TITLE

A spatial approach to combatting wildlife crime

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Geographic profiling, a technique developed in criminology but increasingly applied to ecology, used in an investigation of wildlife crime

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A spatial approach to combatting wildlife crime

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. Here, we 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, using data from an eight-year study in Savé Valley Conservancy, Zimbabwe that in total includes more than 10,000 incidents of illegal hunting and the deaths of 6,454 wild animals. Using a subset of these data for which the illegal hunters' identities are known, we show that the model can successfully identify the illegal hunters' home villages using the spatial locations of hunting incidences (for example, snares) as input, and show how this can be 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 (in criminology, 'commuter crime'). The results of this analysis – combined with rigorous simulations – show 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 that some parts of the study area are unsuitable (e.g. aquatic areas for terrestrial animals, or vice versa), or where landscape permeability differs (for example, forest bats tending not to fly over open areas). More broadly, these results show how geographic profiling can be used to target anti-poaching interventions more effectively and more efficiently, with important implications for the development of management strategies and conservation plans in a range of conservation scenarios.

INTRODUCTION

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, as well as wildlife products such as ivory, rhino horn, pangolin scales and leopard skins for the international (and in some cases, local) trade (Biggs et al. 2013; Blanc et al. 2013; Lindsey et al. 2013, 2017). The resources available to tackle illegal hunting are severely limited, with the effect that 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 provide law enforcement agencies with 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 programme in which subsistence farmers were re-settled onto private farms and wildlife ranches (du Toit 2004). In 2001, settlers began to invade a large wildlife area in southeastern Zimbabwe, the Savé Valley Conservancy (SVC). Financial losses realized through illegal hunting in SVC were calculated to be at least USD 1 million per year (Lindsey et al. 2011), highlighting that the crisis is as much an economic problem as a conservation one.

In this paper, we show how geographic profiling (GP) can be adapted for use in investigations of wildlife crime, using data from an eight-year study in Savé Valley Conservancy, Zimbabwe that includes more than 10,000 incidents of illegal hunting and the deaths of 6,454 wild animals.

Geographic profiling is a statistical technique that was original developed 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 epidemiological and biological data sets such as locating animal roost and nest sites using as input their foraging locations (Le Comber et al. 2006; Buscema et al. 2009; Martin et al. 2009; Raine et al. 2009; Le Comber et al. 2011; Le Comber & Stevenson et al. 2012; Verity et al. 2014; Faulkner et al. 2015, 2016). 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.

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 (as a simple example, freshwater aquatic invertebrates will generally be restricted to ponds, lakes and streams). The particular case examined in this paper provides another good example of this, as although the illegal hunters mostly live outside SVC, the animals they are hunting are found 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; Meany 2004), in commuter crime offenders must travel some distance to specific locations to commit their crimes because of the clustered nature of potential crime sites (for example, opportunities for high-value shoplifting are likely to occur in city centres, with few or no opportunities for the criminal near their home) (Canter & Larkin 1993).

In the case study presented here, we address the issue of commuter crime by a post-hoc manipulation of the geoprofile in which we adjust the model probabilities inside the Conservancy in a variety of ways to reflect the fact that the illegal hunters will in most cases live outside SVC. Our study thus has two main aims. First, we examine how an approach originally developed in crime science can be applied to wildlife crime. Second, we extend the GP method to show how post-hoc adjustment of the resulting geoprofile can improve model performance. Specifically, we ask: (1) Can geographic profiling be used to identify illegal hunters from hunting incidences alone? (2) Can geographic profiling 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 in an earlier study (Lindsay et al. 2011). As part of that study, anti-poaching scouts from the ranches comprising SVC were interviewed on a monthly basis and the locations of incidents of illegal hunting (eg poaching, snares) recorded. For a subset of these incidents, illegal hunters had been observed or caught as part of their routine patrols. Where the hunter was known to the scouts, the location of their town or village (and not individual addresses) was recorded; it is these data that our study utilises. Thus, none of the data in this paper can be used to identify individuals (particularly since the data were collected 12 years ago). No additional data or analysis were shared with the police or with anti-poaching scouts.

