Received: 3 January 2022 | Accepted: 18 January 2022

DOI: 10.1002/eap.2601

ARTICLE

ECOLOGICAL APPLICATIONS
ECOLOGICAL SOCIETY OF AMERICA

Understanding spatial patterns of poaching pressure using ranger logbook data to optimize future patrolling strategies

Arash Ghoddousi[1] | Corinna Van Cayzeele[2] | Pegah Negahdar[3] | Mahmood Soofi[2,4] | Amirhossein Kh. Hamidi[5] | Benjamin Bleyhl[1] | Guillermo Fandos[6] | Igor Khorozyan[2] | Matthias Waltert[2] | Tobias Kuemmerle[1,7]

[1]Geography Department, Humboldt-University Berlin, Berlin, Germany

[2]Department of Conservation Biology, University of Goettingen, Göttingen, Germany

[3]Tropical Ecology, Institute of Evolutionary Ecology and Conservation Genomics, Ulm University, Ulm, Germany

[4]CSIRO Land and Water, Darwin, Northern Territory, Australia

[5]Independent Researcher, Tehran, Iran

[6]Institute for Biochemistry and Biology, University of Potsdam, Potsdam, Germany

[7]Integrative Research Institute for Transformations in Human-Environment Systems (IRI THESys), Humboldt-University Berlin, Berlin, Germany

Correspondence
Arash Ghoddousi
Email: arash.ghoddousi@hu-berlin.de

Present address
Corinna Van Cayzeele, Natural Resources Wales, Bangor, UK

Funding information
Bundesministerium für Bildung und Forschung, SoMo project, Grant/Award Number: 01DK21003; Deutsche Forschungsgemeinschaft, Grant/Award Number: PArCS project #409732304

Handling Editor: Adam T. Ford

Abstract

Poaching is driving many species toward extinction, and as a result, lowering poaching pressure is a conservation priority. This requires understanding where poaching pressure is high and which factors determine these spatial patterns. However, the cryptic and illegal nature of poaching makes this difficult. Ranger patrol data, typically recorded in protected area logbooks, contain information on patrolling efforts and poaching detection and should thus provide opportunities for a better understanding of poaching pressure. However, these data are seldom analyzed and rarely used to inform adaptive management strategies. We developed a novel approach to making use of analog logbook records to map poaching pressure and to test environmental criminology and predator–prey relationship hypotheses explaining poaching patterns. We showcase this approach for Golestan National Park in Iran, where poaching has substantially depleted ungulate populations. We digitized data from >4800 ranger patrols from 2014 to 2016 and used an occupancy modeling framework to relate poaching to (1) accessibility, (2) law enforcement, and (3) prey availability factors. Based on predicted poaching pressure and patrolling intensity, we provide suggestions for future patrol allocation strategies. Our results revealed a low probability (12%) of poacher detection during patrols. Poaching distribution was best explained by prey availability, indicating that poachers target areas with high concentrations of ungulates. Poaching pressure was estimated to be high (>0.49) in 39% of our study area. To alleviate poaching pressure, we recommend ramping up patrolling intensity in 12% of the national park, which could be achievable by reducing excess patrols in about 20% of the park. However, our results suggest that for 27% of the park, it is necessary to improve patrolling quality to increase detection probability of poaching, for example, by closing temporal patrolling gaps or expanding informant

Arash Ghoddousi and Corinna Van Cayzeele contributed equally to the work reported here.

networks. Our approach illustrates that analog ranger logbooks are an untapped resource for evidence-based and adaptive planning of protected area management. Using this wealth of data can open up new avenues to better understand poaching and its determinants, to expand effectiveness assessments to the past, and, more generally, to allow for strategic conservation planning in protected areas.

KEYWORDS
illegal hunting, large herbivores, megafauna, occupancy modeling, patrolling optimization, protected area, rangers, ungulates

INTRODUCTION

Overexploitation of natural resources is one of the most prevalent human pressures in protected areas (Schulze et al., 2018). One of the main forms of overexploitation is unsustainable and illegal hunting (hereafter: poaching), which is driving many species toward extinction (Challender & MacMillan, 2014). Extensive poaching results in defaunation that erodes ecological interactions, disrupts ecosystem functioning, and derails evolutionary processes (Estes et al., 2011). A variety of incentives are known to motivate poaching, including subsistence hunting, hunting to supply local or urban meat markets, retaliation or prevention of human–wildlife conflicts, and hunting for the international trade of wildlife products (Challender & MacMillan, 2014; Montgomery, 2020). Despite the various conservation measures that are in place, such as promoting alternative livelihoods for local communities, educational campaigns, or improving law enforcement, poaching continues unabated in many protected areas and is one of the most pressing global threats to biodiversity (Challender & MacMillan, 2014; Schulze et al., 2018; Travers et al., 2019).

One of the main challenges in the combat against poaching is understanding and predicting where and when it will happen, which is crucial for devising conservation actions (Critchlow et al., 2017; Weekers et al., 2020). Poaching is cryptic, and, unlike other threats such as illegal deforestation that can be tracked using satellites, it is not easily detected (Montgomery, 2020). Poachers leave limited traces on their activities and may be deterred from areas where law enforcement takes place (Plumptre et al., 2014). In addition to data scarcity, the detection of poachers and their signs is a function of search effort, and therefore, comparisons of counts of poaching events can lead to erroneous conclusions (Keane et al., 2011). Scarce and imperfect detections of events, such as in the case of poaching, make most statistical frameworks unsuited for analyzing poaching (e.g., regression models, niche models, species distribution models) (Keane et al., 2008). Given the imminent threat from poaching across the world, approaches to understanding and predicting spatiotemporal patterns of poaching are urgently needed.

In recent years, there have been marked advances in the development of tools to precisely record both patrolling effort and detections of noncompliances. Such information could enable the use of occupancy models that specifically account for imperfect detection (MacKenzie et al., 2017) and would allow for the simultaneous assessment of detection probability and determinants of poaching in the landscape. Only a few applications exist of occupancy modeling for assessing poaching patterns, and though all these studies highlight its applicability, they are limited to sites with digitally collected ranger patrol data (Critchlow et al., 2015; Linkie et al., 2015; Moore et al., 2018). However, most protected areas do not possess enough resources to acquire handheld GPS units for their rangers, and where such devices exist, they have typically been operational for only a few years, limiting the ability to make inferences from such data. In most protected areas across the world, manually kept analog ranger logbooks remain the most common way of documenting ranger patrols and poaching prevalence, but these data are usually not digitized or georeferenced. Therefore, a wealth of information on important aspects of poaching has remained largely untapped. Developing approaches that could make use of such logbooks for predictive modeling would allow for making valuable inferences about poaching distribution across time and space for many protected areas.

Environmental criminology theories can help improve conservation planning by explaining conditions that enable crimes, such as poaching, to occur (Faulkner et al., 2018; Weekers et al., 2020). For example, knowledge of the spatial determinants of poaching could be used to increase patrolling effort in risky areas, a strategy known as hotspot policing, which can reduce crime (Braga et al., 2014). The boost hypothesis (i.e., higher repeated crime in sites with known opportunities) and flag hypothesis (i.e., higher repeated crime in areas with attractive characteristics) are central in this regard (Pease, 1998). Through a poaching lens, the boost hypothesis means that poachers repeatedly visit the same areas (e.g., established illegal fishing spots) (Weekers et al., 2020). The flag hypothesis posits that certain environmental settings determine where poachers operate (e.g., near rivers due to ample woody vegetation to conceal snares) (Critchlow et al., 2015). Testing these hypotheses in the context of poaching can be based on predator–prey concepts (Marescot et al., 2020). For example, poaching pressure can be determined by the occurrence of target species (Critchlow et al., 2015; Marescot et al., 2020) or by the avoidance of detection by rangers (Jenks et al., 2012; Linkie et al., 2015). Finally, proximity to protected area borders, villages, or roads can be a crucial factor for poaching prevalence (Moore et al., 2018; Plumptre et al., 2014). Despite the urgency of the biodiversity crisis, few studies have assessed proxies of site characteristics to identify poaching determinants (Critchlow et al., 2015; Marescot et al., 2020), especially in the context of the boost and flag hypotheses (Weekers et al., 2020). This is unfortunate, because understanding where poaching occurs in landscapes would allow for a more evidence-based allocation of ranger patrols (Keane et al., 2008; Plumptre et al., 2014). A regularly updated assessment would allow for an adaptive strategy in allocating ranger patrol effort. Such an adaptive management strategy constitutes a balance between addressing the requirements of management while acknowledging the necessity of continued learning about the system (McCarthy & Possingham, 2007).

