ser usadas (p. ej.: áreas acuáticas para animales terrestres) o en donde la permeabilidad del paisaje varía (p. ej.: los murciélagos de los bosques tienden a no volar sobre áreas

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abiertas). En general, estos resultados muestran cómo el perfil geográfico puede utilizarse para enfocar las intervenciones anti-caza de manera más efectiva y más eficiente y para desarrollar estrategias de manejo y planes de conservación en una gama de escenarios de conservación.

Palabras Clave: análisis espacial, carne de animales salvajes, cuerno de rinoceronte, marfil, modelos Bayesianos, perfil geográfico, trampas

摘要: *非法捕猎严重威胁着野生动植物的数量。随着盗猎者拥有越来越丰富的经验和技术, 非法捕猎在一些国家甚至上升成了一种危机。利用8年间在津巴布韦赛维谷自然保护区收集到的数据, 我们展示了起源于犯罪学而近年来被应用于动物觅食行为学和流行病学研究当中的一种数学方法——地缘剖绘, 同样能够为野生动植物犯罪调查提供有力帮助。数据集包含了超过10000次非法捕猎活动及所导致的6454次野生动物死亡事件的信息。我们从中抽取了已知盗猎者身份的数据形成一个子数据集。分析显示, 我们建立的模型能够根据非法捕猎事件发生的空间位置确定盗猎者的居住地 (例如陷阱)。虽然盗猎者通常居住在保护区外, 但大部分非法捕猎活动其实发生在保护区内部 (在犯罪学中被定义为通勤犯罪), 针对这一情况, 我们可以通过控制保护区内的概率面来提高识别犯罪者居住地的准确性。这些结果联合严格的模拟分析首次展现了如何将地缘剖绘技术与GIS数据相结合, 并且应用到分析有更复杂空间模式的犯罪场景当中。例如, 分析区域可利用性有差异 (如水域对于陆地动物很少利用) 的高景观异质性场景, 或者分析区域景观可渗透性有差异的场景 (例如森林蝙蝠倾向于在开放空间中活动)。从更广泛的角度来说, 这些结果显示地缘剖绘可以在广泛的保护场景中指导我们进行更精准的反盗猎干预, 以及指定更有效的管理策略和保护计划。***【翻译:胡怡思;审校:魏辅文】***

关键词: 贝叶斯模型, 丛林肉, 地缘剖绘, 象牙, 犀牛角, 陷阱, 空间分析

Introduction

Geographic profiling is a statistical technique developed originally in criminology to prioritise large lists of suspects in cases of serial crime such as murder, rape, and arson (Rossmo 2000). More recently, the model has been successfully applied to biological data sets (Le Comber et al. 2006; Le Comber et al. 2011; Le Comber & Stevenson et al. 2012; Faulkner et al. 2015). In criminology the model uses the locations of linked crimes to calculate the probability of offender residence for each point within the study area. These probabilities are then ranked to produce a geoprofile, with suspects higher on the profile investigated first.

Illegal hunting represents one of the most severe threats to wildlife worldwide (Ripple et al. 2016). The severity of the threat is such that a growing number of species are suffering population declines and becoming threatened with extinction (Ripple et al. 2015, 2016). In Africa, wildlife hunting is conducted to obtain bushmeat for subsistence and for wildlife products such as ivory, rhinoceros horn, pangolin scales, and leopard skins for international and local trade (e.g., Biggs et al. 2013; Lindsey et al. 2013, 2017). The resources available to tackle illegal hunting are severely limited; thus, protecting wildlife populations in the vast landscapes in which they occur is extremely challenging (Mansourian & Dudley 2008; Lindsey et al. 2016). There is an urgent need to develop technological solutions to give law enforcement agencies the edge over illegal hunters.

Although illegal hunting is prevalent even in times of relative peace, it can intensify during times of political instability (Cumming 2004). In Zimbabwe, illegal hunting began to rise with the onset of the land-reform program in which subsistence farmers were resettled onto private farms and wildlife ranches (Du Toit 2004). In 2001, settlers began to move into a large wildlife area in southeastern Zimbabwe, the Savé Valley Conservancy (SVC). Financial losses realized through illegal hunting in SVC were at least US$1 million per year (Lindsey et al. 2011), which highlights the fact that the crisis is as much an economic as a conservation problem.

