




Evidence of deterrence from patrol data: Trialling application of a differenced-CPUE metric

Anthony Dancer¹  | Aidan Keane²  | Colin M. Beale³ |
 Andrew D. M. Dobson² | Rajan Amin¹ | Robin Freeman⁴ | Inaoyom Imong⁵ |
 Kate Jones⁶ | Matthew Linkie⁷ | Barney Long⁸ | Francis O. Okeke⁵ |
 Andrew J. Plumptre⁹  | J. Marcus Rowcliffe⁴ | Emma J. Stokes⁷ |
 Elsabé van der Westhuizen¹⁰ | Ben Collen^{6†}

¹Zoological Society of London, London, UK

²School of Geosciences, University of Edinburgh, Edinburgh, UK

³Department of Biology, University of York, York, UK

⁴Institute of Zoology, Zoological Society of London, London, UK

⁵Wildlife Conservation Society, Nigeria-Program, Calabar, Nigeria

⁶Centre for Biodiversity and Environment Research, University College London, London, UK

⁷Wildlife Conservation Society, Global Conservation, New York, New York, USA

⁸Global Wildlife Conservation, Austin, Texas, USA

⁹Key Biodiversity Areas Secretariat, BirdLife International, Cambridge, UK

¹⁰Frankfurt Zoological Society, Chiredzi, Zimbabwe

Correspondence

Anthony Dancer, Zoological Society of London, London NW1 4RY, UK.
 Email: anthony.dancer@zsl.org

Funding information

Natural Environment Research Council, Grant/Award Number: NE/L002485/1; Wildlife Conservation Society; US Fish and Wildlife Service; MacArthur Foundation; Research England

Abstract

Ranger-led law enforcement patrols are the primary, site-level response to – and the most common source of data on – illegal activity threatening wildlife in protected areas. Yet evidence that patrols effectively deter rule-breaking is limited, and common management metrics for evaluating deterrence, which use ranger-collected data, are particularly vulnerable to bias. “Differenced plots” (of the association between change in patrol effort and subsequent change in illegal activity) were recently proposed as a simple, new metric for deterrence, which, in tests with simulated patrol data, were more robust than the common alternatives. Here, we trial application of differenced plots to real patrol data collected in four protected areas, and explore methods for applying the metric in practice, using two indicators of rule-breaking: snares, and people. We find evidence which is consistent with deterrence in some but not all sites, over shorter timescales than observed hitherto: increases in patrol effort were associated with subsequent reductions in snaring in one site, and in the presence of people in two sites. However, whether pressure on wildlife had been reduced or merely displaced was unclear from differenced plots, nor could the metric confirm absence of deterrence, raising questions for future applications. Our findings suggest differenced plots can be a useful metric, particularly for exploring variation in deterrence within sites, but should be applied and interpreted with care, and further work is urgently needed to determine whether and how patrols deter illegal activity, and to evaluate the effect reliably.

KEYWORDS

illegal activity, law enforcement, poaching, protected areas, rangers, snaring

† Deceased.

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2022 The Authors. *Conservation Science and Practice* published by Wiley Periodicals LLC on behalf of Society for Conservation Biology.

1 | INTRODUCTION

Illegal activity threatens wildlife in protected areas around the world (Schulze et al., 2018). Poaching, for example, is driving declines in ostensibly protected bird and mammal populations throughout the tropics (Benítez-López et al., 2017; Tranquilli et al., 2014). The primary means by which protected area managers in the global south respond to this threat is through investment in ranger-led law enforcement patrols (Henson et al., 2016), which, across sites, are associated with positive conservation outcomes (Bruner et al., 2001; Tranquilli et al., 2012). Conversely, wildlife is most threatened by illegal activity where local enforcement is under-funded (e.g. African elephants; CITES, 2010). However, within sites, whether and how ranger patrols reduce rule-breaking is poorly understood, hampering efforts to improve enforcement effectiveness.

Ranger patrols are assumed to reduce illegal activity in protected areas via two mechanisms: detection and deterrence. Detection involves discovery of illegal activity that has already occurred, via direct observation (e.g. individuals engaged in rule-breaking) or indirect signs (e.g. poaching camps, or passive hunting devices, such as snares), and detection may lead to sanctioning or incapacitation of rule breakers (e.g. by arresting and fining perpetrators), or other enforcement actions (e.g. removal of snares, or camp destruction). Deterrence involves discouraging potential rule-breakers from committing future offenses through fear of apprehension and punishment, and encompasses both the effects on individuals reoffending following punishment, known as specific deterrence, and the effects on illegal actors in general, known as general deterrence (Nagin, 2013; Pratt & Cullen, 2005). In practice, detection rates of illegal activity in protected areas are generally low (e.g. of snares; O'Kelly et al., 2018), so deterrence is the principal mechanism through which patrols are thought to act to reduce illegal activity. Yet evidence for deterrence operating in protected areas is limited, with few empirical studies demonstrating the effect rigorously (e.g. Moore et al., 2018).