Our primary goal was to understand the spatial determinants of poaching pressure in order to provide recommendations for planning future ranger patrol effort. To achieve this, we developed an approach to digitizing and georeferencing patrolling data from analog ranger logbooks and analyzed them in an occupancy modeling framework. We used Golestan National Park (GNP) in Iran as a case study, where poaching has depleted the population of ungulates by 66%–89% in the past four decades (Ghoddousi et al., 2019). Our approach is highly relevant to a vast number of protected areas around the world, where long-term ranger logbook data are kept but rarely analyzed. Specifically, we address the following research questions:

1. How can analog logbook data be used for assessing poaching pressure?
2. What are the spatial determinants of poaching pressure?
3. Where is poaching pressure predicted to be high?
4. How could patrolling strategies be improved based on current patrolling intensity and poaching pressure?

METHODS

Study area

GNP (874 km^2) is located in northeastern Iran and is the oldest protected area in the country (established in 1957) (Figure 1). It encompasses three major vegetation formations: the Hyrcanian broadleaf forest, montane steppe, and arid plains. GNP (International Union for Conservation of Nature [IUCN] Category II) is surrounded by other protected areas, namely, Ghorkhod Protected Area, Loveh Protected Area, and Zav Protected Area (all IUCN Category V). There are several villages around GNP, but not within its boundaries. Six species of wild ungulates occur in the national park: bezoar goat (*Capra aegagrus*), goitered gazelle (*Gazella subgutturosa*), red deer (*Cervus elaphus*), roe deer (*Capreolus capreolus*), urial (*Ovis vignei*), and wild boar (*Sus scrofa*). Almost all of them experience high poaching pressure, except for wild boar, which is not consumed due to religious beliefs (Ghoddousi et al., 2019) and not preferred by poachers (Ghoddousi et al., 2017). Thus, we did not consider wild boar as well as goitered gazelle because of its limited distribution (only ca. 25 km^2) inside the park.

A previous study in GNP showed a variety of poaching incentives, from subsistence and trade of wild meat to tradition, pleasure, and conflict with conservation bodies (Ghoddousi et al., 2019). Poaching is predominantly conducted by people from nearby villages and towns, exclusively in the form of pursuit hunting using rifles (Ghoddousi et al., 2017, 2019). GNP has nine ranger stations where the ranger patrols usually start out from and where the logbooks are located. Daily patrol allocation in GNP is decided rather arbitrarily by the head ranger of each station. Patrols involve locating and intercepting poachers, as well as recording wildlife sightings. Rangers systematically report their daily activities in logbooks (day entries), which contain information on patrol routes, persons involved, wildlife observed, and any noncompliances detected. The routes and observations are approximated using the names of local landmarks such as peaks, valleys, and other prominent geographical features. Park managers occasionally cross-check patrol routes with the involved rangers or directly visit them. Other illegal activities in GNP are limited to the small-scale collection of firewood and nontimber forest products, as well as illegal livestock grazing, which usually occur on the periphery of the park.

Data organization

We first collated and digitized the locations of all 552 landmarks mentioned in the logbooks (Appendix S1: Figure S1),

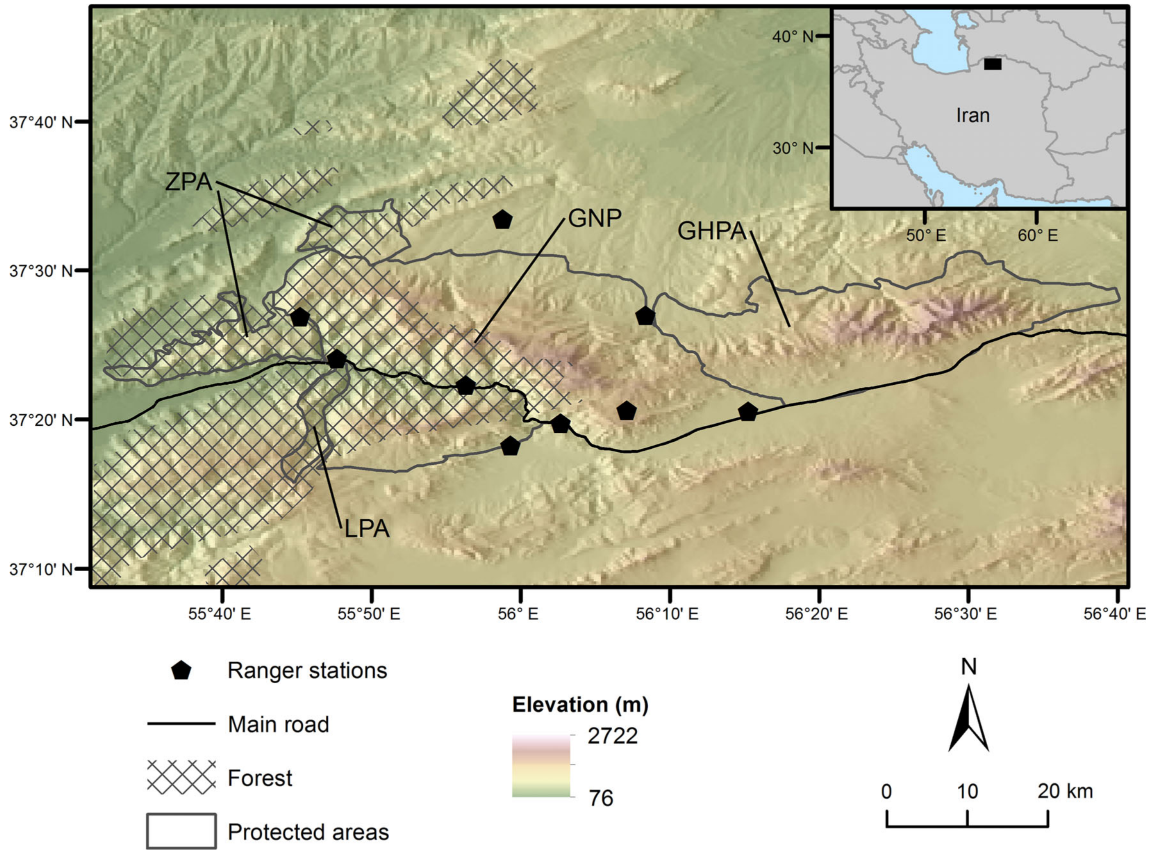

FIGURE 1 Study area in northeastern Iran (inset map) and location of Golestan National Park (GNP), Ghorkhod Protected Area (GHPA), Loveh Protected Area (LPA), and Zav Protected Area (ZPA)

as well as the main patrolling trails (754 km), with the help of an experienced ranger (Gh. Sadizadeh, personal communication) in Google Earth. The resulting map provided a reference for the geolocation of ranger patrols and sightings from logbook entries. We then superimposed a grid system of 3×3 km^2 cells over the study area to identify sampling units (hereafter: cells) in ArcGIS 10.5 (ESRI, Redlands, CA, USA). We included only cells with more than 50% of their area inside the GNP ($n = 96$ cells). We chose this cell size based on both ecological and patrolling considerations to be large enough to ensure that poachers and ungulates could occupy a sufficient number of cells (MacKenzie et al., 2017) and to reflect the typical distribution of ranger patrols in GNP (i.e., median distance of 10.62 km from 1029 daily patrols) (this study; Appendix S1: Figure S2) (Marescot et al., 2020). Moreover, this cell size reduced potential errors from imprecise locations in our data set that may occur at smaller cell sizes.