We examined how geographic profiling (GP) can be adapted for use in investigations of wildlife crime with data from an 8-year study in SVC that include more than 10,000 incidents of illegal hunting and records of the deaths of 6,454 wild animals.

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Despite the success of GP in a range of disparate fields within biology, the model's application has to date largely ignored a great deal of spatial complexity and differences in habitat, many of which are likely to be important; for example, freshwater aquatic invertebrates are generally restricted to ponds, lakes, and streams. In SVC, illegal hunters live mostly outside the conservancy, but the animals they are hunting occur almost exclusively inside the conservancy. In criminology, such a scenario results in what would be referred to as commuter crime. In contrast to the normal assumptions of the model, in which the majority of offenders commit crimes close to their anchor point (usually a home or workplace) (Brantingham & Brantingham 1981; Meaney 2004), in commuter crime offenders travel some distance to specific locations to commit their crimes because of the clustered nature of potential crime sites (e.g., opportunities for high-value shoplifting are likely to occur in city centers, with few or no opportunities for criminals near their homes) (Canter & Larkin 1993).

We addressed the issue of commuter crime with a post hoc manipulation of the geoprofile in which we adjusted the model probabilities inside SVC in ways that reflected the fact that the illegal hunters would in most cases live outside SVC. We sought to determine first how an approach originally developed in crime science could be applied to wildlife crime and second to extend the GP method to show how post hoc adjustment of the resulting geoprofile might improve model performance. Specifically, we asked whether GP can be used to identify illegal hunters from hunting incidences alone and whether it can be improved by incorporating geospatial data, in this case to deal with the issue of commuter crime.

Methods

Ethics

The data relating to the incidents of illegal hunting are a subset of data collected by Lindsey et al. (2011). As part of that study, antipoaching scouts from the ranches comprising SVC were interviewed on a monthly basis and the locations of incidents of illegal hunting (e.g., poaching, snares) recorded. For a subset of these incidents, illegal hunters had been observed or caught by scouts as part of their routine patrols. Where the hunters were known to the scouts, the locations of their towns or villages (and not individual addresses) were recorded; these are the data we used. Thus, none of the data we used can be used to identify individuals (particularly because the data were collected 12 years ago). No additional data or analyses were shared with the police or antipoaching scouts.

General Approach

We examined how an approach originally developed in crime science could be applied to wildlife crime and extended the GP method to show how post hoc adjustment of the geoprofile can improve model performance. In the particular case examined here, the majority of incidents of illegal hunting originated outside SVC, even though the incidents themselves mostly occurred inside the conservancy. To address this, we divided the geoprofile—a matrix describing, for each point in the study area, the probability that there is a source at that point –into areas inside SVC and outside SVC with a shapefile. We then adjusted our estimate of the probability of source location inside the conservancy to reflect our belief that source locations within the conservancy are less likely than source locations outside the conservancy. We considered a range of manipulations in which we reduced the probability of source location for points inside the conservancy by factors from 0.1 to 0.000001. We also considered the extreme case where the probability of source location is set to zero inside the conservancy.

Study Area

The SVC (20°24′48.10″S, 32° 8′19.61″E) is a wildlife area (3450 km^2) in arid southeastern Zimbabwe (Fig. 1) composed of 26 individual wildlife ranches held in ownership by private, government, and local community entities. Although there are no internal fences between ranches, 350 km of double perimeter fencing serves as a boundary between wildlife within SVC and the surrounding high-density human settlements. The SVC is home to an abundance of animals such as impala (*Aepyceros melampus*), zebra (*Equus quagga*), wildebeest (*Connochaetes taurinus*), buffalo (*Syncerus caffer*), giraffe (*Giraffa camelopardalis*), elephant (*Loxodonta africana*), leopard (*Panthera pardus*), cheetah (*Acinonyx jubatus*), wild dog (*Lycaon pictus*), and black (*Diceros bicornis*) and white rhinoceros (*Ceratotherium simum*).

