Rangers and modellers collaborate to build and evaluate spatial models of African elephant poaching

Article *in* Biological Conservation · March 2020

DOI: 10.1016/j.biocon.2020.108486

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Biological Conservation 243 (2020) 108486

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

Rangers and modellers collaborate to build and evaluate spatial models of African elephant poaching

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ARTICLE INFO

Keywords:
Ranger-based monitoring
Encounter data
Ranger patrols
Elephant poaching
Ensemble models
Biomod
Spatial bias
Loxodonta Africana
Patrol bias

ABSTRACT

Globally, tens of thousands of wildlife rangers patrol wide areas and record evidence of poaching activity such as elephant carcasses and snares. Such data have significant potential to inform conservation, but patrols are non-random in space and time, so conclusions from raw patrol data may be biased. Here we model spatial patterns of elephant poaching based on detections of carcasses by ranger patrols in the Zambezi Valley, Zimbabwe (201 carcasses, 2000–2017), using different methodological scenarios to correct for patrol bias. We follow a participatory modelling framework, using interviews with practitioners (rangers and managers) to help build and evaluate these models. We found that poaching patterns in the bias-corrected scenarios differed among themselves and from the uncorrected scenario. Practitioners interrogated the credibility of the predictions in each scenario and thus helped discern true poaching patterns from those explained by patrol bias. We uncovered proximity to water as the strongest driver of poaching, likely reflecting both poacher and elephant behaviour. Our results show that it is essential to account for observer bias before developing management actions (such as ranger patrol strategies) from raw observational data. We further demonstrate the value of combining multiple lines of evidence (statistical models and interview responses) for more robust inference in the face of uncertainty.

1. Introduction

Monitoring trends within socio-ecological systems (species populations, illegal harvest rates, etc.) is essential for adaptive management, helping managers understand and manage change (Nichols and Williams, 2006). Evaluating anti-poaching strategies, for example, requires reliable measurement of real poaching trends. Data on biodiversity and threats are however difficult to gather at relevant scales, and are often biased and imprecise (Field et al., 2007). Time and resource constraints often mean that monitoring data are collected by people doing other jobs, such as wildlife rangers detecting snares while on patrol or fisherman providing records of bycatch species landed. Such opportunistic data present unique challenges to interpretation (Keane et al., 2011). A drop in the detection of poachers' snares, for example, may reflect a shift in patrolling to a 'non-hotspot' area, rather than an actual change in poaching levels.

Another challenge to interpreting observational data is the complexity of the underlying mechanisms generating the data. The behaviours of data generators (e.g. poachers), data collectors (e.g. rangers) and species of concern (e.g. elephants) are likely to interact in complex ways and their relative influence is difficult to disentangle. Dobson et al., (2018), for example, show how deterrence of poachers by rangers can confound inferred trends on the prevalence of illegal activity. Imperfect detectability of illegal activity (like bushmeat snares in thick forest; O'Kelly et al., 2018), and patrol observations that are biased towards certain areas (Critchlow et al., 2015), may similarly confound true patterns.

Participatory modelling is a promising way to design quantitative models that are robust to uncertainty arising from the bias and complexity discussed above (Voinov and Bousquet, 2010). Bringing together people familiar with the system of interest provides essential qualitative context to modelling (Milner-Gulland and Shea, 2017). These may be fisherman, wildlife rangers, or protected area managers that have a grounded understanding of how a system works (e.g. where elephant poaching happens) and how data are collected (e.g. what affects ranger movements). Participatory or collaborative modelling

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https://doi.org/10.1016/j.biocon.2020.108486
Received 27 November 2019; Received in revised form 5 February 2020; Accepted 18 February 2020

involves using the qualitative insights of on-the-ground practitioners and stakeholders in both the design and validation stages of statistical/mathematical modelling (Voinov and Bousquet, 2010). Quantitative models are vulnerable to the data and assumptions used to build them, while qualitative insights are often subjective or incomplete. Combining multiple lines of evidence (statistical outputs and interview responses) is a useful way of addressing this uncertainty. Engaging practitioners in modelling may also create a sense of ownership that amplifies its real-world relevance (Basco-Carrera et al., 2017).

Globally, tens of thousands of park rangers spend significant amounts of time on patrol, encountering plants, animals, and illegal activities. Such data are becoming an increasingly important source of information for both science and conservation (Gray and Kalpers, 2005; Moore et al., 2018). The MIKE programme (Monitoring of the Illegal Killing of Elephants), is a high-profile example of the use of data collected by ranger patrols to inform local and international conservation policy (CITES Secretariat, 2019). MIKE covers 60 sites across Africa, within which > 19,000 elephant carcasses have been detected by rangers to date. The data have been used in high profile global and continental analyses (Wittemyer et al., 2014; Hauenstein et al., 2019), but less so at the local site level. In this paper, we investigate spatial patterns in poached elephant carcasses detected by rangers at a MIKE site in the Zambezi Valley, Zimbabwe. We combine quantitative models with interviews with widlife rangers and their supervisors to address the following research questions:

(1) What spatial patterns are evident in poached elephant mortalities at the case study site?
(2) How are these patterns influenced by monitoring bias?

2. Methods

2.1. Study area

The Chewore Safari Area MIKE site (3390 km^2; hereafter Chewore) in Zimbabwe is part of the World Heritage Site comprising three adjacent protected areas (PAs): Mana Pools National Park and the Chewore and Sapi Safari Areas (Fig. 1). The elephant population in the broader Zambezi Valley declined by an estimated 42% (19,981 to 11,656) between 2003 and 2014, primarily due to poaching (Dunham, 2015; ZPWMA, 2015). Chewore is divided into two management units (north and south) and is also a sport hunting area, with several operators hunting over the dry season (April to October). Elevation varies widely (350–1200 m) and the wet season is short (November to April) with average annual rainfall of 750 mm (Sibanda et al., 2015). Chewore is dominated by miombo (*Brachystegia julbernardia*) and mopane (*Colophospermum mopane*) woodland. The area is well-drained, and rivers are mostly seasonal, apart from the Zambezi. There are two main ranger stations, and three sub-stations, with a total of 58 rangers as of July 2018 (Fig. 1).

2.2. Participatory modelling

We engaged practitioners to help build and evaluate spatial ensemble models of elephant poaching, with different scenarios to account for ranger patrol bias. Practitioners were engaged at two stages: (1) model construction, and (2) model interrogation (Fig. 2). More details are provided under the subheadings below.

2.3. Elephant mortality data

Rangers recorded elephant carcasses encountered during patrols (Jan 2000 - Dec 2017). Rangers recorded both poached (n = 201) and other (n = 390) elephant mortalities (the latter including natural, sport-hunted, and problem animal-control mortalities, as well as carcasses categorised as ‘unknown mortality’). Several patrol types were employed, the most common being seven-day extended patrols away from ranger stations, during which rangers either moved between temporary bases on a daily basis or remained at the same base for the seven-day period. Also, one ranger was always present on each sport hunting trip (7–21 days), with poached and natural mortalities occasionally encountered. The cause of death, the GPS location of the carcass, the sex and age category of the animal when it died, the age (state of decomposition) of the carcass, and the status of the ivory (removed or present) were recorded (MIKES Programme, 2015).