General approach

Our study examines how an approach originally developed in crime science can be applied to wildlife crime, and extends the GP method to show how post-hoc adjustment of the geoprofile can improve model performance. In the particular case we examine here, the majority of incidents of illegal hunting originate outside SVC, even though the incidents themselves mostly occur inside the conservancy. To address this, we first divide 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 using a shapefile. We then adjust 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 sources outside. We consider a range of manipulations in which we reduce the probability of source location for points inside the conservancy by factors from 0.1 to 0.000001; we also consider the extreme case where the probability of source location is set to zero inside the conservancy.

Study area

The Savé Valley Conservancy (20°24'48.10"S, 32° 8'19.61"E) is a wildlife area (3,450 km^2) in arid, southeastern Zimbabwe (Fig. 1). The Conservancy is comprised of 26 individual wildlife ranches held in ownership by private, government, and local community entities. While there are no internal fences between ranches, 350 km of double, perimeter fencing has served as a boundary between wildlife within SVC and the surrounding high-density human settlements. The Conservancy is home to an abundance of wildlife species such as impala, zebra, wildebeest, buffalo, giraffe, elephant, leopard, cheetah, wild dog, and both black and white rhino.

In 2001, trends of increasing wildlife populations within the Conservancy began to reverse with the implementation of Zimbabwe's land reform programme. 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]).

<u>Data</u>

Illegal hunting data were collected between August 2005 and July 2009. We received data monthly from anti-poaching managers on each ranch in SVC. We compiled: number of illegal hunting incidents, number of hunters and dogs, number of illegal hunters caught (or shot in the case of dogs), how they were caught, number of snares recovered, number/species/gender/age of animals killed in each snare as well as the status of carcasses; i.e. recovered by illegal hunters, recovered by ranch, rotten or scavenged. Data on wildlife killed included records of observations of carcasses in snares, carcasses found in the possession of hunters, at their homes or in hunting camps, or from identifiable hair or body parts left in snares. The location of illegal hunting incidents was indicated by the anti-poaching managers on 1:50,000-scale maps overlaid with 1-km grid squares, with an average error of approximately 1 km (Lindsey et al. 2011). For this analysis we used a subset of these data for which the illegal hunter identities are known. This included 151 hunting incidents, and a total of 47 known illegal hunters. The most hunting incidents per individual was 32, with most individuals, hunting just one time. The method of hunting varied: snares (66), dogs (60), fishing (13), snares and dogs (3), and other (9).

Geographic profiling: the DPM model

The DPM model is described fully in Verity et al. (2014) and extended in Faulkner et al. (2016). In brief, though, it can be explained as follows. Constructing a geoprofile can be broken down into two related problems – allocating 'crimes' to clusters, and finding the sources of the clusters. Solving these two problems together is difficult, but each is simple if the answer to the other is known. That is, if we know which crimes come from which source, finding the sources is straightforward, since they are most likely to be found at the spatial means of these clusters. Similarly, if we know where the sources are, allocating crimes to clusters is easy, since 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 – it reassigns crimes to clusters. These two steps are repeated many thousands of times using 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, since at each step there is a finite, positive probability that a crime comes from a previously unseen source.

<u>Model implementation</u>

The DPM model described here was implemented in R (R Core Team 2014) using version 2.0.0 of the package Rgeoprofile introduced by Verity et al. (2014) and extended in Faulkner et al (2016); this package is available at 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*=10000, *chains*=10, *burnin*=1000. Broadly speaking sigma represents the standard deviation (in km) of the dispersal distribution around the source, and *sigma_mean* is the initial prior on this. The parameter *sigma_squared_shape* relates to the shape parameter of the inverse-gamma prior on sigma, with a value of 2 corresponding to a weakly informative distribution; see Faulkner et al. (2016) for details of the underlying mathematics. These settings correspond to a diffuse prior on sigma of 1km, implying that 39% of the poaching events occur within 1km from the source, 87% within 2km and 99% within 3km; however, the model will disregard this prior if the data warrant it. A value of 1km 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.