We analyzed 6888 logbook day entries from May 2014 to April 2016, of which 6499 reported ranger patrols. We excluded motorized patrols conducted by motorbike or vehicle, limited to a few roads inside and surrounding the park, because they (i) may produce a different level of poacher and wildlife detection probability compared to patrols on foot or horseback and (ii) may be due to other purposes than antipoaching (e.g., maintenance, transport of personnel) (Hötte et al., 2016; Marescot et al., 2020). We geolocated the remaining 4810 patrol entries by extracting the dates and locations of landmarks and sightings of ungulates and poachers by manually assigning them to corresponding cells with the help of the reference map (see preceding discussion). We used only direct sightings (i.e., visual detection of poachers) because there is a higher chance of misidentification of indirect signs (e.g., camps, firepits, or animal carcasses). We acknowledge that these signs, whenever validated, can provide important information on the prevalence of poaching, but they are currently potentially underreported by rangers in logbooks. Wherever route descriptions were unclear, we determined them based on the least effort movement strategy along the standard patrol routes and using the recorded locations of wildlife sightings (Critchlow et al., 2015). For very imprecise descriptions or unknown routes (=398 entries), we marked only those cells as patrolled that had been definitely surveyed. A cell was regarded as patrolled if the part of the patrol route in that cell exceeded 500 m or if rangers were known to patrol inside the cell for several hours. Although rangers report the patrol route regardless of wildlife sightings, in some cases reported sightings allowed for better allocation of routes to the respective cells. Multiple visits of rangers to a cell within 1 day (e.g., from different stations) were treated as a single survey for that day.

Occupancy modeling

We applied occupancy modeling to estimate the probability of poachers' distribution in GNP using the *occu* function in the *unmarked* package (version 0.13-2) in R (Fiske & Chandler, 2011). Occupancy modeling accounts for the imperfect detection bias (MacKenzie et al., 2017), which is an important consideration in antipoaching patrols since poachers may be present but go undetected by rangers (Critchlow et al., 2015; Marescot et al., 2020; Moore et al., 2018). We treat each cell as a site and each month as an occasion (i.e., the temporal unit in which sightings of poachers are counted as one detection), with all patrolling efforts and sightings of ungulates and poachers assigned to that occasion. We created a table of poaching detection history and entered a 1 if at least one poaching event was detected by rangers in the cell during that occasion, a 0 if no poaching was detected, and NA if the cell was not patrolled. Given the heterogeneity in patrolling effort across sites (Appendix S1: Figure S3), we also tested the effects of other occasion configurations on our model performance by aggregating monthly data to 3-month and 4-month occasions and comparing their detection probabilities and numbers of NA (Mackenzie & Royle, 2005). These occasion lengths also correspond to management and ecological considerations in our study area (e.g., seasonal changes in detection probability due to weather, foliage, species behavior, and possibly poacher activity). We conducted our analysis at the finest grain ($3 \times 3\ \mathrm{km}^2$) that our data could accommodate, because coarser resolutions would be less relevant in terms of informing management decisions regarding future patrol allocations.

We expected that there might be random changes in poachers' presence at any site at the time of patrols, which would violate the closure assumption of occupancy modeling (MacKenzie et al., 2017). Therefore, we interpreted the occupancy estimates as the probability of site use by poachers (MacKenzie et al., 2017). We estimated site use (Ψ) as the probability of poacher presence in a certain site during the study period based on detection/nondetection data collected from all ranger patrols. We separately estimated the detection probability (p) of poachers (i.e., the probability of detecting poachers by rangers in a specific site) (MacKenzie et al., 2017). We opted for a single-season occupancy framework because our data from 2 years was insufficient for a multiseason analysis, and a trial with multiseasonal models showed credible intervals for colonization and local extinction rates that were too large to be interpretable (Royle & Kéry, 2007).

Poacher detection covariates

To disentangle the effects of survey-specific conditions on , we developed and tested two survey covariates. We used the number of times each cell was patrolled on each occasion as a covariate named effort, assuming that a higher patrol intensity would result in a higher chance of poacher detection. Moreover, we assumed that landscape openness could impact and developed a visibility index by combining the average ruggedness (see *Spatial determinants of poacher distribution*) and the share of forest cover in each cell. We obtained forest cover data from Landsat 8 satellite images with a 30-m spatial resolution (Ghoddousi et al., 2020). We reduced forest cover values by 50% for the winter months (October–March), when lack of foliage increases the visibility. We standardized and summed forest cover and ruggedness values to create a visibility index for each site and occasion.

Spatial determinants of poacher distribution

To assess the spatial determinants of poaching distribution, we developed three a priori scenarios related to the flag hypothesis of repeated noncompliance. We tested variables related to each of these scenarios as site covariates impacting Ψ. We assumed that poachers would prefer areas with higher availability of target species (Critchlow et al., 2015; Marescot et al., 2020), so we developed a prey availability scenario. Three out of four of the ungulate species studied (bezoar goat, red deer, and urial) are preferred by poachers in GNP (Ghoddousi et al., 2017), and therefore, the areas of their concentration could determine poaching distribution. We tested this scenario by calculating and comparing two alternative prey covariates. First, we developed a catch per unit effort (CPUE) index from ranger sightings in the logbooks. CPUE includes species biomass information, an important aspect in poachers' choice of prey, and it also reflects the detectability and relative abundance of the species that poachers encounter in different landscapes. We calculated CPUE for each ungulate species by multiplying the total count from independent detections by the species' average biomass and dividing by the number of visits to that cell (Ghoddousi et al., 2020). We are confident that there was a minimal chance of misidentification of ungulate species in our study owing to the marked differences in their appearance, behavior, and habitats. We obtained the average biomass of ungulate species from Lumetsberger et al. (2017). We then calculated a cumulative CPUE as the sum of CPUEs of all four ungulates for each cell (Figure 2). Second, to account for the detection probability of prey sightings, we ran single-species, single-season occupancy models for each of the four ungulate species. We used survey covariates related to effort and visibility, as detailed, as well as site covariates related to ruggedness, distance to ranger stations, and distance to roads or borders (a detailed description follows). Furthermore, we included vegetation greenness as a factor impacting ungulate distributions using the average normalized difference vegetation index (NDVI) for each cell. We obtained NDVI data from Moderate Resolution Imaging Spectroradiometer (MODIS) data available from the National Aeronautics and Space Administration (NASA) (http://modis/gsfc.nasa.gov/data). We built and selected models using the same approach as in our poaching models (see following discussion) (Appendix S1: Table S1). Using the covariates of the best models, we estimated Ψ of each prey species for each site. We additionally calculated mean prey Ψ for each site by averaging the single-species estimates across all four prey species. Comparing single-species and cumulative CPUE and prey Ψ using the same criteria as our poaching models (see subsequent discussion), we selected CPUE as our site covariate for the prey availability scenario (Appendix S1: Table S2).

As an alternative scenario, we assumed that poachers may avoid areas with higher ranger presence (Jenks et al., 2012; Linkie et al., 2015) and developed a so-called law enforcement scenario. An earlier study by Ghoddousi et al. (2016) showed that ranger stations in GNP play an essential role in deterring poachers. Hence, we measured the shortest distance from the centroid of each cell to the ranger stations in ArcGIS 10.5. Additionally, we calculated the number of patrols in each cell in the corresponding year. Finally, we assumed that poachers may use areas with ease of access (Moore et al., 2018; Plumptre et al., 2014) and developed an accessibility scenario. We measured the shortest distance between the centroid of each cell and GNP borders and the main highway intersecting the park (Figure 1). We included the distance to the highway because it provides easy access to the park and is occasionally used by poachers to enter or exit the park (GNP, unpublished reports). We did not consider the border in areas where GNP adjoins one of the surrounding protected areas. Additionally, we tested the impact of landscape ruggedness and calculated its mean value in each cell using Shuttle Radar Topography Mission data (search.earthdata.nasa.gov). We also assumed that there might be a temporal effect in poaching distribution and used year as a site covariate in our analyses.

Analysis

We tested multicollinearity between all covariates using the Pearson correlation test with a cutoff point of $r = |0.60|$. Moreover, we scaled all the covariates to have a unit variance and to minimize overdispersion (MacKenzie et al., 2017). We used a multistep modeling approach by first building models using survey covariates while keeping Ψ constant. Then, we held the p covariates in the top models and built models with site covariates. We refrained from combining covariates from different scenarios in our models (apart from one global model) but tested the combinations and interactions between variables within each scenario, resulting in 12 models.