2.4. Ranger and manager insights for model construction

Before model construction, we conducted semi-structured interviews with 14 rangers and four managers at two ranger stations in Chewore in August 2018 (average experience at site: 5.8 years). Each participant was interviewed individually in a private room, with interviews lasting between 30 min and 2 h (average 58 min). Rather than seeking to elicit particular answers, we sought to stimulate discussion by asking broad questions in three main areas:

(a) Ranger patrol patterns: questions around spatial patrols strategies, fine scale patrol patterns, stories of recent patrols, and areas difficult to access by patrol.
(b) Perceived patterns of poacher behaviour: questions around perceived hotspots of poaching, and perceived poacher strategy.
(c) Observations of elephant movements: questions around local knowledge of elephant movements and habitat preferences.

Next, a conceptual framework of factors affecting the distribution of detected poached elephant carcasses was developed based on these qualitative data and the broader literature (Table 1; Fig. 3). Respondent descriptions of patrol patterns also provided valuable context to help develop the quantitative scenarios for accounting for patrol bias. Interviews were audio-recorded and transcribed, followed by focussed coding to identify patterns of meaning in relation to the factors of interest (patrol patterns, elephant movements, and poacher behaviour) (Newing, 2010).

2.5. Ensemble distribution models

In total, 187 poached carcasses had accurate location data and so could be used in the models. We employed ensemble species distribution modelling (Thuiller et al., 2009) to relate the distribution of detected poached elephant carcasses to the spatial variables identified above (Table 1). Details on the datasets used for predictors are in the Supporting information, along with raster plots showing their values across Chewore (Fig. S1). Ensembles have the advantage of incorporating results from a range of modelling techniques based on their explanatory power, frequently performing better than single models (Araújo and New, 2007; Marmion et al., 2009). The locations of poached carcasses were compared to randomly generated background locations. Following Barbet-Massin et al. (2012) we generated 1000 absences across Chewore. We used a set of four machine-learning algorithms (including random forests and generalised boosted models) and four regression techniques (including generalised linear and additive models) to build our ensembles (see Supporting information). We used the R package ‘*biomod2*’ for analysis (Thuiller et al., 2016). For model evaluation, the full dataset was randomly divided into training and test datasets using a 70:30% split, with 20 different training sets produced by repeated splits (thus capturing model uncertainty). Thus 140 single models were run (seven modelling techniques x 20 splits). Model accuracy was measured using the area under the receiver operating characteristic curve (AUC) as well as the True Skills Statistic (Thuiller et al., 2009). Only those single model runs which performed well (> 85% of the AUC of the highest single model run) were used in the ensemble by weighted average consensus (Marmion et al., 2009).

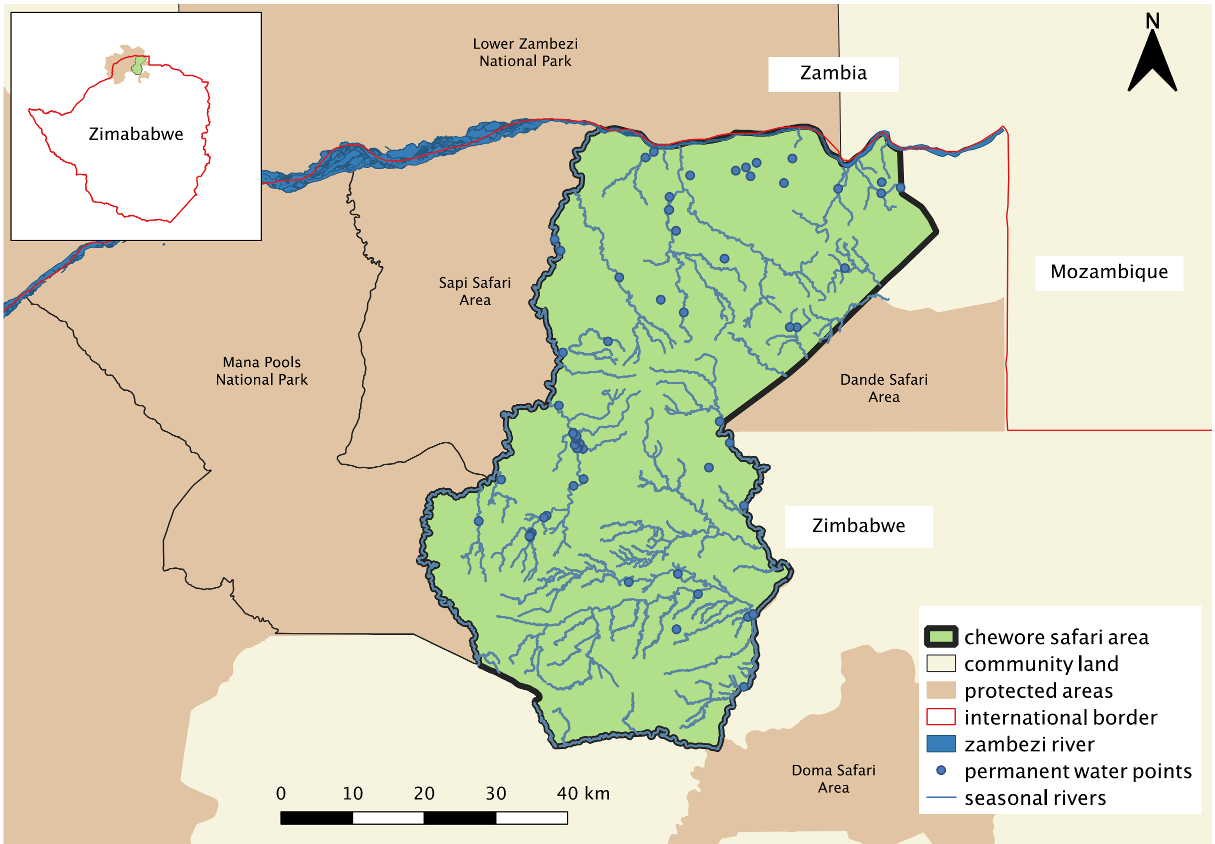

Fig. 1. Study area: the Chewore Safari Area in the Zambezi Valley region of northern Zimbabwe.

Predictor pairs with correlations $r > 0.60$ were excluded (Dormann et al., 2013). Predictor strength in explaining carcass distribution was determined using 'variable importance' (the correlation between the prediction of the full model and a model without the predictor in question; Thuiller et al., 2009)

2.6. Accounting for patrol bias

Background data in species distribution models are often sampled randomly from the full study area, whereas sampling of occurrence data is often spatially biased (focussed on certain areas), leading to biased inference (Marmion et al., 2009). Ranger patrols are a typical case, given how variable they are in time and space (Critchlow et al., 2015). In such contexts, Barbet-Massin et al. (2012) recommend using geographically-biased background data sampling to match sampling bias. Phillips et al. (2009) achieve this by using as background data a 'target group' of occurrences of additional observations obtained through similar sampling methods, and thus with similar bias. They show, for 226 species from diverse global regions, that target group sampling significantly improves model performance. Mathematically, occurrence records are not samples from the true distribution of poached carcasses (π), but from the distribution $\delta\pi$, where δ is the biased sample distribution (e.g. ranger patrols). The target group represents a set S of independent samples from δ, so when it is used as background data the resultant estimated distribution approaches the true distribution π, for large S (Phillips et al., 2009). MIKE data are useful here because rangers record other (natural, unknown, and management-related) elephant mortalities while on patrol, providing a useful target group. We used the location of other mortalities detected by rangers in Chewore over the long term (2000–2017, $n = 318$ records) as a surrogate for patrol locations. A caveat is that the unknown mortalities may contain poached mortalities, but this number is probably low because poached carcasses are mostly detected early and evidence of poaching is clear. To understand the effect of patrol bias on conclusions about spatial patterns in poaching, we produced three scenarios of background data sampling: a null scenario and two bias-corrected scenarios:

(1) Null scenario: generate background points across the entire polygon of Chewore.
(2) 'Target group' scenario: non-poaching elephant mortalities used as background data.
(3) 'Circular buffer' scenario: generate background data within a buffer of known patrol locations.