<u>Model evaluation</u>

The model output is assessed in two ways. 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 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 between 0 and 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 – can be 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). Here, we compare the proportion of illegal hunting incidents whose sources have been identified to the proportion of the total area searched. A strategy that finds sources exactly in proportion to the area searched would have a gini coefficient of 0. In contrast, a perfect search strategy would have 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 with a study area spanning -1º to 1º longitude and -1º to 1º latitude, with a central 'conservancy' from -0.5º to 0.5º longitude and -0.5º to 0.5º 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 dataset. For each of these 47 sources, we generated a large number of crimes from a bivariate normal distribution with a standard deviation of 20km around the source, and sub-sampled from this distribution to select a maximum of 12 crimes per source such that all of the crimes occurred within the simulated conservancy (note that this constraint meant that for sources further from the conservancy, the realised number of crimes was in some cases less than 12; sources for which no crimes fell within the conservancy were excluded from the analysis). For each data set, eight analyses were carried out: the unmodified DPM model, and then using the same modifications used on the real data set (that is, multiplying by factors from 0.1 to 1 x 10^{-6}, and also by zero). To account for the paired nature of the design (each analysis was run on the same data set), the data were analysed 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 indicate cases in which the modified version of the model outperforms the unmodified DPM.

Spatial data

To account for the issue of commuter crime as mentioned previously, 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 reduced by multiplying points within the Conservancy by 1 x 10^{n}, where n ranged from -1 to -6; in addition, we considered the case where the Conservancy was excluded entirely by multiplying by zero within SVC. Effectively, this forces the model to give greater weight to potential locations outside SVC to varying extent. This approach was compared to a simple ‘ring search’ strategy based on searching outwards from illegal hunting incidents in circles of increasing radii (see for example Smith et al. (2015).

RESULTS

Simulations

Across the 1000 replicates, the model identified the sources 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/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 Figure 3. Figure 3a shows the basic DPM model results 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 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/outside) $F_{1,360} = 1241.61$, $p < 0.0001$, interaction $F_{7,360} = 77.328$, $p < 0.0001$) (Fig 2b). Proportions of illegal hunters located using the different methods of spatial targeting were also compared. All of the analyses using the adjusted geoprofiles located 50% of the illegal hunters by searching less than 20% of the area, with hit scores for sources outside SVC improving and hit scores for those inside SVC becoming worse.

The adjusted geoprofile (using a multiplication of 0.001 inside SVC) (Fig. 3b) also outperformed a simple 'ring search' strategy based on searching outwards from illegal hunting incidents in circles of increasing radii (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 ($t = 18.5$, $df = 35$, $p < 0.0001$), 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 to 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 that have been committed against the environment and animals – variously termed 'green criminology' (Lynch & Stretsky 2003), 'conservation criminology', and 'environmental criminology' (Gibbs et al. 2010) have had an increasing profile in recent years (Wellsmith 2011). The field of criminology has historically shown little interest in these issues, largely leaving environmental issues to other disciplines (Lynch & Stretsky 2003). Our study shows that GP can be successfully used 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. In addition, we demonstrate for the first time how incorporating spatial information can improve the efficiency of the model, with the model outperforming 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%. Clearly, across the spatial scales that often characterise reserves and conservancies, such an improvement in efficiency may be of considerable benefit.