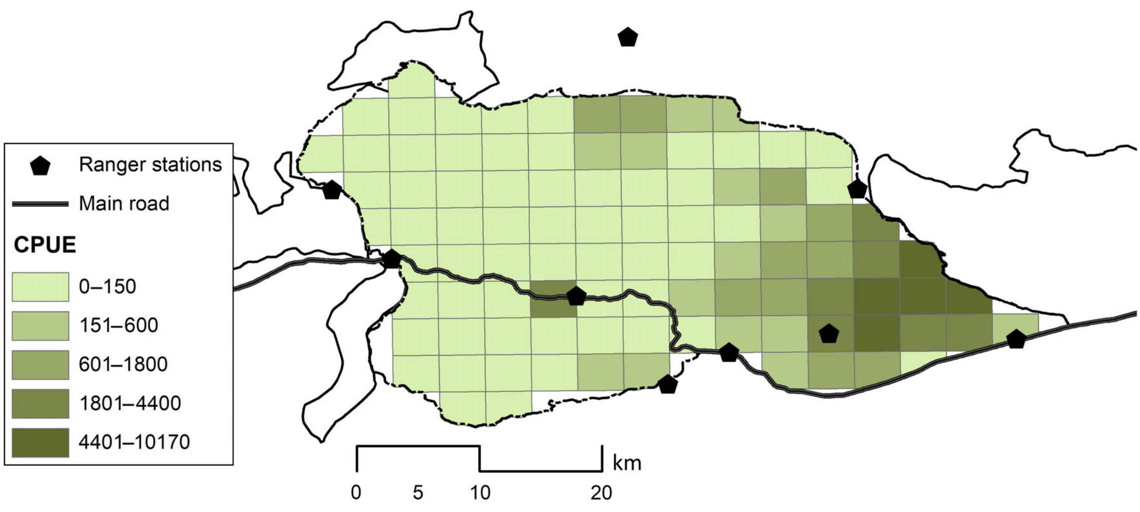

FIGURE 2 Availability of ungulate species in Golestan National Park approximated by cumulative catch per unit effort (CPUE) for bezoar goat, red deer, roe deer, and urial from ranger patrols

We used the Akaike information criterion (AIC) corrected for small sample size (AIC_c) for model ranking and considered those with $\Delta AIC_c < 2$ as the best model(s) (Burnham & Anderson, 2002). We tested the goodness of fit of the best models using a bootstrap method with 1000-fold cross-validation (MacKenzie & Bailey, 2004). Finally, we predicted Ψ for each year and each cell given the parameters of the best model(s) using the *predict* function of the *unmarked* package.

Future patrolling strategies

We used Ψ and patrolling intensity as the two criteria for suggesting the location and intensity of future patrolling strategies (Critchlow et al., 2017; Plumptre et al., 2014). We used the mean of Ψ over 2 years and across all cells as a threshold to identify areas with high and low poaching pressure. For patrolling intensity, we averaged the number of patrols over 2 years per cell and divided by the median annual number of patrols across all cells. This yielded an index where values >1 indicated cells with higher than median patrolling effort and values <1 indicated lower than median patrolling effort. We classified cells with high poaching pressure and high patrolling effort as areas requiring improvement in patrol quality, especially related to the detection of poachers (Hötte et al., 2016). Conversely, cells with high poaching pressure and low patrolling effort should receive higher patrolling intensity. Cells with low poaching pressure and high patrolling effort could have less patrolling effort in the future, while those with low poaching pressure and low patrolling effort may not require a change in strategy.

RESULTS

We digitized all ranger patrols recorded in the logbooks of 9 ranger stations for 2 years, which yielded 7668 total sightings (Appendix S1: Figure S4) of bezoar goat (1180 sightings), red deer (374), roe deer (410), and urial (5704) and 38 poacher detections. Over the study period, all cells ($n = 96$) were patrolled at least once, but there was a high variation in the number of visitations per year. A higher frequency of daily patrols was conducted in summer compared to winter, with the highest rates in May (birth season of ungulates) and August–October (red deer rut) (Appendix S1: Figure S3). Around 23% of the cells were patrolled less than once a month. The median number of patrols per year across all cells was 42 (0–331 patrols per year) (Appendix S1: Figure S5). In total, 555 day entries were missing from the logbooks.

To build our occupancy models, we first tested the impact of different occasion lengths (1, 3, and 4 months) on the of the null model. The 4-month occasions had the highest and lowest NA numbers, and we performed all subsequent occupancy analyses at this temporal scale (Table 1). Our covariates did not show a high correlation ($r < 0.6$), so we retained them in the analyses. The in our null model was 0.12 (SE = 0.05, 95% CI = 0.04–0.26), showing the rate of poacher detections during ranger patrols. None of the covariates was selected in our top models.

Among the three competing scenarios of the spatial determinants of poaching, prey availability was the most parsimonious model (Table 2). The model suggests increasing poaching probability in areas with higher ungulate availability approximated by CPUE. The mean Ψ across all cells from the best model was 0.49 (SE = 0.09). The goodness-of-fit test of the best model did not indicate overdispersion in our data set ($\hat{c} = 0.71$; $p = 0.57$).

Projection of the estimates of our best model across our study area (Figure 3) showed that poaching was highest in the eastern parts of the park where the highest concentration of urial (the most abundant ungulate in the park) occurs. Overlaying our predicted poaching pressure with the patrolling effort provided useful insights on how patrolling effort could be optimized. We identified 37 cells (38.5% of all cells) with high poaching pressure ($\Psi > 0.49$). Based on our defined patrolling strategies, we suggest improvements in patrolling quality in 26 cells (27.0%) and higher patrolling intensity in 11 cells (11.5%) (Figure 4). In 40 cells (41.7%), patrols may continue unchanged, and in 19 cells (19.8%), lower patrolling effort is suggested (Figure 4).

TABLE 1 Effect of different occasion lengths on detection probability (P) and naïve occupancy ($\psi_{\text{naïve}}$)

Setup	No. cells	No. occasions	No. NAs	$\psi_{\text{naïve}}$	p
3 × 3 km^2 cells, 1-month occasion	96	24	600	0.63	0.03
3 × 3 km^2 cells, 3-month occasion	96	8	85	0.68	0.07
3 × 3 km^2 cells, 4-month occasion	96	6	45	0.55	0.12

Note: The bold text indicates the setup selected for our subsequent analysis based on the highest p and lowest number of NAs.
Abbreviations: NA, cells not patrolled.

TABLE 2 Occupancy models of poaching distribution ranked by Akaike information criterion corrected for small sample size (AIC_c) with detection probability (P) and site use (ψ) covariates representing prey availability (Prey avail), law enforcement (LE), and accessibility (Access) scenarios