The latter two bias-corrected scenarios mitigate against concluding that an area is free of poaching when it is in fact simply seldomly patrolled. For (3), we generated background points within a patrol region defined by circular buffers around confirmed patrol locations (all locations where carcasses were detected, both poached and other mortalities; $n = 557$). This approach is intermediate to the target group and null scenario in that background locations are constrained by confirmed patrol locations, but also generated more widely. Thus, data from regions where rangers are likely to have been present, but where their location was not formally recorded through a carcass record, are included. Three buffer diameters were chosen (1, 3, and 6 km) to adequately represent a range of assumptions about true ranger patrol patterns. Thus, five background data sampling sets were generated (Fig. 4). We generated the same number of random points within each circular buffer so that more points were generated in areas with more confirmed patrolling (Fig. 4).

We acknowledge that a more robust approach to accounting for patrol bias would be to directly weight model predictions by fine scale patrol effort data, using approaches like hierarchical modelling (as in

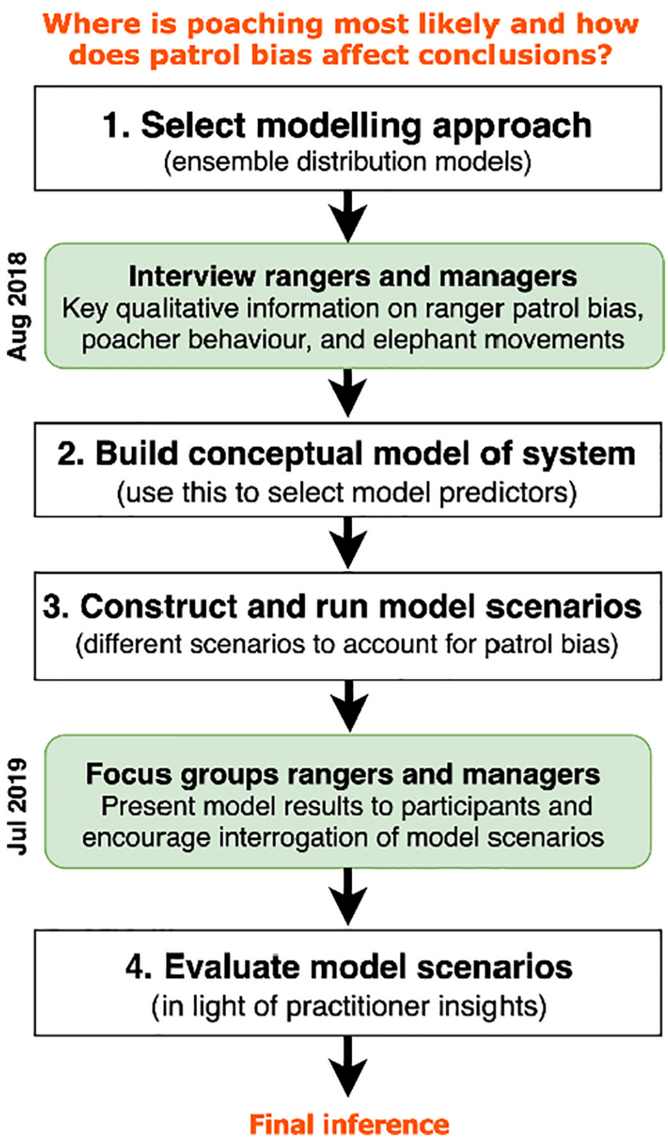

Fig. 2. The participatory modelling approach by stages, showing where practitioners contributed to model building and interrogation. Preliminary interviews with rangers and PA managers were used to build a grounded understanding of poacher, ranger and elephant movement dynamics, and better understand spatial patrol patterns and bias. This aided model construction. To discern among the different modelling scenarios, results were presented to rangers and managers who critically interrogated model predictions based on their on-the-ground experience.

Critchlow et al., 2015). Such data were however not available at our site. Indeed, in many developing country protected areas, patrol effort data are seldom consistently and reliably available over wide areas and time periods (Dancer, 2019).

2.7. Rangers and mangers interrogate model predictions

Results from the various modelling scenarios were presented to two separate groups of rangers and managers at two ranger stations in Chewore in July 2019, using a focus group format (Newing, 2010). Participants included eight rangers and two managers at Kapirinhengu base, and seven rangers and one manager at Mkanga base (average experience at site: 5 years). A large computer screen was used to present graphs and maps of the modelling results to each group, with a focus on the graphs of the effect of each spatial predictor on the probability of poaching (Fig. 5 below). Participants were encouraged to interrogate

Table 1
Predictors of the spatial distribution of poached elephant carcasses detected by rangers, with their hypothesized effect on elephant, ranger and poacher behaviour. Variable selection was guided by interviews with rangers and managers (statements marked with *), as well as the academic literature. Blank cells are where there is no prior hypothesis. Detail on the data source for each variable is included in the Supporting information.

	Predictor	Elephant behaviour	Ranger behaviour	Poacher behaviour
1	Distance to (km):			
2	*River (mostly seasonal)*	Surface water availability a strong determinant of elephant ranging patterns in similar systems (Redfern et al., 2003)	Occasionally conduct river patrols or use rivers for navigation*	
3	*Permanent water (mostly springs)*	As above	Perceived as hotspots for poaching and therefore frequently patrolled. Also, need access to water on extended patrols*	
4	*Road*		May occasionally use roads for navigation*	Accessibility and navigation
5	*Communal land (human settlement)*	May avoid areas nearer densely populated communal areas (particularly the southern boundary of Chewore)*		Infiltration point, affects travel cost and accessibility (Beale et al., 2017). See Fig. 1.
6	*International border*			Poachers from Zambia and Mozambique documented*
7	*Ranger camp*		Often patrol more intensely nearer camps due to logistical constraints (e.g. vehicle limitations)*	Avoid ranger camps to minimise detection (Beale et al., 2017; Moore et al., 2018)
8	Elevation (m)	Elephants generally avoid high, steep elevations due to poor navigation, but avoid low-lying muddy areas during the wet season (see TRI below)*	Highest elevations infrequently patrolled due to logistical challenges (steep and difficult terrain)*	Higher elevations are difficult to access and navigate through*
9	Topographic Wetness Index (TRI)	Measure of soil moisture and thus forage availability (Redfern et al., 2003). Elephants may avoid wet/muddy areas due to slow navigation and risk of getting stuck* (Douglas-Hamilton and Wall, 2008)	Patrol extent is limited in the wet season due to muddy/flooded roads that are not navigable by vehicle*	
10	Slope	Harder to navigate steeper areas.	Harder to patrol if slope is higher*	Harder to navigate areas of steeper slope*
11	Percentage Tree Cover	Forage availability (Asner et al., 2016)	Harder to detect carcasses in woodland* (O'Kelly et al., 2018)	Cover for poachers (Sibanda et al., 2015)
12	Normalized Difference Vegetation Index (NDVI)	Proxy for forage availability. Indicator of elephant abundance in other studies (Duffy and Pettorelli, 2012)	Harder to detect carcasses in thicker vegetation* (O'Kelly et al., 2018)	Provides cover. May also obstruct poacher movement and lower elephant visibility