In 2001, trends of increasing wildlife populations within SVC began to reverse with the implementation of Zimbabwe's land-reform program. Subsistence farmers began to settle within SVC and removed large tracts of perimeter fencing, enough to make over 400,000 wire snares (Lindsey et al. 2009), which are used to catch wildlife for bushmeat. In Zimbabwe, hunting using snares is prohibited by law (Trapping of Animals [Control] Act [Chapter 20:21]), as is the possession or sale of illegally obtained bushmeat (Parks and Wildlife Act chapter 20:14).

Data

Illegal hunting data were collected from August 2005 to July 2009 from antipoaching managers on each ranch in SVC (Lindsey et al. 2011). We used a subset of these data for which the illegal hunters' identities were known. This included 151 hunting incidents and 47 known illegal hunters. The most hunting incidents per individual was 32; most individuals hunted just one time. The method of hunting varied: snares (66), dogs (60), fishing (13), snares and dogs (3), and other (9).

Geographic Profiling and the DPM Model

The Dirichlet process mixture (DPM) model is described fully in Verity et al. (2014) and extended in Faulkner

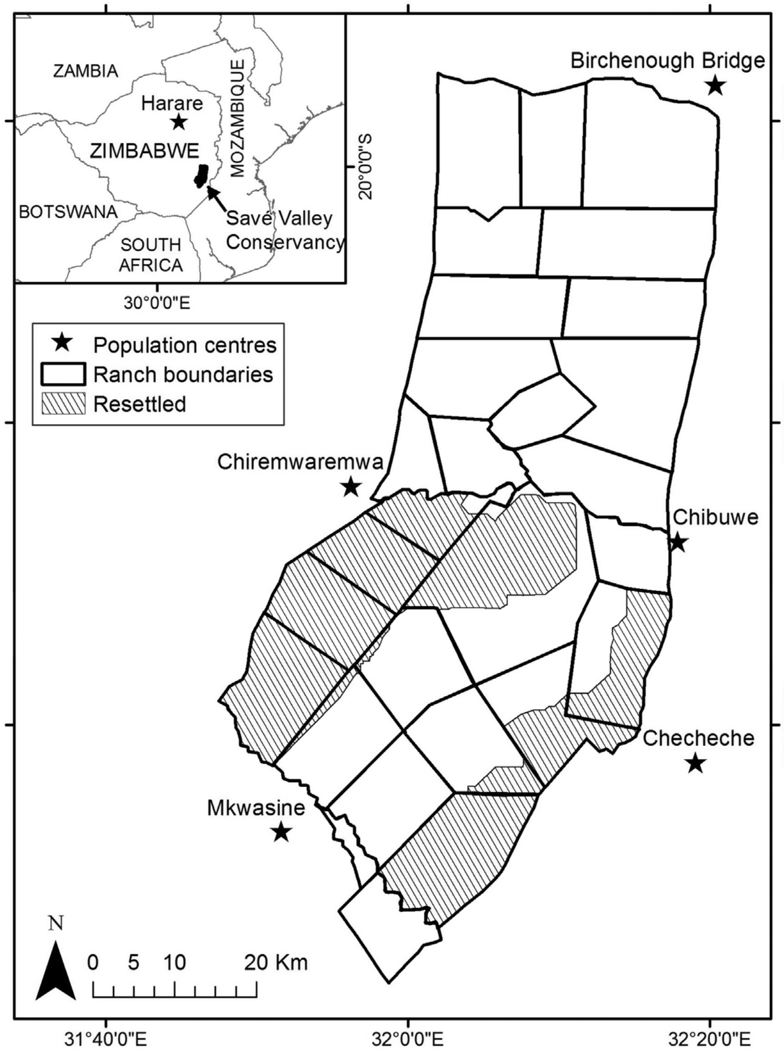

Figure 1. Savé Valley Conservancy in southeastern Zimbabwe.