	Model coefficient (SE)															
	ψ									p						
Variable	Intercept	CPUE	Rug	B/H	RS	Rug + BH	RS × patrol	Patrol	Year	Intercept	Effort	Vis	k	AIC_c	ΔAIC_c	AIC_c w (%)
Prey avail	4.47 (2.68)	14.12 (7.03)	...	...	...	...	...	...	...	−1.87 (0.24)	...	...	3	253.94	0.0	88.08
Access1	41.4 (49.7)	...	−67.8 (86.5)	17.8 (22.3)	...	−70.8 (89.3)	...	...	...	−2.42 (0.17)	...	...	5	260.07	6.13	4.10
Global	84.94 (73.90)	−6.48 (10.36)	1.61 (6.61)	−4.12 (5.23)	−2.50 (7.25)	...	...	−0.56 (0.48)	0.13 (5.61)	−2.94 (0.34)	0.0.3 (0.00)	−0.18 (0.19)	10	260.42	6.48	3.44
LE1	−1.47 (0.88)	...	...	...	...	...	...	0.06 (0.03)	...	−2.23 (0.22)	...	...	3	261.98	8.04	1.57
LE2	−1.50 (0.93)	...	...	...	−0.69 (0.58)	...	...	0.06 (0.03)	...	−2.23 (0.22)	...	...	4	262.30	8.36	1.34
LE3	−1.38 (1.02)	...	...	...	−1.59 (0.80)	...	0.03 (0.01)	0.05 (0.03)	...	−2.18 (0.25)	...	...	5	263.51	9.57	0.73
Null	0.32 (1.03)	...	...	...	...	...	...	...	...	−2.02 (0.51)	...	...	2	266.03	12.09	0.20
LE4	0.30 (1.05)	...	...	...	−0.55 (0.49)	...	...	...	...	−2.02 (0.49)	...	...	3	266.03	12.09	0.20
Access2	0.27 (0.96)	...	...	0.18 (0.32)	...	...	...	...	...	−2.00 (0.49)	...	...	3	267.67	13.74	0.09
Year	0.73 (1.72)	...	...	...	...	...	...	...	−0.27 (0.78)	−2.02 (0.51)	...	...	3	267.90	13.97	0.08
Access3	0.31 (1.02)	...	−0.09 (0.37)	...	...	...	...	...	...	−2.02 (0.51)	...	...	3	267.96	14.02	0.07
Access4	0.26 (0.95)	...	−0.05 (0.34)	0.17 (0.32)	...	...	...	...	...	−1.99 (0.49)	...	...	4	269.65	15.71	0.03

Abbreviations: B/H, border/highway: distance (km) from each cell to national park borders or highway; CPUE, cumulative catch per unit effort for four ungulate species during ranger patrols; Effort, number of ranger patrols in each cell and occasion; k, number of parameters; Patrol, number of ranger patrols in each cell; RS, ranger station: distance (km) from each cell to ranger stations; Rug, ruggedness: average ruggedness index in each cell; Vis, visibility: combined average ruggedness and share of forest cover in each cell; Year, year number.

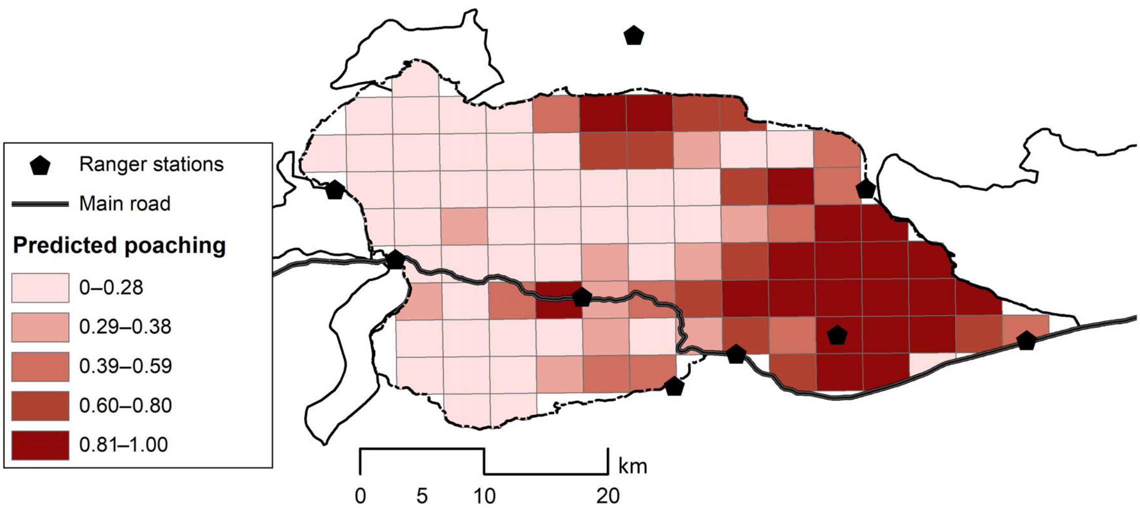

FIGURE 3 Distribution of predicted poaching pressure in Golestan National Park based on results of best model in occupancy framework

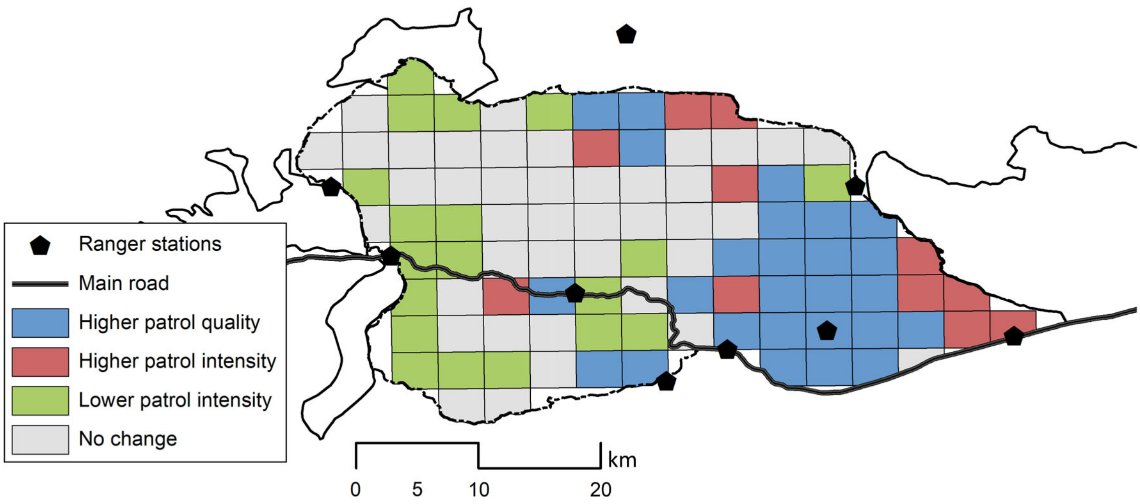

FIGURE 4 Suggested strategies for optimizing patrolling effort in Golestan National Park based on past patrolling intensity and our estimated poaching pressure

DISCUSSION

Poaching is a widespread conservation challenge in many protected areas worldwide (Schulze et al., 2018), and mapping poaching pressure is vital for identifying and implementing effective antipoaching measures. However, assessing poaching pressure is often hampered by the scarcity of appropriate data on poaching events, and as a result, which spatial factors determine poaching pressure remains poorly understood (Keane et al., 2011; Marescot et al., 2020). Here, we developed an approach to extracting and geolocating ranger patrols and poaching detections from analog logbooks across GNP in Iran. Using an occupancy modeling framework, we estimated the locations of poaching hotspots, which were chiefly determined by the availability of ungulate species. We also identified large areas of mismatch between patrolling effort and poaching pressure, which gives clear guidance on how to optimize future patrolling strategies by redirecting excess patrolling to underpatrolled areas. Our approach based on logbook data and occupancy modeling can be highly relevant for many protected areas where poaching is an imminent threat to wildlife and evidence-based allocation of antipoaching patrols is lacking.

Our study highlights the considerable, but largely untapped, resource that analog ranger logbooks represent to facilitate adaptive management (McCarthy & Possingham, 2007). Records of ranger patrols and observations are often compiled in logbooks, and when these records include information on locations and timing of both, these data can be used to investigate threat patterns and trends (Arias et al., 2016; Hötte et al., 2016; Keane et al., 2011). Our approach provides conservation practitioners without a georeferenced patrolling data set with a flexible and robust tool to draw inferences on the prevalence of poaching and other noncompliances. This approach can be a cost-effective alternative to the digitized recording of patrolling effort when resources for procuring devices and training of staff are unavailable. Despite the lack of exact coordinates, we were able to conduct our analysis at a scale (3×3 km^2) relevant for management and finer than some previous studies using GPS locations (Linkie et al., 2015; Marescot et al., 2020). To further facilitate the usefulness of analog logbook records, logbooks could include a map of the protected area with the location of patrol cells, the main landmarks, and patrol routes. This would allow rangers to directly mark their patrols and allocate their sightings to corresponding cells (Linkie et al., 2015), which would simplify later digitizing and georeferencing of records. An additional major advantage of our approach is that logbook data from the past can be utilized, expanding the time span of poaching assessments to provide information on conservation effectiveness over time. This could be valuable also for protected areas where analog logbooks are no longer used and digital recording of ranger patrols has become the standard.