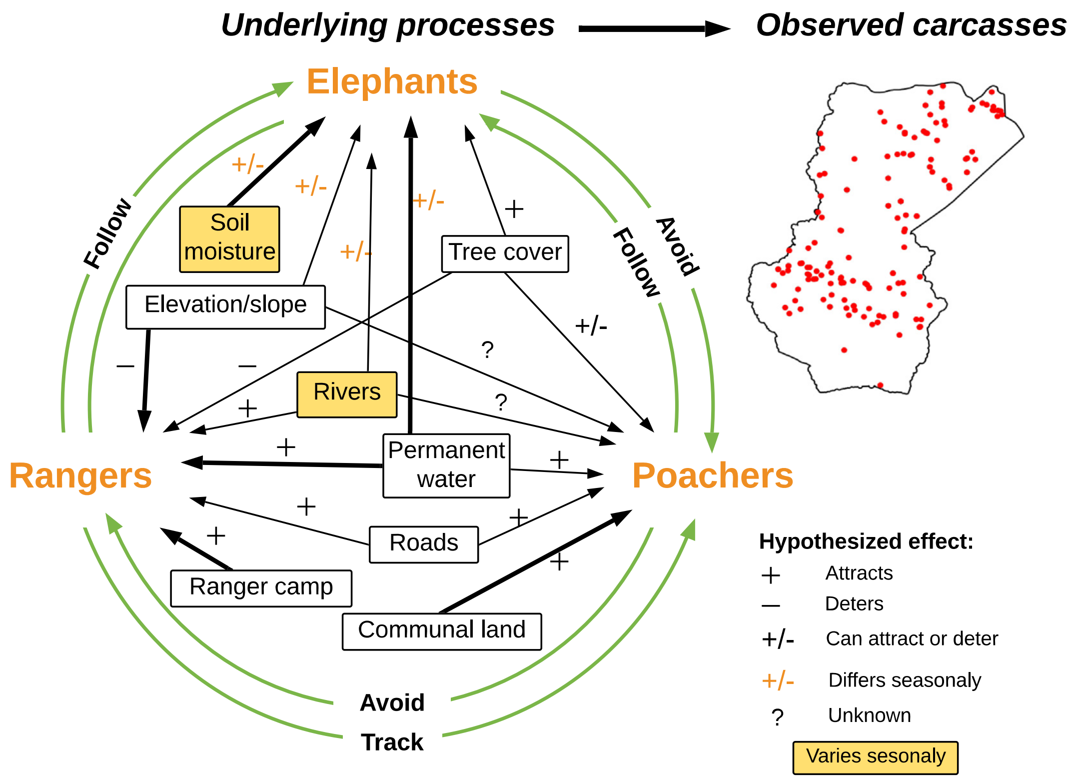

Fig. 3. A conceptual diagram showing the processes underlying the observed distribution of poached elephant carcsses detected by rangers, based on ranger and manager interviews as well as the literature (information sources and references in Table 1). We hypothesized that the behaviours of all three agents (elephants, rangers and poachers) are affected by both other agents and certain environmental and anthropogenic spatial predictors (square boxes). Line thickness represents the hypothesized relative strength of the associations.

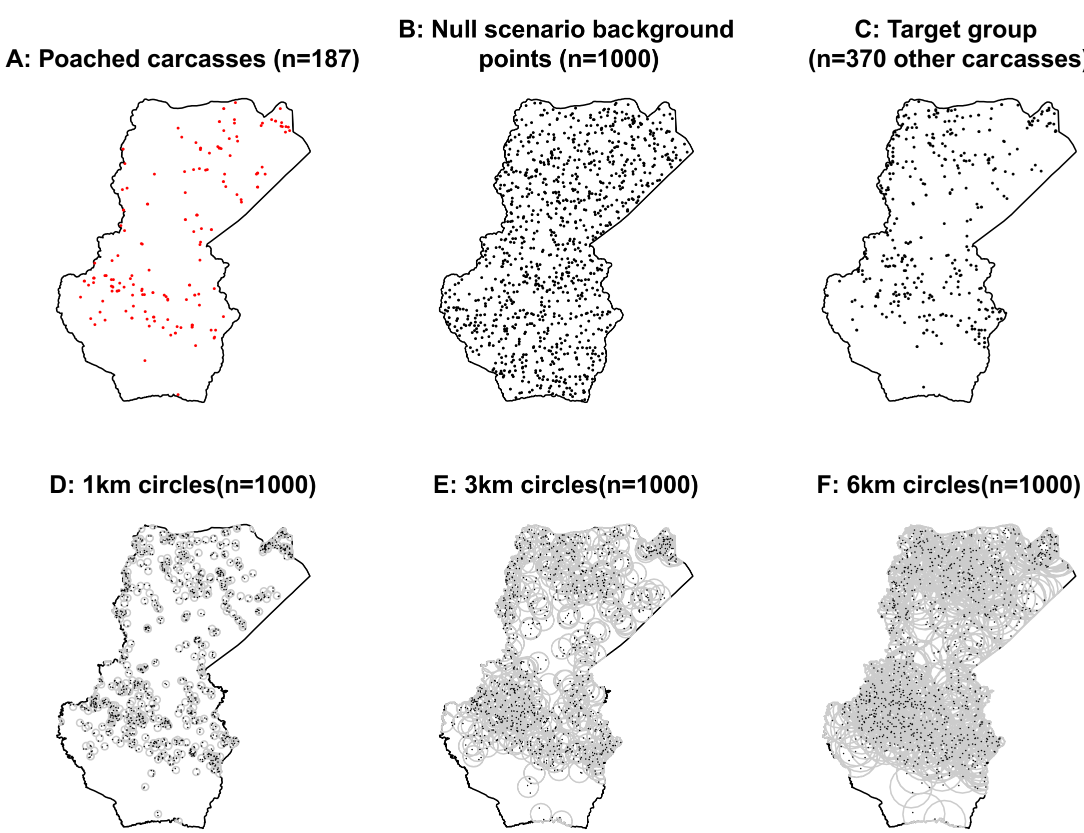

Fig. 4. Different scenarios to understand the effect of patrol bias on spatial patterns in elephant poaching. The distribution of (A) poached carcasses in Chewore (2000–2017), (B) the null scenario background data, (C) the target group scenario background data (non-poaching elephant mortalities), and (D–F) the background data for the circle method with different buffer radii.