et al. (2016). In brief, constructing a geoprofile can be broken down into 2 related tasks: allocating crimes to clusters and finding the sources of the clusters. Solving these 2 problems together is difficult, but each is simple if the answer to the other is known. That is, if one knows which crimes come from which sources, finding the sources is straightforward because they are most likely to be found at the spatial means of these clusters. Similarly, if one knows where the sources are, allocating crimes to clusters is easy because crimes are most likely to originate from the closest source. The solution is to alternate between these two problems in a process known as Gibbs sampling (Geman & Geman 1984). The Gibbs sampler begins by randomly assigning crimes to clusters and then—conditional on this clustering—estimates the locations of the sources. Then—conditional on these source locations—crimes are reassigned to clusters. These two steps are repeated thousands of times with standard Bayesian Markov chain Monte Carlo (MCMC) methods until the model converges on a posterior distribution of interest. Crucially, it is not necessary to decide on the number of clusters because at each step there is a finite, positive probability that a crime comes from a previously unseen source.

Model Implementation

We implemented the DPM model described in R (R Core Team 2014) with version 2.0.0 of the package Rgeoprofile introduced by Verity et al. (2014) and extended by Faulkner et al (2016) (available from https://github.com/bobverity/Rgeoprofile). Models settings are explained in detail in Verity et al (2014). Here, the settings used were sigma mean = 1, sigma squared shape = 2, samples = 10,000, chains = 10, burnin = 1,000. Broadly speaking sigma represents the standard deviation (in kilometers) of the dispersal distribution around the source, and sigma mean is the initial prior on this. Sigma squared shape relates to the shape parameter of the inverse-gamma prior on sigma and has a value of 2, which corresponds to a weakly informative distribution. Faulkner et al. (2016) contains details of the underlying mathematics. These settings correspond to a diffuse prior on sigma of 1 km, implying that 39% of the poaching events occur within 1km of the source, 87% within 2 km, and 99% within 3 km; however, the model disregards this prior if the data warrant it. A value of 1 km is a value typical of human patterns of movement (Rossmo 2000). The parameters samples, chains, and burnin are all standard parameters relating to the MCMC.

Model Evaluation

The model output is assessed in 2 ways: hit score and Gini coefficient. The model's performance in finding an individual source can be calculated using the hit score. The hit score is the proportion of the total area covering the crimes (in this case the hunting incidents) that has to be searched before that source is located. This score is calculated by ranking each grid square within the total search area and dividing the ranked score of the grid square in which the source is located by the total number of grid squares to give a value from 0 to 1: the smaller the hit score the more efficient the search strategy. For example, a suspect site with a hit score of 0.1 would be located after searching one-tenth of the total search area.

Overall model performance—across all sources—was compared by calculating the gini coefficient or Gini index. The Gini coefficient is essentially a measure of inequality (it is often used to look at wealth distribution) (Gini 1921). We compared the proportion of illegal hunting incidents that had identified sources with the proportion of the total area searched. A strategy that finds sources exactly in proportion to the area searched has a Gini coefficient of 0. In contrast, a perfect search strategy has a Gini coefficient of 1. The higher the Gini coefficient, the more effective the search.

Simulations

To further test the accuracy of the model with and without the incorporated spatial data, we compared 1000 simulated data sets; each dealing with a simplified case of a study area spanning $-1°$ to $1°$ longitude and $-1°$ to $1°$ latitude and a central conservancy from $-0.5°$ to $0.5°$ longitude and $-0.5°$ to $0.5°$ latitude. We randomly generated 36 sources from a uniform distribution within the study area but outside the simulated conservancy and 11 sources within the conservancy, again from a uniform distribution. The ratio of 36:11 was chosen because it reflected the spatial distribution of crimes in the SVC data set. For each of these 47 sources, we generated a large number of crimes from a bivariate normal distribution with a standard deviation of 20 km around the source and subsampled from this distribution to select a maximum of 12 crimes per source such that all of the crimes occurred within the simulated conservancy. This constraint means that for sources farther from the conservancy, the realized number of crimes was in some cases <12. Sources for which no crimes fell within the conservancy were excluded from the analysis. For each data set, 8 analyses were carried out: the unmodified DPM model and then the same modifications that were used on the real data set (that is, multiplying by factors from 0.1 to 1×10^{-6} and by zero). To account for the paired nature of the design (each analysis was run on the same data set), the data were analyzed using an analysis of variance on the differences obtained by subtracting the unmodified DPM hit scores from the hit scores for each of the other analyses. Thus, negative values indicated cases in which the modified version of the model outperformed the unmodified DPM.