Modeling of poaching pressure in an occupancy framework provided deep insights into the spatial determinants of poaching. We tested alternative models, all related to the flag hypothesis in environmental criminology, assuming that repeated noncompliances were concentrated in space and determined by site characteristics. We found that prey availability, approximated by ungulate biomass, was the main determinant of poaching pressure, in line with other studies (Barichievy et al., 2017; Critchlow et al., 2015; de Matos Dias et al., 2020). Several studies (Critchlow et al., 2015; Weekers et al., 2020) also showed the relevance of the boost hypothesis to spatial patterns of poaching pressure. These two hypotheses are not mutually exclusive but are rather intertwined and could be considered complementarily (Tseloni & Pease, 2003). Because our data were only from 2 years and contained a limited number of poaching detections, we were unable to directly test the boost hypothesis, which would be a beneficial extension of our work in future studies, once sufficient data have been collected.

Our predictive maps showed that poaching pressure was higher in the eastern half of the park. This trend was mainly determined by the abundance of urial in the montane steppes, a preferred prey species for poaching (Ghoddousi et al., 2019). Considering this finding, as well as poaching incentives in Golestan (Ghoddousi et al., 2019), we inferred that commercial incentives (e.g., supplying illegal meat markets) were of particular importance, because poachers seek to maximize their offtake in areas with higher prey biomass. Given these context-specific variations in poaching pressure, resulting from different incentives (e.g., subsistence vs. recreational), determinants (e.g., prey availability vs. terrain), and modalities (e.g., snaring vs. shooting), we discourage the use of large-scale approximations through indices such as accessibility (Benitez-Lopez et al., 2017) for devising conservation actions.

The low detection probability of poaching ($p = 0.12$) in our study highlights that despite the prevalence of poaching (Ghoddousi et al., 2019) and regular patrols, poachers frequently go undetected. A similarly low rate of poaching detection probability over 10 years was found in an African protected area (Moore et al., 2018). Generally, this highlights the need to improve the detection of poachers during patrols, which is easier said than done. We were unable to identify survey covariates affecting the detection probability, which could help identify avenues for improved detection. Given the importance of understanding factors influencing poaching detection for optimizing patrolling strategies, future studies should focus on testing a wider set of detection covariates. For example, the influence of the number of rangers per patrol or local informants' tip-offs on poacher detection could be considered in the future (Linkie et al., 2015; Moore et al., 2018). Until it becomes clearer what determines detection probability, directing patrols to areas under high poaching pressure, as highlighted by our approach, should be a priority.

Although a growing body of literature suggests that targeted patrolling effort is linked to improved compliance and species responses (Hilborn et al., 2006; Linkie et al., 2015; Moore et al., 2018), robust allocation of patrol distribution and intensity is not easy (Dhanjal-Adams et al., 2016; Keane et al., 2008). Our results provide ample opportunities for guiding antipoaching measures and, more generally, for adaptive management through periodic assessment of where poaching is most likely to occur in landscapes, thus feeding into an updated planning of future law enforcement allocations. We estimated that in around 58% of the park, restructuring of patrolling efforts would be beneficial in terms of reducing the poaching pressure using three complementary strategies. Specifically, we determined that excess patrolling effort in areas under low poaching pressure (20% of the park) could be redirected to underpatrolled areas (12% of the park). Such adaptations in resource allocation based on levels of illegal activity and patrolling effort are known to improve law enforcement efficiency (Critchlow et al., 2017) and represent cost-effective ways to reduce poaching pressure without requiring additional resources, which should be part of an adaptive management framework.

While redirecting patrolling effort could address law enforcement deficiency in some areas, in around 39% of Golestan high poaching pressure persisted despite a high patrolling effort. Given the current level of resources available for law enforcement, a further increase of patrolling effort in these areas might not be feasible. Yet, the quality of patrols could be improved (Critchlow et al., 2017; Milner-Gulland & Leader-Williams, 1992; Plumptre et al., 2014). Previous studies (Barichievy et al., 2017; Haines et al., 2012) showed that poachers might be more active during evening hours, benefitting from temporal patrolling gaps, which matches our observations from GNP. An increase in evening patrols in the identified hotspots is thus strongly recommended (Hötte et al., 2016). Moreover, higher patrolling intensity close to and on public holidays, as well as further expanding the local informant network, could increase poaching detection (Linkie et al., 2015; Risdianto et al., 2016; Weekers et al., 2020).

Our analyses provide an evidence-based approach to the adaptive allocation of future antipoaching patrols (Hötte et al., 2016; Keane et al., 2011). However, improved law enforcement is not the only avenue for poaching pressure mitigation (Holden et al., 2019). Given the evidence that poaching in Golestan is driven by commercial interests, promoting alternative livelihoods for poachers should be a priority conservation action (Ghoddousi et al., 2019). As in other experiences (Cooney et al., 2017; Travers et al., 2019), employment of ex-poachers in nature-based tourism, research, and conservation professions has been successfully implemented in Golestan (Ghoddousi et al., 2016), which should be expanded. To make this measure effective, these initiatives should ensure that the benefits from these alternative livelihoods are directed toward those people who are impacted by and highly dependent on the national park (Ghoddousi et al., 2018; Harrison et al., 2015). In this study, we focused on the probability of detection of poachers by rangers and, thus, factors that are under the control of protected area managers and conservation practitioners. There are other important considerations within the enforcement chain, such as the probability of prosecution after a crime has been detected, conviction, and punishment (Arias et al., 2016). However, these factors depend on legal and socioeconomic settings beyond the protected areas. Therefore, we did not consider these factors in our analyses but acknowledge their importance.

We acknowledge limitations in our analyses, which could be addressed by future studies once more long-term monitoring data become available. Specifically, using a multispecies occupancy approach (Marescot et al., 2020) would have allowed for the use of poacher and prey detections in the same model, which in turn could have helped to further unravel poacher–prey spatial dynamics. However, in our case, the highly unbalanced number of detections between poaching events (very low) and prey occurrences (very high) did not allow for such a multispecies occupancy model (Guillera-Arroita et al., 2019). Moreover, we acknowledge that the relatively short time period over which patrol data were available prevented us from employing a multiseason occupancy approach. While we believe that the inferences based on our data set are valid and useful for optimizing patrol effort, we encourage conservation practitioners to use multiseason, multispecies occupancy modeling wherever their data allow for doing so.

Because the coverage of protected areas is increasing, it is key that managers efficiently allocate limited resources. Our study provides a practical approach to doing so, using the potentially huge but so far largely untapped resource of analog ranger patrol data in logbooks in an occupancy framework. Adapting our approach should therefore be possible in many protected areas around the globe and would make it possible to (i) account for the often low and imperfect detection of poaching; (ii) assess and understand the spatial patterns of poaching pressure; (iii) reconstruct poaching pressure and hotspots back in time and, thus, establish baselines against which to evaluate effectiveness; and (iv) optimize patrolling effort and strategies. More generally, our findings highlight that one-size-fits-all recommendations for law enforcement (e.g., optimum ranger number per area) fail to account for variation in illegal activities among and within protected areas and should be replaced by evidence-based and adaptive law enforcement allocation strategies.

AUTHOR CONTRIBUTIONS

Arash Ghoddousi and Corinna Van Cayzeele conceived the idea and contributed equally to the investigation. Corinna Van Cayzeele, Pegah Negahdar, Mahmood Soofi, and Amirhossein Kh. Hamidi collected and processed the raw data. Arash Ghoddousi, Corinna Van Cayzeele, Mahmood Soofi, Benjamin Bleyhl, Guillermo Fandos, and Igor Khorozyan carried out the data analysis. Arash Ghoddousi, Matthias Waltert, and Tobias Kuemmerle led the writing. All coauthors critically contributed to interpretation and manuscript drafts.

ACKNOWLEDGMENTS

We thank the staff and all rangers of GNP who contributed to this study. This project was carried out with the approval of the Golestan provincial office of the Department of Environment. We are grateful to Associate Editor Adam Ford and two anonymous reviewers for constructive and encouraging comments. Arash Ghoddousi appreciates the financial support of the German Research Foundation (DFG) (PArCS Project 409732304). Benjamin Bleyhl gratefully acknowledges funding from the German Federal Ministry of Education and Science (BMBF, project SoMo, 01DK21003).