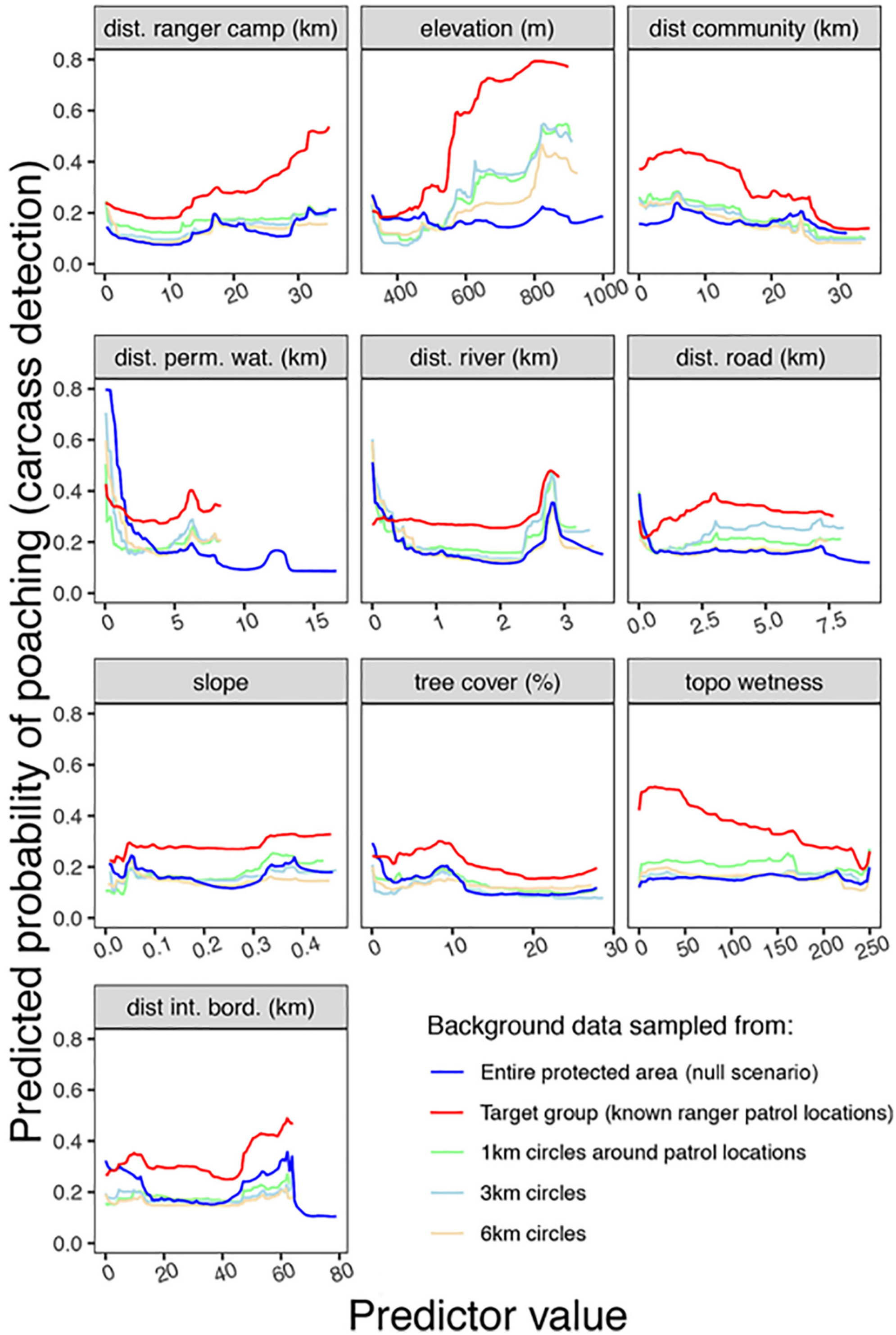

Fig. 5. The spatial relationship between the probability of elephant poaching and each of 10 environmental and anthropogenic predictors, for each scenario of background data sampling. The lines for each scenario are derived from an ensemble model representing the consensus among the top performing of 140 single model runs (7 model techniques with 20 iterations each).

model predictions, giving reasons for supporting or not supporting predictions. This lead to extensive discussions about the credibility of the different scenarios. Responses were audio-recorded and transcribed, followed by coding relevant to the theme of model interrogation (Newing, 2010). Interview protocols were reviewed and approved by the Human Research Ethics Committee at Oxford University (CUREC REF: R58336/RE001).

2.8. Critical reflection on model scenarios

The final stage involved the lead author critically reflecting on the strength of the different modelling scenarios in light of both practitioner responses to their predictions and the internal logic and assumptions of each scenario.

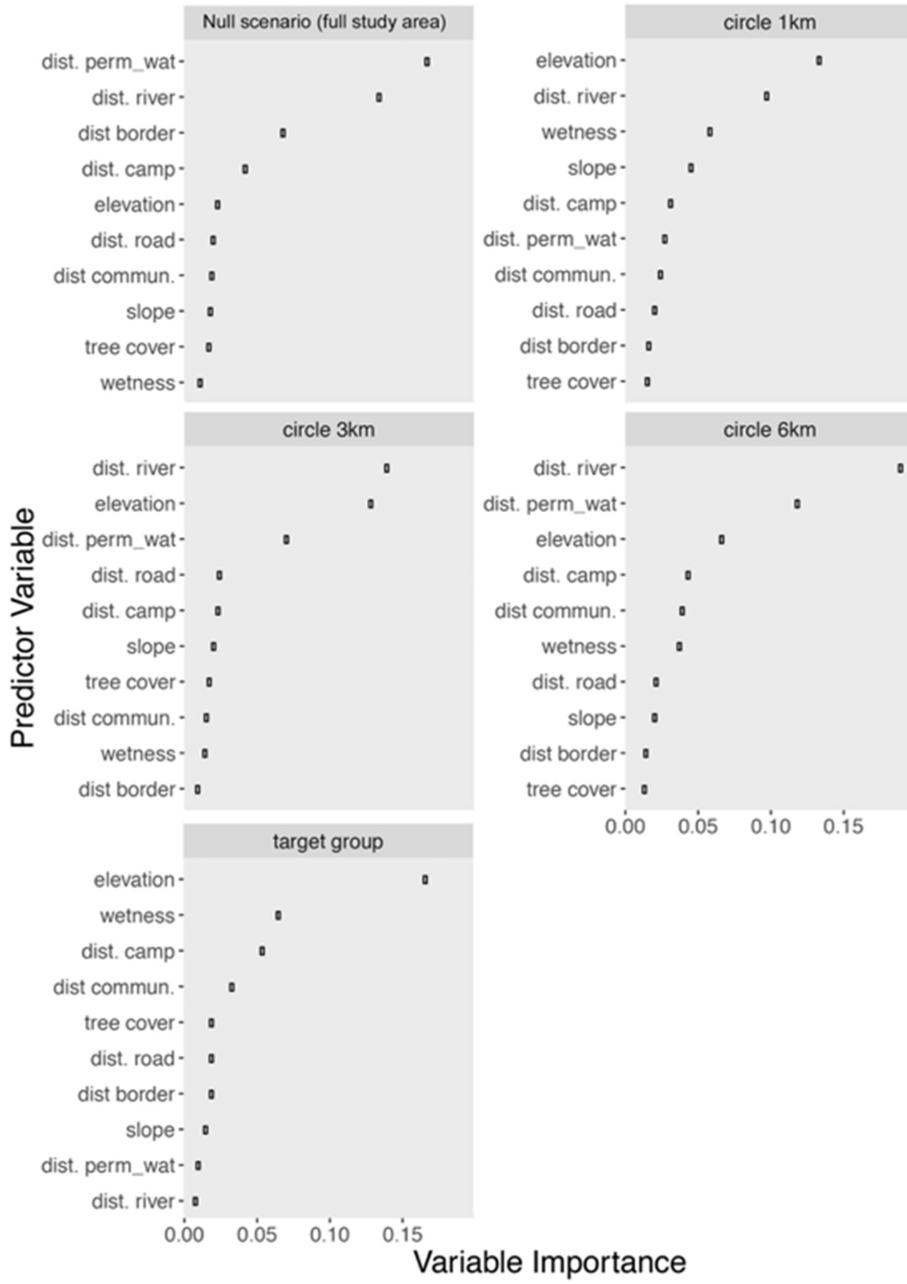

Fig. 6. The variable importance (VI) scores for each of the predictors in the ensemble model in each scenario of background data sampling. VI scores are computed as 1- r, where r is the correlation coefficient between the predictions of the model without the predictor in question. Note that values are comparable among predictors within a model, but not among models.
Refer to Table 1 for details on each variable.