The origins of geographic profiling lie in criminology, and this study takes 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 prioritisation 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 (Fa & Brown 2009; Peres 2009; Di Minin et al. 2015; Naidoo et al. 2016). Traditionally conservation actions have been dependent on the hypothesis that different illegal wildlife actions occur in different places; commercial trade will occur closer to cities and coastal areas (Di Minin et al. 2015) and illegal hunting incidents will 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 will differ from case to case, just as the techniques used by the illegal hunters and the pressures driving hunting will vary between countries, time of year species and protected areas as illegal hunters adapt to – for example –

difference in terrain and accessibility to protected areas and to the population changes that will occur amongst 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 since it could allow limited law enforcement resources to be focused on communities where it is needed most and help focus conservation efforts and generate economic benefits from wildlife to these local communities (Knapp 2012; Cooney et al. 2016). Such focusing of efforts is key. Law enforcement and protected area management is expensive and enormous budget deficits exist in African countries (Lindsey et al. 2016, 2017). Traditional anti-poaching patrols are reactive and attempt to find evidence of hunting after it has already happened, or after illegal hunters have already entered the area (Lotter & Clark 2014). Due to the large areas that are often involved and the difficulty associated with finding snares and traps, or of 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 potential to allow for both preventative outreach efforts with the communities and households most involved in illegal hunting, and also much more targeted law enforcement efforts (Lotter & Clark 2014).

Beyond the interest of the particular case we describe here, our study illustrates 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 we are searching for plants that only occur above 400m, or mosquitoes that only breed in water, it may well be the case that large parts of our study area can be excluded from the search, creating a more efficient search strategy. More complex manipulations of the model output – using continuous variables, rather than the categorical inside/outside here – are also possible – for example, if the probability of finding an anchor point is proportional to altitude, 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 this study, for example, it is clear that entirely excluding areas inside SVC from the search misses a number of sources (Figure 3c); multiplying by 0.001, on the other hand, effectively excluded large areas within SVC which are unlikely to be of interest, while still prioritising the areas of highest probability within the Conservancy (Figure 3b).

This study shows that geographic profiling can successfully identify areas where illegal hunters may live, using only 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 by being able to target control efforts in this way, will make hunting interventions more efficient and cost effective. More broadly, we demonstrate for the first time how incorporating additional spatial information can improve the overall efficiency of the DPM model.

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FIGURE LEGENDS

Figure 1. Map of Savé Valley Conservancy in southeastern Zimbabwe.

Figure 2. Boxplot of (a) simulated and (b) Savé Valley data. The plot shows the difference in hitscore for sources located inside and outside the conservancy (or simulated area) (grey and white boxes respectively).

Figure 3. Geoprofiles showing the results of the geospatial analyses (a) standard – no adjustment, (b) 0.001 probability and (c) 0 probability. Locations of hunting incidents are shown as black circles and locations of illegal hunters by red squares. Contours show bands of 5%, with lighter colours corresponding to higher parts of the geoprofile.

Figure 4. An alternative search strategy, based on searching outwards from incidents of illegal hunting in circles of expanding radii.