Spatial Data

To account for the issue of commuter crime, we incorporated spatial information into the model post hoc. Shapefiles for SVC were superimposed on the geoprofile, and the probability of offender residence within SVC were reduced by multiplying points within the SVC by 1×10^{n}, where n ranged from -1 to -6. We also considered the case in which SVC was excluded entirely by multiplying by zero within SVC. Effectively, this forced the model to give greater weight to potential locations outside SVC to different extents. The results of this approach were compared with a simple ring-search strategy in which searches are conducted outward from an illegal hunting incident in circles of increasing radii (e.g., Smith et al. 2015).

Results

Simulations

Across the 1,000 replicates, the model identified the sources of illegal hunting located outside the specified area (here, the area comprising the simulated conservancy) better when the model was adjusted (Fig. 2a). The hit scores improved as the adjustment on the surface increased until it stopped having an effect at an adjustment of 0.001. [ANOVA: adjusted surface $F_{7,226504} = 21953, p < 0.0001$; location (inside or outside) $F_{1,226504} = 3181562$, $p < 0.0001$, interaction $F_{7,226504} = 201110, p < 0.0001$].

Spatial Data

The geoprofiles produced by the standard DPM model and the subsequent adjusted surfaces are shown in Fig. 3. Figure 3a shows the results of the basic DPM model before we corrected for the commuter crime issue. Figures 3b and 3c show the geoprofiles when the probability values inside SVC were multiplied by 0.001 and 0. Hit scores improved as the adjustment

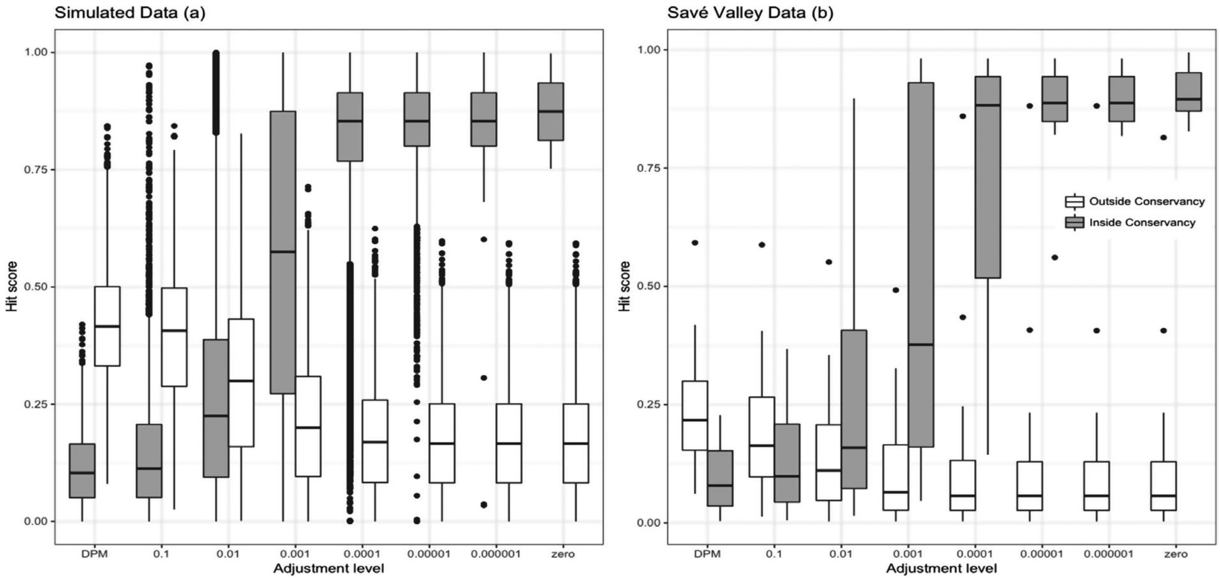

Figure 2. The difference in hit score (proportion of area that has to be searched before the source of the wildlife crime is located) for sources of wildlife crime located inside and outside Savé Valley Conservancy based on (a) actual or (b) simulated data for the Dirichlet process mixture model and for different manipulations of the probability surface inside the conservancy, from 0.1 to 1 × 10^{-6} and for 0. Each boxplot shows hinges (versions of the first and third quartiles); notches show 1.58 times the IQR/sqrt(n) and roughly correspond to 95% confidence limits. For a detailed description, see the R help file for boxplot.stats (R Development Core Team 2014 [http://www.R-project.org]).