3. Results

In all scenarios, the random forests and generalised boosted models performed best at predicting poached carcass distribution (AUC/TSS scores, Fig. S2 Supporting information). The ensemble model in each scenario performed markedly better than the single models (Fig. S2). NDVI and tree cover were correlated ($r = 0.69$). We excluded NDVI because it varies widely between seasons whereas the models averaged 17 years of data. All other predictor pairs had $r < 0.6$.

The effect of each predictor on poached carcass distribution varied according to the scenario of bias-correction (Figs. 5 and 6). In the target group scenario, poached carcasses were detected with higher probability at higher elevations, lower topographic wetness, further from ranger camps, and closer to communal land (while distance to rivers and permanent water had no effect; Figs. 5 and 6). Distance to permanent water and rivers were the strongest predictors in the null scenario (Figs. 5 and 6). The buffer scenario predictions were intermediate between the target group and null scenarios, with elevation and wetness becoming increasingly less important and distance to water and rivers becoming more important from the 1 km (most like the target group scenario) to the 6 km (most like the null scenario; Figs. 5 and 6) scenario. The variable importance scores were low for most variables in each scenario (< 0.05). The combined effect of predictors is represented in the probability maps of poached carcass distribution, with different approaches to bias-correction leading to different inferred patterns (Fig. 7).

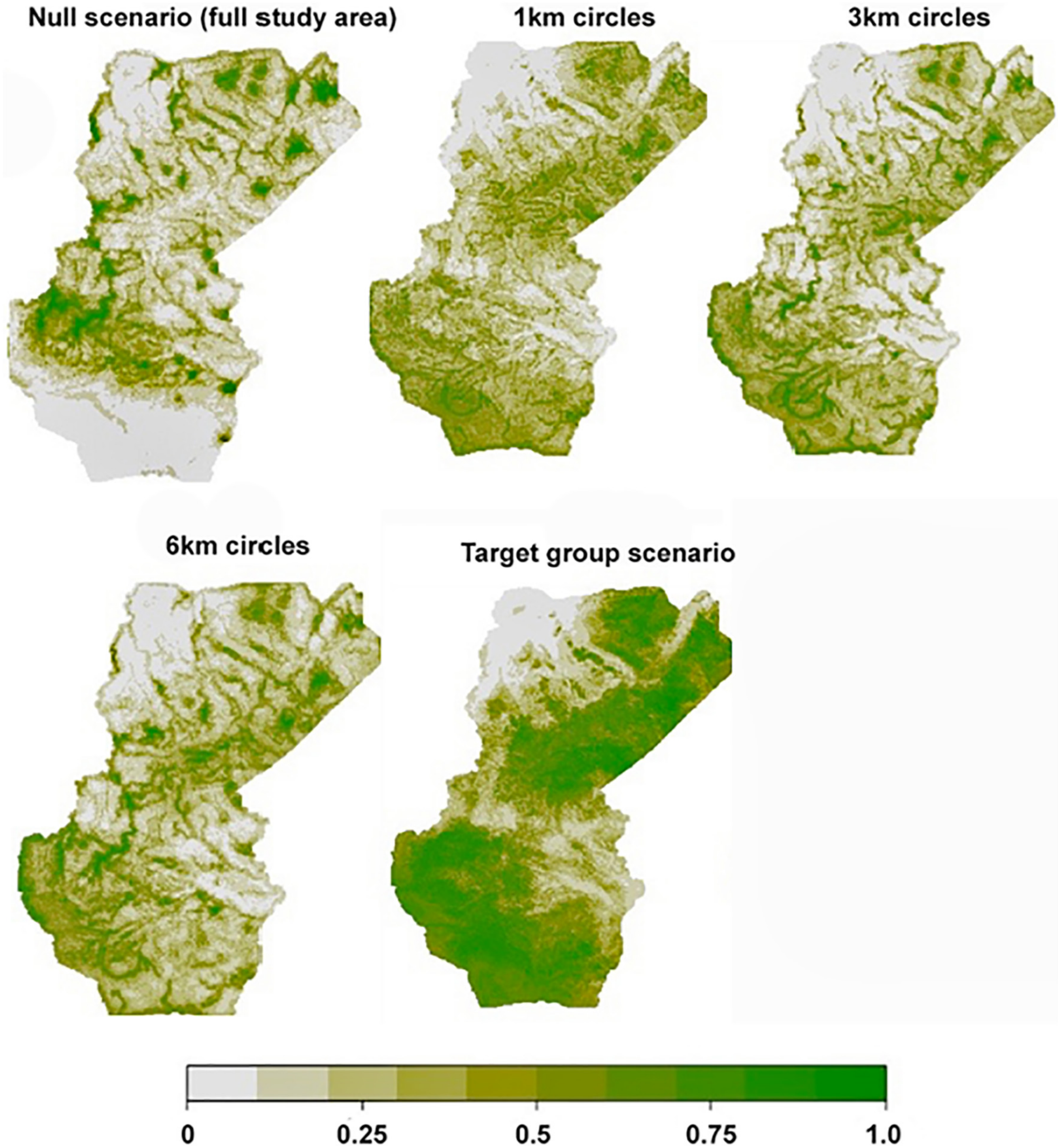

Fig. 7. The relative probability of elephant poaching across Chewore Safari Area based on caracsses detected by rangers, for each scenario of background data sampling. Predictions in each scenario are based on an ensemble model representing the consensus among the top performing of 140 single model runs (7 model techniques with 20 iterations each).

3.1. The influence of patrol monitoring bias

The shape (Fig. 5) and strength (Fig. 6) of the effect of each predictor on spatial patterns of poaching differed between the null and bias-corrected scenarios, providing evidence for how patrol bias influences inference about spatial patterns of poaching. In particular, the large differences in the effect of elevation among the different scenarios suggest that that elevation has a strong influence on ranger movements, and hence spatial patterns in what they observe. This accords with rangers own descriptions of avoiding hilly areas (see below). Overall, however, many of the predictor effects did not differ significantly among the scenarios, suggesting that patrol bias may not have as large an affect as originally expected. Small differences did combine to produce larger differences in final predictions, however, as evidenced by the quite different spatial patterns shown in Fig. 7.

3.2. Rangers and managers interrogate model predictions

More time was spent discussing the distance to water and elevation effects as these were simultaneously the strongest and most contentious. The target group predictions were the most strongly questioned by rangers and managers. The predictions of higher levels of poaching at higher elevations, and the absence of distance-to-permanent-water and distance-to-river effects, were particularly challenged because they did not make sense in light of rangers' understanding of elephant distribution, developed over multiple years. Participants described routinely tracking elephants, "that is the tactic we use, we follow the elephants…so when the poachers want to poach an elephant we will be there" (R4). "We focus where there is more concentration of elephant" (R11). Participants agreed that poachers target areas where they can reliably find elephants, "Where elephants are more concentrated, there are poachers there" (R9).