FIGURES

FIGURE 1

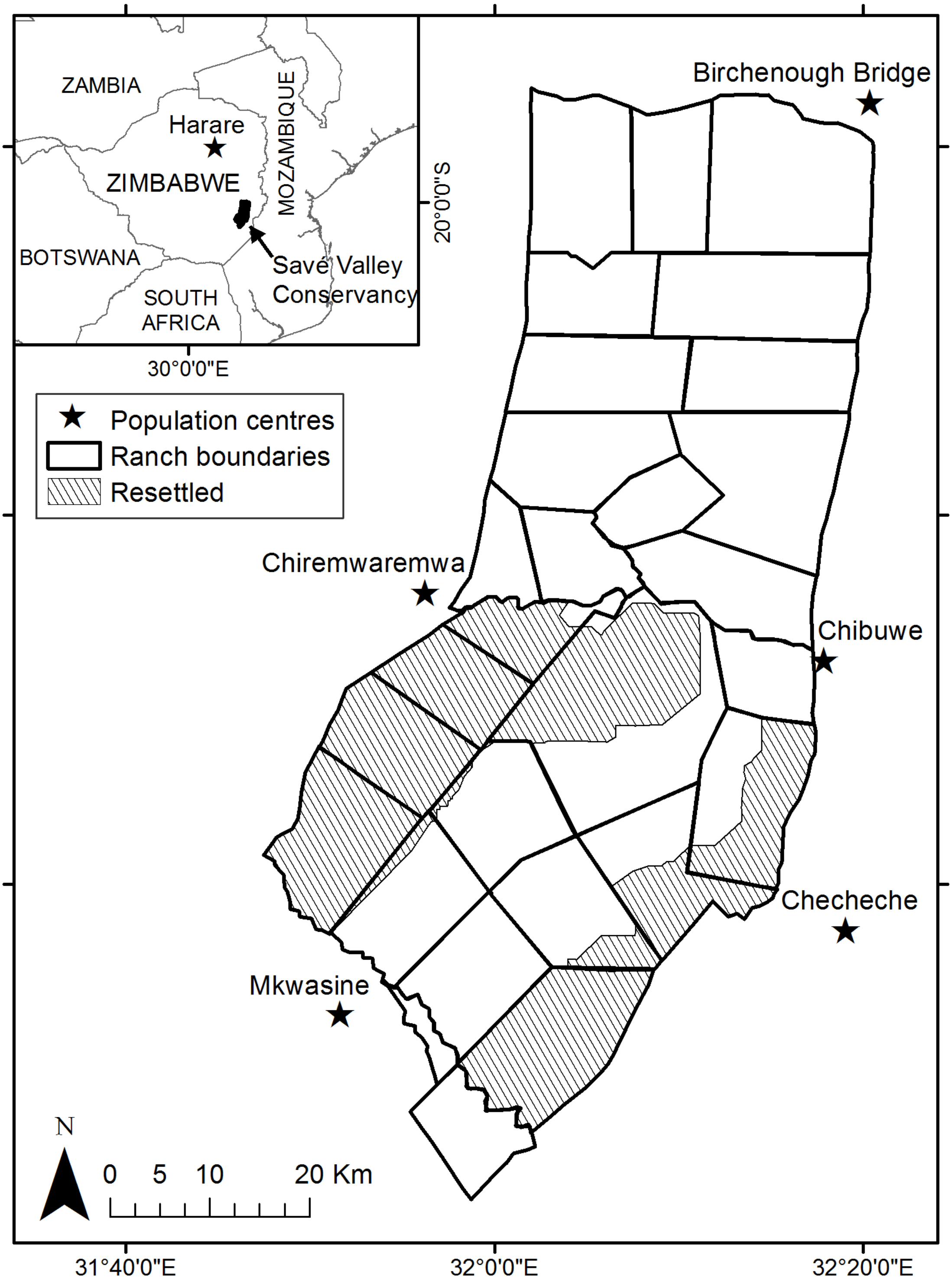

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FIGURE 2