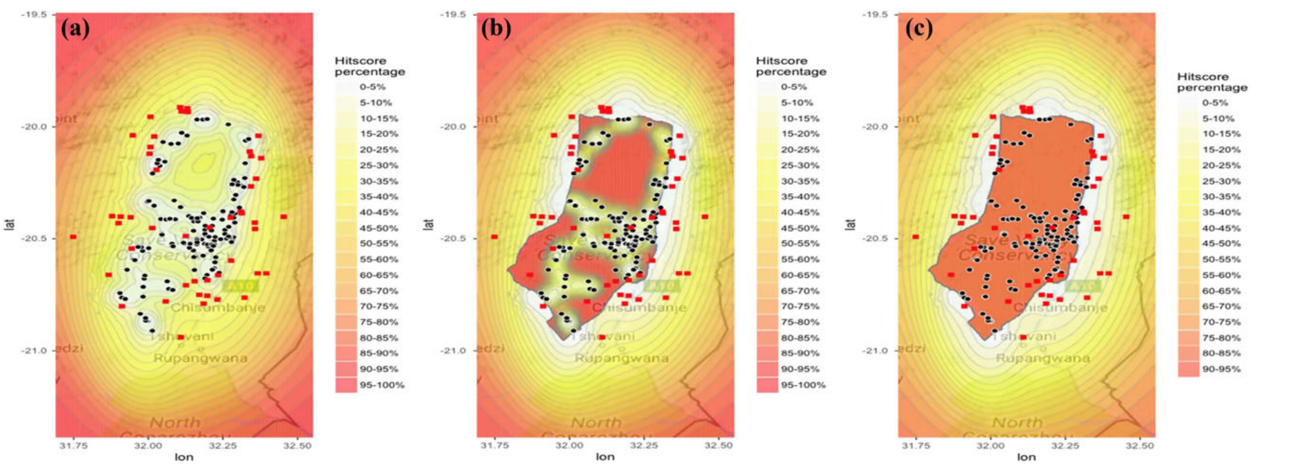

Figure 3. Geoprofiles showing (a) the unadjusted Dirichlet process mixture (DPM) model (b) when areas inside the conservancy are multiplied by 0.001 and (c) when areas inside the conservancy are multiplied by 0. Black circles show the locations of hunting incidents and red squares the locations of illegal hunters. Contours show 5% increments of the geoprofile; lighter colors represent higher parts of the geoprofile.

on the surface increased, and again the model identified the sources located outside the specified area better when the model was adjusted (ANOVA: adjusted surface $F_{7,360} = 7.993$, $p < 0.0001$; location (inside or outside) $F_{1,360} = 1241.61$, $p < 0.0001$, interaction $F_{7,360} = 77.328$, $p < 0.0001$) (Fig 2b). The proportions of illegal hunters located using the different methods of spatial targeting were also compared. All of the analyses in which we used the adjusted geoprofiles located 50% of the illegal hunters through searches of <20% of the area; hit scores for sources outside SVC improved and hit scores for those inside SVC worsened.