CONFLICT OF INTEREST

The authors declare no conflict of interests.

DATA AVAILABILITY STATEMENT

R code (Ghoddousi, 2022) available from Figshare: https://doi.org/10.6084/m9.figshare.17714903.v1. Poaching data supporting this research are sensitive and not available publicly; they are available to qualified researchers from the Golestan provincial office of the Department of Environment, Naharkhoran Boulevard, Gorgan, Iran 49171-45185, with relevant permits and agreements.

ORCID

Arash Ghoddousi https://orcid.org/0000-0001-9605-3091
Mahmood Soofi https://orcid.org/0000-0002-6167-2527
Benjamin Bleyhl https://orcid.org/0000-0002-4858-950X
Guillermo Fandos https://orcid.org/0000-0003-1579-9444
Igor Khorozyan https://orcid.org/0000-0002-0657-7500
Matthias Waltert https://orcid.org/0000-0001-7053-0291
Tobias Kuemmerle https://orcid.org/0000-0002-9775-142X

REFERENCES

Arias, A., R. L. Pressey, R. E. Jones, J. G. Álvarez-Romero, and J. E. Cinner. 2016. "Optimizing Enforcement and Compliance in

Offshore Marine Protected Areas: A Case Study from Cocos Island, Costa Rica." *Oryx* 50(1): 18–26. https://doi.org/10.1017/S0030605314000337.

Barichievy, C., L. Munro, G. Clinning, B. Whittington-Jones, and G. Masterson. 2017. "Do Armed Field-Rangers Deter Rhino Poachers? An Empirical Analysis." *Biological Conservation* 209: 554–60. https://doi.org/10.1016/j.biocon.2017.03.017.

Benitez-Lopez, A., R. Alkemade, A. M. Schipper, D. J. Ingram, P. A. Verweij, J. A. J. Eikelboom, and M. A. J. Huijbregts. 2017. "The Impact of Hunting on Tropical Mammal and Bird Populations." *Science* 356: 180–3.

Braga, A. A., A. V. Papachristos, and D. M. Hureau. 2014. "The Effects of Hot Spots Policing on Crime: An Updated Systematic Review and Meta-Analysis." *Justice Quarterly* 31(4): 633–63. https://doi.org/10.1080/07418825.2012.673632.

Burnham, K. P., and D. R. Anderson. 2002. *Model Selection and Multimodel Inference*, 2nd ed. New York, NY: Springer.

Challender, D. W. S., and D. C. MacMillan. 2014. "Poaching is More Than an Enforcement Problem." *Conservation Letters* 7(5): 484–94. https://doi.org/10.1111/conl.12082.

Cooney, R., D. Roe, H. Dublin, J. Phelps, D. Wilkie, A. Keane, H. Travers, et al. 2017. "From Poachers to Protectors: Engaging Local Communities in Solutions to Illegal Wildlife Trade." *Conservation Letters* 10(3): 367–74. https://doi.org/10.1111/conl.12294.

Critchlow, R., A. J. Plumptre, M. Driciru, A. Rwetsiba, E. J. Stokes, C. Tumwesigye, F. Wanyama, and C. M. Beale. 2015. "Spatiotemporal Trends of Illegal Activities from Ranger-Collected Data in a Ugandan National Park." *Conservation Biology* 29(5): 1458–70. https://doi.org/10.1111/cobi.12538.

Critchlow, R., A. J. Plumptre, B. Alidria, M. Nsubuga, M. Driciru, A. Rwetsiba, F. Wanyama, and C. M. Beale. 2017. "Improving Law-Enforcement Effectiveness and Efficiency in Protected Areas Using Ranger-Collected Monitoring Data." *Conservation Letters* 10(5): 572–80. https://doi.org/10.1111/conl.12288.

de Matos Dias, D., Á. C. Ferreguetti, and F. H. G. Rodrigues. 2020. "Using an Occupancy Approach to Identify Poaching Hotspots in Protected Areas in a Seasonally Dry Tropical Forest." *Biological Conservation* 251: 108796. https://doi.org/10.1016/j.biocon.2020.108796.

Dhanjal-Adams, K. L., K. Mustin, H. P. Possingham, R. A. Fuller, and A. Mori. 2016. "Optimizing Disturbance Management for Wildlife Protection: The Enforcement Allocation Problem." *Journal of Applied Ecology* 53(4): 1215–24. https://doi.org/10.1111/1365-2664.12606.

Estes, J. A., J. Terborgh, J. S. Brashares, M. E. Power, J. Berger, W. J. Bond, S. R. Carpenter, et al. 2011. "Trophic Downgrading of Planet Earth." *Science* 333(6040): 301–6. https://doi.org/10.1126/science.1205106.

Faulkner, S. C., M. C. A. Stevens, S. S. Romañach, P. A. Lindsey, and S. C. Le Comber. 2018. "A Spatial Approach to Combatting Wildlife Crime." *Conservation Biology* 32(3): 685–93. https://doi.org/10.1111/cobi.13027.

Fiske, I. J., and R. B. Chandler. 2011. "Unmarked: An R Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance." *Journal of Statistical Software* 43(10): 1–23.

Ghoddousi, A. 2022. "R codes.docx." Figshare. https://doi.org/10.6084/m9.figshare.17714903.v1.

Ghoddousi, A., A. K. Hamidi, M. Soofi, I. Khorozyan, B. H. Kiabi, and M. Waltert. 2016. "Effects of Ranger Stations on Predator and Prey Distribution and Abundance in an Iranian Steppe Landscape." *Animal Conservation* 19(3): 273–80. https://doi.org/10.1111/acv.12240.

Ghoddousi, A., B. Bleyhl, C. Sichau, D. Ashayeri, P. Moghadas, P. Sepahvand, A. K. Hamidi, M. Soofi, and T. Kuemmerle. 2020. "Mapping Connectivity and Conflict Risk to Identify Safe Corridors for the Persian Leopard." *Landscape Ecology* 35(8): 1809–25. https://doi.org/10.1007/s10980-020-01062-0.

Ghoddousi, A., M. Soofi, A. K. Hamidi, S. Ashayeri, L. Egli, S. Ghoddousi, J. Speicher, I. Khorozyan, B. H. Kiabi, and M. Waltert. 2019. "The Decline of Ungulate Populations in Iranian Protected Areas Calls for Urgent Action Against Poaching." *Oryx* 53(1): 151–8. https://doi.org/10.1017/s003060531600154x.

Ghoddousi, A., M. Soofi, A. K. Hamidi, T. Lumetsberger, L. Egli, S. Ashayeri, I. Khorozyan, B. H. Kiabi, and M. Waltert. 2017. "When Pork is Not on the Menu: Assessing Trophic Competition Between Large Carnivores and Poachers." *Biological Conservation* 209: 223–9. https://doi.org/10.1016/j.biocon.2017.02.032.

Ghoddousi, S., P. Pintassilgo, J. Mendes, A. Ghoddousi, and B. Sequeira. 2018. "Tourism and Nature Conservation: A Case Study in Golestan National Park, Iran." *Tourism Management Perspectives* 26: 20–7. https://doi.org/10.1016/j.tmp.2017.12.006.

Guillera-Arroita, G., M. Kéry, and J. J. Lahoz-Monfort. 2019. "Inferring Species Richness Using Multispecies Occupancy Modeling: Estimation Performance and Interpretation." *Ecology and Evolution* 9(2): 780–92. https://doi.org/10.1002/ece3.4821.

Haines, A. M., D. Elledge, L. K. Wilsing, M. Grabe, M. D. Barske, N. Burke, and S. L. Webb. 2012. "Spatially Explicit Analysis of Poaching Activity as a Conservation Management Tool." *Wildlife Society Bulletin* 36(4): 685–92. https://doi.org/10.1002/wsb.194.