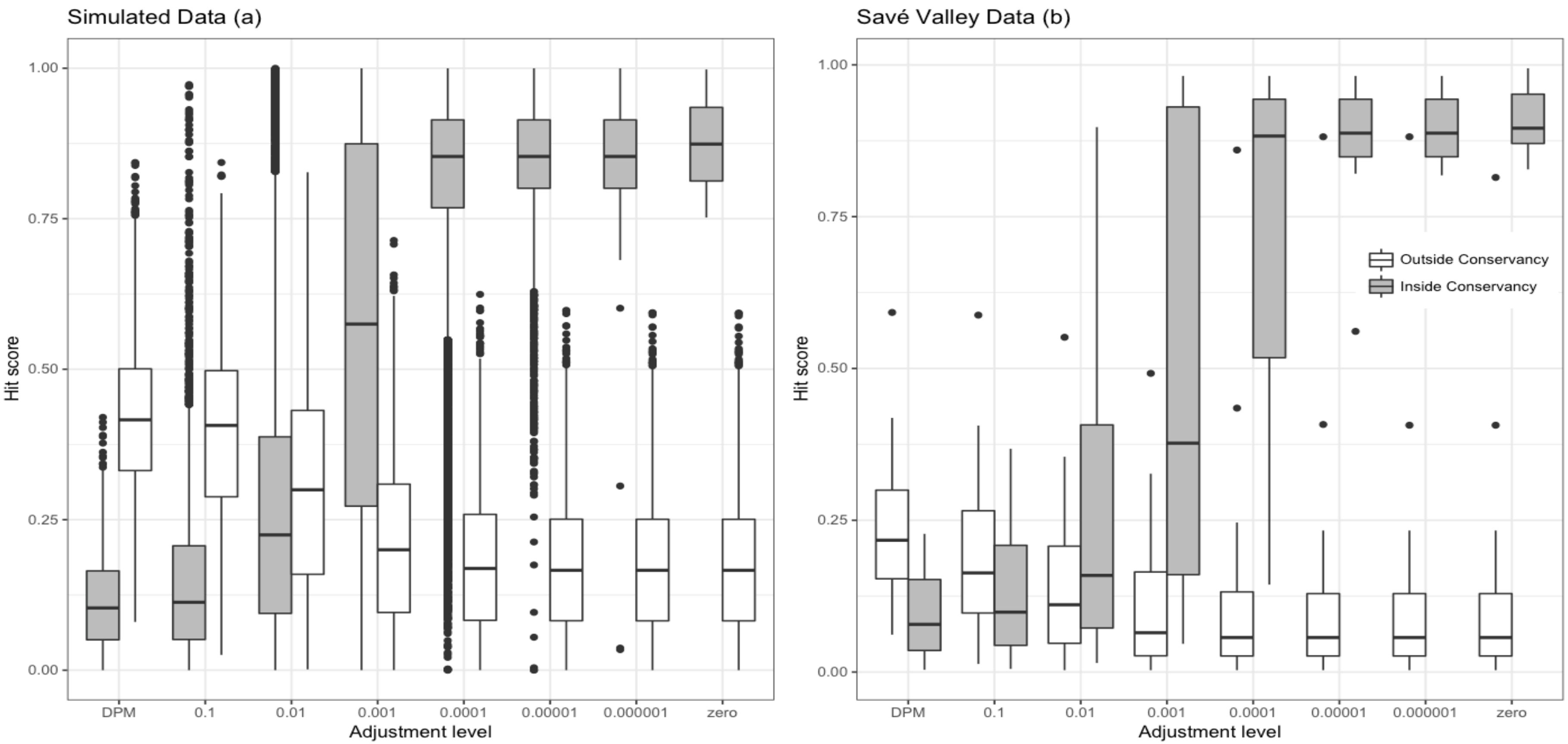

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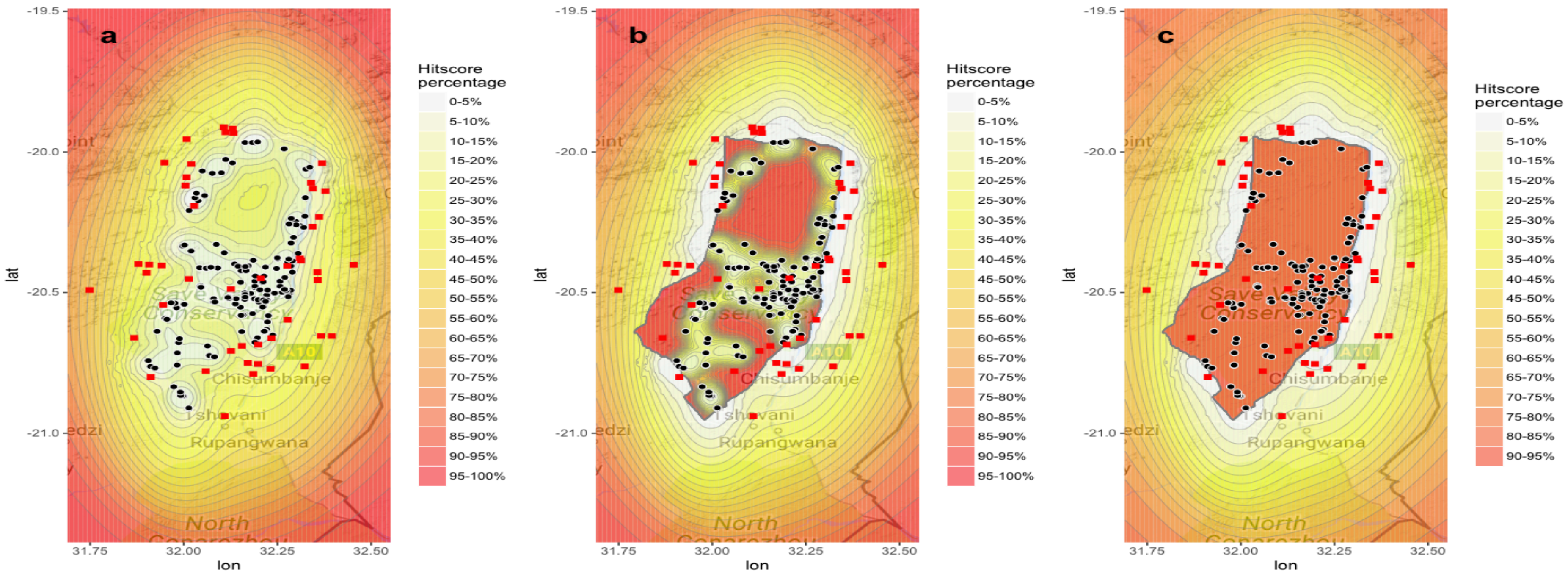
FIGURE 3