The adjusted geoprofile (with a multiplication of 0.001 inside SVC) (Fig. 3b) also outperformed a simple ring search (Fig. 4). Although the GP hit scores were higher for the small number of sources inside the conservancy ($t = 6.00$, df $= 10$, $p = 0.0001$), they were lower for the larger number of sources outside the conservancy ($t =$

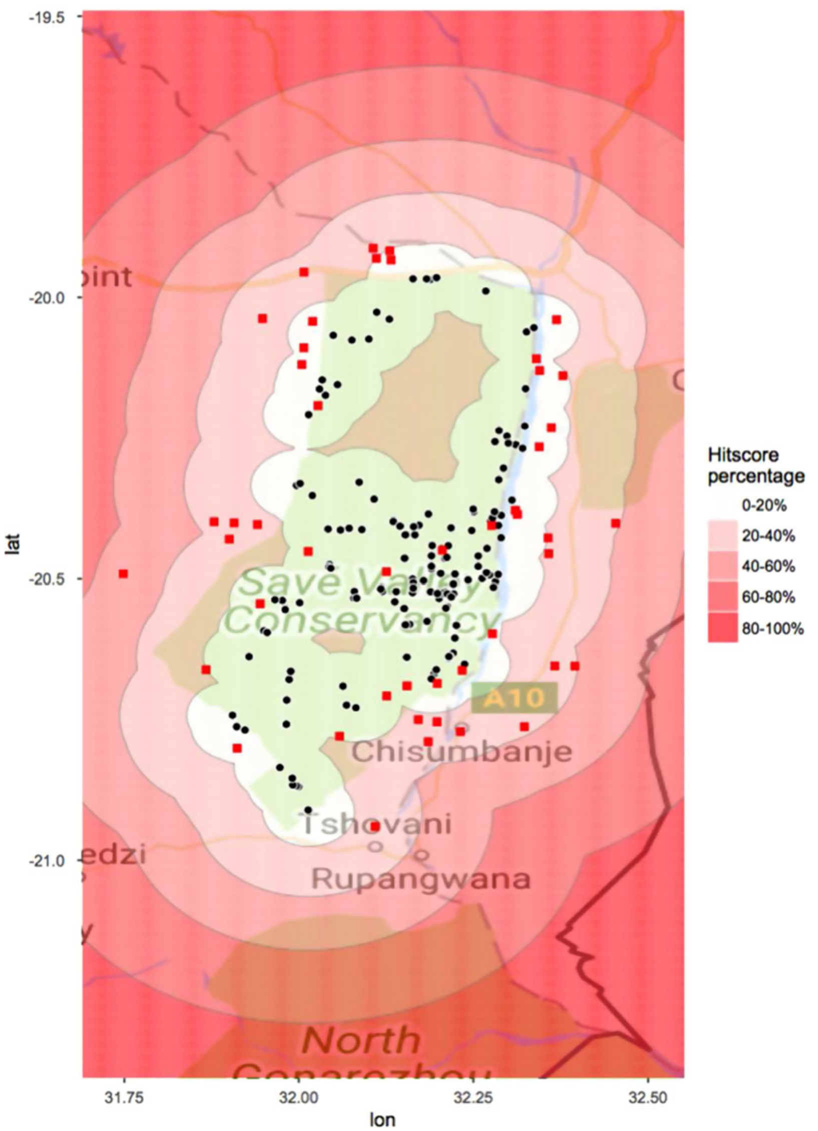

Figure 4. Results of a ring-search strategy in which the search for the perpetrator of a wildlife crime extends outward from an incident of illegal hunting in circles of expanding radii (black circles, locations of hunting incidents; red squares, locations of illegal hunters; contours, increments of 20%).

18.5, df = 35, $p < 0.0001$), searching on average 13% less of the total area than the ring search. Overall, the adjusted geoprofile identified the sources of more incidents of illegal hunting while searching a smaller area, with a Gini coefficient of 0.879 compared with 0.825 for the ring search, finding the sources for 50% of the incidents while searching 11% of the search area, as opposed to 18%.

Discussion

Crimes committed against the environment and animals—variously termed *green crime* (Lynch & Stretsky 2003), *conservation crime*, and *environmental crime* (Gibbs et al. 2010)—have had an increasing profile in recent years (Wellsmith 2011). The field of criminology has historically shown little interest in such crimes, largely leaving environmental issues to other disciplines (Lynch & Stretsky 2003). We found that GP can be used successfully to identify areas where illegal hunters may live and could be used to target law enforcement interventions and community engagement efforts in these areas to prevent reoffending. We also demonstrated for the first time how incorporating spatial information can improve the efficiency of the model; the model outperformed an alternative ring-search strategy. Crucially, the DPM model identified the sources of 50% of illegal hunting incidents after searching just 11% of the study area, as opposed to 18% with the ring-search method. Clearly, across the spatial scales that often characterize reserves and conservancies, such an improvement in efficiency may be of considerable benefit.