Harrison, M., J. Baker, M. Twinamatsiko, and E. J. Milner-Gulland. 2015. "Profiling Unauthorized Natural Resource Users for Better Targeting of Conservation Interventions." *Conservation Biology* 29(6): 1636–46. https://doi.org/10.1111/cobi.12575.

Hilborn, R., P. Arcese, M. Borner, J. Hando, G. Hopcraft, M. Loibooki, S. Mduma, and A. R. E. Sinclair. 2006. "Effective Enforcement in a Conservation Area." *Science* 314(5803): 1266–6. https://doi.org/10.1126/science.1132780.

Holden, M. H., D. Biggs, H. Brink, P. Bal, J. Rhodes, and E. McDonald-Madden. 2019. "Increase Anti-Poaching Law-Enforcement or Reduce Demand for Wildlife Products? A Framework to Guide Strategic Conservation Investments." *Conservation Letters* 12(3): e12618. https://doi.org/10.1111/conl.12618.

Hötte, M. H., I. A. Kolodin, S. L. Bereznuk, J. C. Slaght, L. L. Kerley, S. V. Soutyrina, G. P. Salkina, O. Y. Zaumyslova, E. J. Stokes, and D. G. Miquelle. 2016. "Indicators of Success for Smart Law Enforcement in Protected Areas: A Case Study for Russian Amur Tiger (*Panthera tigris altaica*) Reserves." *Integrative Zoology* 11(1): 2–15. https://doi.org/10.1111/1749-4877.12168.

Jenks, K. E., J. G. Howard, and P. Leimgruber. 2012. "Do Ranger Stations Deter Poaching Activity in National Parks in Thailand?" *Biotropica* 44(6): 826–33.

Keane, A., J. P. G. Jones, G. Edwards-Jones, and E. J. Milner-Gulland. 2008. "The Sleeping Policeman: Understanding

Issues of Enforcement and Compliance in Conservation." *Animal Conservation* 11(2): 75–82. https://doi.org/10.1111/j.1469-1795.2008.00170.x.

Keane, A., J. P. G. Jones, and E. J. Milner-Gulland. 2011. "Encounter Data in Resource Management and Ecology: Pitfalls and Possibilities." *Journal of Applied Ecology* 48(5): 1164–73. https://doi.org/10.1111/j.1365-2664.2011.02034.x.

Linkie, M., D. J. Martyr, A. Harihar, D. Risdianto, R. T. Nugraha, N. Leader-Williams, W.-M. Wong, and M. Hayward. 2015. "Safeguarding Sumatran Tigers: Evaluating Effectiveness of Law Enforcement Patrols and Local Informant Networks." *Journal of Applied Ecology* 52(4): 851–60. https://doi.org/10.1111/1365-2664.12461.

Lumetsberger, T., A. Ghoddousi, A. Appel, I. Khorozyan, M. Waltert, and C. Kiffner. 2017. "Re-Evaluating Models for Estimating Prey Consumption by Leopards." *Journal of Zoology* 302(3): 201–10. https://doi.org/10.1111/jzo.12449.

MacKenzie, D. I., and L. L. Bailey. 2004. "Assessing the Fit of Site-Occupancy Models." *Journal of Agricultural, Biological, and Environmental Statistics* 9(3): 300–18. https://doi.org/10.1198/108571104x3361.

MacKenzie, D. I., J. D. Nichols, J. A. Royle, K. Pollock, L. L. Bailey, and J. E. Hines. 2017. *Occupancy Estimation and Modeling 2nd Edition; Inferring Patterns and Dynamics of Species Occurrence*. Academic Press.

Mackenzie, D. I., and J. A. Royle. 2005. "Designing Occupancy Studies: General Advice and Allocating Survey Effort." *Journal of Applied Ecology* 42(6): 1105–14. https://doi.org/10.1111/j.1365-2664.2005.01098.x.

Marescot, L., A. Lyet, R. Singh, N. Carter, and O. Gimenez. 2020. "Inferring Wildlife Poaching in Southeast Asia with Multi-species Dynamic Occupancy Models." *Ecography* 43(2): 239–50. https://doi.org/10.1111/ecog.04536.

McCarthy, M. A., and H. P. Possingham. 2007. "Active Adaptive Management for Conservation." *Conservation Biology* 21(4): 956–63. https://doi.org/10.1111/j.1523-1739.2007.00677.x.

Milner-Gulland, E. J., and N. Leader-Williams. 1992. "A Model of Incentives for the Illegal Exploitation of Black Rhinos and Elephants: Poaching Pays in Luangwa Valley, Zambia." *Journal of Applied Ecology* 29(2): 388–401. https://doi.org/10.2307/2404508.

Montgomery, R. A. 2020. "Poaching is Not One Big Thing." *Trends in Ecology & Evolution* 35(6): 472–5. https://doi.org/10.1016/j.tree.2020.02.013.

Moore, J. F., F. Mulindahabi, M. K. Masozera, J. D. Nichols, J. E. Hines, E. Turikunkiko, M. K. Oli, and M. Hayward. 2018. "Are Ranger Patrols Effective in Reducing Poaching-Related Threats Within Protected Areas?" *Journal of Applied Ecology* 55(1): 99–107. https://doi.org/10.1111/1365-2664.12965.

Pease, K. 1998. *Repeat Victimisation: Taking Stock*. Vol. Paper No. 90. *Crime Detections and Prevention Series*. London: Home Office.

Plumptre, A. J., R. A. Fuller, A. Rwetsiba, F. Wanyama, D. Kujirakwinja, M. Driciru, G. Nangendo, J. E. M. Watson, H. P. Possingham, and E. J. Milner-Gulland. 2014. "Efficiently Targeting Resources to Deter Illegal Activities in Protected Areas." *Journal of Applied Ecology* 51(3): 714–25. https://doi.org/10.1111/1365-2664.12227.

Risdianto, D., D. J. Martyr, R. T. Nugraha, A. Harihar, H. T. Wibisono, I. A. Haidir, D. W. Macdonald, N. D'Cruze, and M. Linkie. 2016. "Examining the Shifting Patterns of Poaching from a Long-Term Law Enforcement Intervention in Sumatra." *Biological Conservation* 204: 306–12. https://doi.org/10.1016/j.biocon.2016.10.029.

Royle, J. A., and M. Kéry. 2007. "A Bayesian State-Spece Formulation of Dynamic Occupancy Models." *Ecology* 88(7): 1813–23. https://doi.org/10.1890/06-0669.1.

Schulze, K., K. Knights, L. Coad, J. Geldmann, F. Leverington, A. Eassom, M. Marr, S. H. M. Butchart, M. Hockings, and N. D. Burgess. 2018. "An Assessment of Threats to Terrestrial Protected Areas." *Conservation Letters* 11: e12435. https://doi.org/10.1111/conl.12435.

Travers, H., L. J. Archer, G. Mwedde, D. Roe, J. Baker, A. J. Plumptre, A. Rwetsiba, and E. J. Milner-Gulland. 2019. "Understanding Complex Drivers of Wildlife Crime to Design Effective Conservation Interventions." *Conservation Biology* 33(6): 1296–306. https://doi.org/10.1111/cobi.13330.

Tseloni, A., and K. Pease. 2003. "Repeat Personal Victimization. 'Boosts' or 'Flags'?" *The British Journal of Criminology* 43(1): 196–212. https://doi.org/10.1093/bjc/43.1.196.

Weekers, D., L. Mazerolle, and R. Zahnow. 2020. "Space-Time Patterns of Poaching Risk: Using the Near-Repeat Hypothesis to Inform Compliance Enforcement in Marine Protected Areas." *Biological Conservation* 248: 108652. https://doi.org/10.1016/j.biocon.2020.108652.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Ghoddousi, Arash, Corinna Van Cayzeele, Pegah Negahdar, Mahmood Soofi, Amirhossein Kh. Hamidi, Benjamin Bleyhl, Guillermo Fandos, Igor Khorozyan, Matthias Waltert, and Tobias Kuemmerle. 2022. "Understanding Spatial Patterns of Poaching Pressure Using Ranger Logbook Data to Optimize Future Patrolling Strategies." *Ecological Applications* 32(5): e2601. https://doi.org/10.1002/eap.2601