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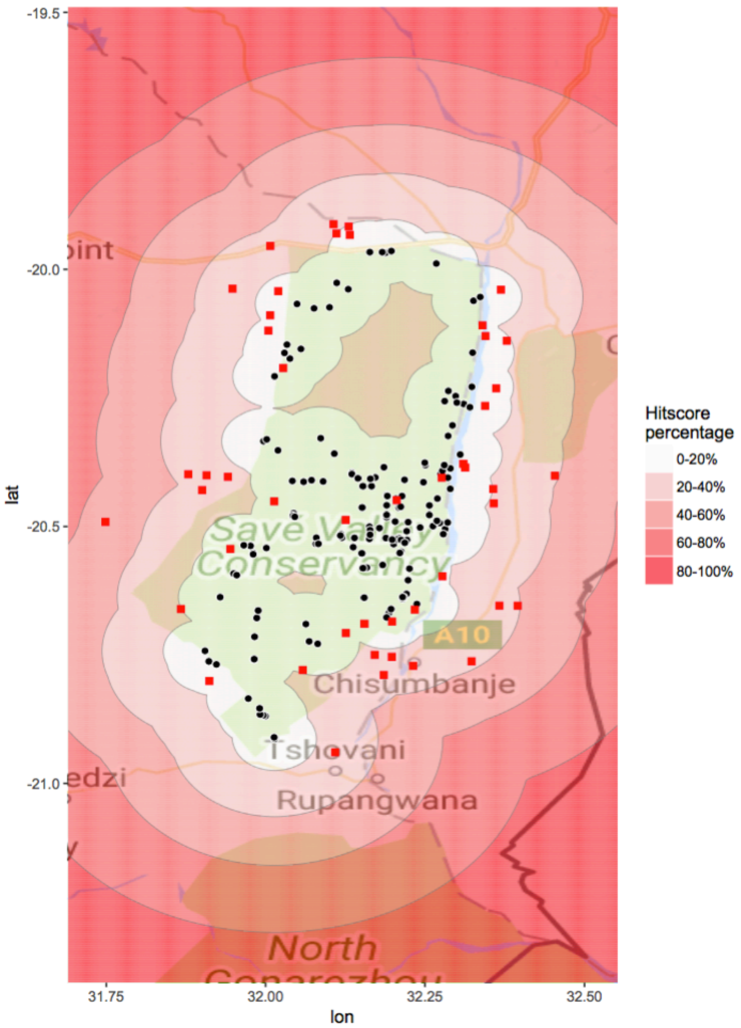

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