There was strong consensus among participants that elephant abundance was low at high elevations: "The area is mountainous, so it is very difficult for elephants to navigate, so they avoid it" (R13). When questioned whether carcasses (poached and other) in mountainous areas remain undetected because patrols avoid these areas, rangers again invoked elephant distribution. While admitting they spend little time at higher elevations ("the area is very difficult for rangers to access and patrol" [R6]), rangers said that when they do visit these areas they find little evidence of elephant presence (visual, spoor, etc.). "There might be some poached carcasses in the mountains, but the probability is very low…the area is difficult for animals and people" (R1). Rangers also suggested that mountains limit poacher access; "those mountainous areas…even the poachers can hardly move there" (R16). Rangers also pointed out that the extensive mountain escarpment along the southern boundary of the park (see Supporting information Fig. S1, elevation) is adjacent to densely populated communal land. Human incursion into Chewore for bushmeat hunting and wood collection was described as another reason why elephants avoid the mountains. Finally, they referred to a 2014 aerial survey which reported very few live elephants or carcasses in the mountainous regions (Fig. S3 Supporting information). Thus, while low patrol effort may play a role, low carcass detections at higher elevations is likely to be principally driven by low elephant abundance.

Participants repeatedly cited permanent water points as key hotspots for elephant abundance and poaching, and thus ranger deployments. "We go along covering the water points…because poachers don't go where there are no animals…so we concentrate on those areas. Elephants don't move very far from water" (S2). "Elephants are abundant there because of water" (R15). Participants therefore supported scenarios that predicted high levels of poaching near permanent water (the null and circular scenarios), and strongly questioned the weak distance-to-permanent-water effect in the target group scenario. They were similarly unsupportive of the neutral distance-to-river effect on poaching in the target group scenario, while supporting the positive effect observed in the circular buffer scenarios (again due to elephant distribution). "These elephants will be moving along those riverine areas looking for those ilala palms, most rivers have ilala palms…elephants love those… they also like the shade of the riverine vegetation" (S3). Rangers do not routinely patrol along rivers ("Most of the time we don't follow roads and rivers because you can be easily detected" [R1]), suggesting therefore that this effect is not due to patrol bias.

3.3. Critical reflection on modelling scenarios

Elephant distribution effects on poaching patterns were a common thread in participants' responses, suggesting that elephant distribution is a strong driver of spatial patterns in poaching. This led to our critical reflection on the target group method, exposing a particular weakness. The target group background dataset is composed of elephant carcass locations and is therefore heavily dependent on elephant distribution. By comparing poached carcass locations to the locations of other elephant mortalities (which may be considered a coarse proxy of live and poachable elephant distribution), the effect of elephant distribution on poaching patterns is controlled away. This explains the predictions of higher-than-expected levels of poaching in areas of low perceived elephant density (higher elevations) and lower-than-expected levels of poaching in areas of perceived higher elephant density (near water). Thus, while the target group may act as a proxy for patrol locations and bias, it negates elephant abundance effects. This is problematic for managers, because anti-poaching strategies should target areas of higher poaching regardless of the underlying cause (in this case, higher elephant density). Conversely, greater practitioner support for the predictions of the circular buffer scenario may be because it is a better reflection of reality. This may be because using random locations within the vicinity of carcass detections is a robust approach to accounting for patrol bias (unlike the null scenario), while not being too tied to elephant distribution (as in the target group scenario).

4. Discussion

Uncertainty is recognised as an important topic within socio-ecological systems research. These systems comprise complex and uncertain linkages between human behaviour and natural systems (Milner-Gulland and Shea, 2017). In line with this, applied ecologists are developing more robust tools for dealing with one particular class of uncertainty: observation uncertainty, the discrepancy between the true and observed states of the natural system under management (Bunnefeld et al., 2017). However, we should be careful not to introduce another class of uncertainty, through modelling bias, in our quest to correct for observation uncertainty. In this study we demonstrate the power of combining statistical tools to correct for observation bias with participatory approaches to guide us away from model bias, thereby reducing uncertainty in inference on spatial patterns of poaching. Using practitioner perspectives and the literature to generate hypotheses to guide model construction, and then comparing the different scenarios generated by the model with practitioners, helped us tease apart real patterns from those explainable either by patrol bias, or by model assumptions. Bias correction and qualitatively-guided model interpretation revealed water distribution as a key driver of poaching patterns.

4.1. Patrol bias and inferred spatial patterns of poaching

Our second research question sought to understand how spatial patrol bias affects conclusions made from patrol observations. Overall, the differences in the predictions of the null and bias-corrected scenarios indicate that patrol bias does indeed influence inferred spatial patterns of poaching. In particular, the avoidance by rangers of higher elevation areas had a large effect on conclusions drawn (see below). Apart from elevation, however, the predictions of the null and circular buffer scenarios were similar for most other predictors (Fig. 5), suggesting either the buffer scenario does not adequately account for bias or the effect of patrol bias on inferences may in fact not be large. The fact that the 1 km buffer predictions (reflecting the strongest assumption about patrol bias) were similar to those of the null scenario predictions suggests the latter may be true. Carcass data are aggregated from 17 years of patrols, so many of the carcasses from elephants poached outside heavily patrolled regions would eventually be detected, thus reducing patrol bias effects. While both the target group and circular buffer scenarios aim to account for patrol bias, both are influenced to some degree by elephant distribution as they rely on elephant carcass data. Practitioners helped us discern that this was more of a problem for the target group method, with the circle method less affected.

4.2. Practitioners help distinguish true patterns from those explained by patrol bias

The marked effect of higher predicted levels of poaching closer to water in the null scenario was weaker in the target group scenario, suggesting that the effect may be due to high patrol intensity near water. The water effect remained positive in all three scenarios that corrected for patrol bias through circular buffers, suggesting that higher detections near water are not solely due to patrol bias. This result, together with practitioner insights (which favoured the circular buffer method and pointed to predictable elephant abundance near water) suggests that higher detections of poaching near water may in fact primarily be driven by elephant distribution. Practitioners explained these patterns as poachers targeting water sources as sites of high and predictable elephant abundance. This result is in line with previous studies: Sibanda et al. (2015) predicted higher levels of elephant poaching near rivers in a Zimbabwean protected area. Beale et al. (2017) similarly found elephant poaching to correlate with elephant abundance in the Ruaha system in Tanzania, while Critchlow et al.

(2016) found that spatial hotspots of large animal poaching in a Ugandan PA to coincided with high density of target species.

The higher predicted levels of poaching at higher elevations in the target group scenario, questioned by practitioners, was also likely also due to the target method weakening the effect of elephant distribution. This argument cannot however explain why all the circular buffers scenarios also predicted a positive, albeit weaker, elevation effect. Rangers said that they rarely patrolled higher elevations due to navigation challenges, so the bias-corrected methods will have better captured the true bias in ranger patrols by excluding the infrequently patrolled highest elevations. Thus, the existence of an elevation effect seems credible, despite practitioner objections and lower elephant abundance at higher elevations. This demonstrates how, while practitioners must rightly interrogate model predictions, non-intuitive model predictions must also be allowed to challenge practitioner experience. Background data in all the bias-corrected scenarios was, however, scant at the highest elevations (> 800 m), so extrapolation of a positive elevation effect to these highest elevations may be tenuous.