The origins of GP lie in criminology, and we took the modifications to the model that have been developed in biology back to this source. In criminal investigations, limitations of resources and time mean that a search-prioritization tool such as GP can be of great practical utility. The same can be said for conservation where resources and time are likely to be heavily limited (Stevenson et al. 2012; Faulkner et al. 2016).

There has been an increase in the scale of commercial hunting and the wildlife trade as the population expands and as techniques used by hunters improve (e.g., Fa & Brown 2009; Di Minin et al. 2015; Naidoo et al. 2016). Traditionally conservation actions have depended on the hypothesis that different illegal wildlife actions occur in different places; commercial trade occurs close to cities and coastal areas (Di Minin et al. 2015) and illegal hunting incidents cluster in rural areas, where the primary motivation for hunting is subsistence (Sanchez-Mercado et al. 2016). However, it has recently been shown that subsistence hunting and wildlife trade maybe spatially correlated (Sanchez-Mercado et al. 2016). In fact, spatial patterns of hunting differ from case to case, just as the techniques used by the illegal hunters and the pressures driving hunting vary among countries, time of year, species, and protected areas as illegal hunters adapt to—for example—differences in terrain and accessibility to protected areas and to the population changes that occur among the animals (Risdianto et al. 2016). Geographic profiling provides one way of identifying locations that are the source of hunting—in most cases areas where illegal hunters live—on a case-by-case basis. This could have important implications for the design and implementation of effective and efficient conservation actions because it could allow limited law enforcement resources to be focused on communities where it is needed most and help focus conservation efforts in and generate economic benefits from wildlife for these local communities (Knapp 2012; Cooney et al. 2016). Such focusing of efforts is key. Law enforcement and protected-area management are expensive, and enormous budget deficits exist in African countries (Lindsey et al. 2016, 2017). Traditional antipoaching patrols are reactive and attempt to find evidence of hunting after it has happened or after illegal hunters have entered the area (Lotter & Clark 2014). Due to the large areas that are often involved and the difficulty associated with finding snares and traps and catching illegal hunters on the move, such interventions often fail to prevent hunting incidents and are of limited efficacy. Our method, especially if combined with information from intelligence operations, has the potential to allow for both preventative outreach efforts with the communities and households most involved in illegal hunting and much more targeted law enforcement efforts (Lotter & Clark 2014).

Beyond the case we describe here, our results illustrate how more complex spatial information can be incorporated within the DPM model framework. In many instances—notably in biology but also in criminology—treating the study area—the target backcloth in criminology—as homogenous will fail to take into account important information. For example, if one were to search for plants that occur only above 400 m or mosquitoes that breed only in water, it may be the case that large parts of the study area could be excluded from the search, creating a more efficient search strategy. More complex manipulations of the model output – use of continuous variables rather than the categorical inside or outside—are also possible, for example, when the probability of finding an anchor point is proportional to elevation, soil pH, distance from water, etc.

In some cases, of course, it will not be obvious precisely what manipulation of the final model output will be most appropriate, and selecting a particular manipulation will require expert input. In our study, for example, it is clear that entirely excluding areas inside SVC from the search would miss a number of sources (Fig. 3c). Multiplying by 0.001, in contrast, effectively excluded large areas within SVC that were unlikely to be of interest while prioritizing the areas of highest probability within SVC (Fig. 3b).

Our results show that GP can successfully identify areas where illegal hunters may live based only on the spatial locations of hunting incidents such as traps and snares. This has important implications for management strategies and conservation plans in terms of targeting particular areas with community-based initiatives. We suggest that being able to target control efforts in this way will make hunting interventions more efficient and cost-effective. More broadly, we demonstrated for the first time how incorporating additional spatial information can improve the overall efficiency of the DPM model.

Acknowledgments

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