4.3. Do we trust models or practitioners?

Model results should not simply be disregarded if their predictions are non-intuitive to those with intimate knowledge of the systems they represent. Otherwise, modelling would simply be a confirmatory exercise. A strength of quantitative models is their ability to predict outcomes of complex interactions that would be impossible to predict non-mathematically (Dobson et al., 2018). Models might also be more objective than practitioner predictions (Addison et al., 2013). For example, practitioners may fall into a confirmation trap whereby perceived poaching hotspots are reinforced by intense patrolling. On the other hand, model predictions are only as good as their input data and assumptions. The sensitivity of predictions to the different scenarios of background data sampling in this study is illustrative of this. Practitioners helped identify a weakness in the target group modelling scenario which may otherwise have gone unrecognised. Participatory modelling helps minimise those assumptions that are too abstract and identify those that are tenuous, while maximising those that align with on-the-ground reality. The key, then, is to retain the power of models to interrogate data and test assumptions, while not producing insights that are based on abstract notions rather than on-the-ground realities.

4.4. Complex mechanisms and randomness

The pattern of poached carcasses observed by rangers was produced by a complexity of processes representing the interactive behaviours of elephants, rangers, and poachers with each other and their environment (Fig. 3). Ranger presence can, for example, deter poachers and thus override the effect of other spatial predictors (Moore et al., 2018). Furthermore, spatial predictors may be mediated by the effects of agents on each other. If elephants are attracted to water, poachers will learn to target waterholes. Interactions can also involve negative feedbacks; poachers may prefer to use roads for quick access, but rangers may also use roads for navigation, possibly leading to poachers avoiding roads. Without robust data on these behaviours, interpretation of the mechanisms behind observed patterns will be uncertain.

A notable result is the low variable importance scores for most variables (< 0.10), showing they had only small effects on poaching distribution. This suggests some level of randomness in the spatial distribution of poaching, with consistent patterns difficult to elucidate. Critchlow et al. (2015) concluded that the lack of strong predictor effects on the spatial distribution of illegal activity may be due to complexity in how these covariates affect poachers and wildlife. The effect of predictors may also change over time or operate at different temporal scales, leading to further complexity. Variation in the spatial pattern of poaching through time (i.e. space-time clusters in poaching at monthly or yearly scales) may have confounded the effects of spatial predictors. The upshot of this randomness and complexity is that the predictors of poacher behaviour can be difficult to unmask, and therefore it may not be possible to make simple management recommendations about patrol targeting.

4.5. Key priorities for future research

We acknowledge a number of limitations with our analysis. First, the target group method, while demonstrated to work in other contexts, is only a crude measure of patrol effort. A more robust target group will have included the locations of additional ranger patrol observations (e.g. all animal sightings). Such data were not, however, consistently available for the period under study. Ideally, model results would have been weighted by fine grain data on spatial patrol effort. Critchlow et al. (2015), for example, used hierarchical models to develop estimates of the true distribution of illegal activities in Queen Elizabeth National Park in Uganda by combining an occupancy model of detected illegal activities with robust measures of survey effort (per grid cell across the PA). The effort data needed for these approaches are however only available at well-managed sites with the capacity and resources to collect them (Dancer 2019). We also do not consider changes in the spatial patterns of poaching among years and seasons, so the results presented here represent average effects over several years. In this study, only elephant carcasses detected fresh (66 records) could reliably be assigned to seasons, so robust seasonal ensemble models were precluded. Finally, we do not explicitly account for the effects of elephant distribution on poaching patterns. Aerial survey data from our study area could have been used as a proxy for this, but these surveys sample only 15% of the land area, have only been conducted twice in the last 20 years, and offer only a dry season snapshot of elephant distribution.

4.6. Application to conservation management: implementation in the real world

Our results demonstrate the importance of accounting for observer bias when drawing inferences from observational data. The patterns of elephant poaching documented here show a high degree of sensitivity to spatial ranger patrol bias. Management strategies, such as the deployment of patrols in areas of highest illegal activity, should not be uncritically based on raw patrol data. Patrol deployments that account for patrol bias can lead to significant gains in detection of illegal activities; Critchlow et al. (2016) demonstrated as much as a 250% increase in detections compared to the baseline, using the same amount of effort and resources. Without some measure of patrol effort, it is impossible to draw robust conclusions about poaching trends and hence predict where and when future poaching might happen. This underscores the importance to PA management of collecting regular patrol effort data at a relevant scale. An obvious challenge is developing capacity and resources for robust data collection. Interviews at our study site show that data collection is only one among many, often more pressing, responsibilities like anti-poaching. The collection and integrated analysis of effort and observational data is a large undertaking that will require a step-change in resource allocation. Ultimately, developing an organizational culture that values and prioritises data collection, analysis and use for adaptive management is perhaps the biggest obstacle to robust monitoring (Field et al., 2007). We suggest that investment in such structural changes is worthwhile. Robust monitoring can also lead to more resource-efficient anti-poaching strategies in the long term. Yet there exists a trade off between allocating resources to more efficient monitoring versus direct anti-poaching (McDonald-Madden et al., 2010). The simple scenarios of patrol bias correction employed here offer promise for spatial analysis at other MIKE sites, since more fine-scale data on patrol effort has already been identified as logistically infeasible at the majority of MIKE sites (Malpas and D'Udine, 2013).

Finally, our participatory modelling approach may prove useful in many other socio-ecological research contexts. Both quantitative models and practitioner insights can be biased, so integrating these alternate lines of evidence is likely to lead to stronger evidence and better adaptive management (Voinov and Bousquet, 2010). This is particularly important in contexts such as ranger-based monitoring, where data are not collected systematically and where results are of distinct practical relevance (Keane et al., 2011). Participatory modelling is also more likely to lead to actual use of models in conservation management because end users are already engaged and less likely to see models as detached abstractions (Addison et al., 2013). Finally, this work emphasizes the importance of recognising the knowledge and analytical agency of wildlife rangers. Their perspectives should be sought, rather than seeing them as passive implementers of conservation work or science planned by others (Moreto and Lemieux, 2015).

Data archiving

We intent to archive the data on which our analysis is based in the Dryad digital repository, pending necessary permissions from the Zimbabwe Parks and Wildlife Management Authority.

CRediT authorship contribution statement

Timothy Kuiper: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Blessing Kavhu:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Data curation. **Nobesuthu Ngwenya:** Conceptualization, Writing - original draft, Writing - review & editing, Data curation. **Roseline Mandisodza-Chikerema:** Conceptualization, Writing - original draft, Writing - review & editing, Data curation. **E.J. Milner-Gulland:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank the Research Council of Zimbabwe and the Zimbabwe Parks and Wildlife Management Authority (ZPWMA) who provided permission to carry out this research. TRK is funded by the Commonwealth Scholarship Commission (PhD scholarship ZACS-2017-648). Danica Kuiper and Sally Kuiper are thanked for their help with logistics during field work. Richard Maasdorp and Lynne Taylor provided invaluable on-the-ground knowledge to help plan field work. The rangers and managers of Chewore Safari Area are thanked for their enthusiastic and helpful participation in this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2020.108486.

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