Identifying the deterrent effect of patrolling on crime is difficult, even in non-conservation contexts with ample data where crime is regularly reported, and where offenders' interpretations of the risks of punishment are commonly studied (Paternoster, 2010). In protected areas, where crime is rarely reported and offenders' perspectives are poorly understood, the issue is acute. Most available data on illegal activity in protected areas are collected opportunistically by rangers themselves during enforcement patrols (Critchlow et al., 2015). Opportunistic or unstructured observation data in general, such as those

from voluntary biological surveys, are subject to numerous biases and sources of error arising from uneven sampling effort and detectability (Dobson et al., 2020; Isaac et al., 2014). Patrol data are particularly vulnerable to bias (Keane et al., 2011), because rangers' primary focus is enforcement not monitoring (Gray & Kalpers, 2005). Consequently, survey effort is typically directed towards times and locations where patrols expect to find illegal activity (Hötte et al., 2016). Patrol effort is also often low, and skewed towards accessible locations (e.g. around patrol posts; Plumptre et al., 2014). Moreover, the identity of perpetrators is rarely known, so distinguishing between general deterrence and recidivism is generally unfeasible.

Compounding issues of scarce and biased data, common metrics of deterrence designed for application to ranger-collected illegal activity data can be difficult to interpret or misleading (Keane et al., 2011). To account for variation in survey effort, patrol managers often use simple Catch Per Unit Effort (CPUE) indices of the number of illegal activities detected per unit effort (e.g. snares encountered per patrol day; Stokes, 2010), and evaluate enforcement effectiveness by assessing whether CPUE illegal activity declines linearly over time in the presence of increased patrolling, or vice versa. This method is straightforward to apply and only uses patrol data, which is critical for uptake by managers who may lack the capacity to implement more sophisticated methods, but can be misleading, as CPUE measures can change over time for reasons unrelated to levels of patrolling (e.g. changing wildlife abundance [Holmern et al., 2007], or illegal activity detectability [Henson et al., 2016]). Recognizing this shortcoming, some authors argue for use of a different metric, plots of CPUE over patrol effort, wherein a negative correlation ostensibly indicates deterrence (Hilborn et al., 2006). However, CPUE-effort plots can also misdiagnose deterrence if both CPUE and effort show similar linear trends over time, and fail to account for temporal autocorrelation in time series data (Dobson et al., 2019).

“Differenced plots”, of change between consecutive observations of CPUE illegal activity over change between consecutive observations of patrol effort in the preceding timestep, have recently been proposed as an alternative metric to diagnose whether patrols deter illegal activity using ranger-collected data (Dobson et al., 2019). These plots use differencing – computing differences between consecutive observations – to render them robust to confounding temporal effects and autocorrelation, without the need for sophisticated statistics (Dobson et al., 2019). A negative correlation between change in patrol effort and change in CPUE in the subsequent timestep, indicating that increases in patrolling are

associated with subsequent declines in rates of illegal activity, would suggest that deterrence is operating (Dobson et al., 2019). When applied to synthetic patrol data derived from simple, mechanistic models of poacher-patrol interactions with and without deterrence, differenced plots reliably identified deterrence, regardless of any changes in levels of poaching unrelated to patrolling (Dobson et al., 2019).

Differenced plots, although promising, have only been applied to synthetic data, and there are remaining questions for application of the approach in practice. Generating differenced plots using real patrol data necessitates multiple data processing decisions, including choice of a suitable: a) time lag between patrol effort and illegal activity (e.g. one or more timesteps); b) indicator of illegal activity (e.g. counts of observations of snares, gun cartridges, etc.); c) patrol effort measure (e.g. distance patrolled, spatial coverage, etc.); d) monitoring period (since recording began, or a temporal subset); e) study area (whole park, or spatial subset); f) level of spatial data aggregation (e.g. by square km, or whole area); and g) level of temporal data aggregation (e.g. by month, year, etc.) (Dobson et al., 2019). However, at present, appropriate choices for some of these aspects are unclear. For example, there is limited understanding of the spatiotemporal scales over which deterrence should be expected to operate, and thus over what intervals data should be aggregated. Deterrence – and its detectability – may also vary with context, according to site-level characteristics such as habitat type, and between illegal activity types (Dobson et al., 2019). Deterrence of persistent activity types, which remain detectable in the landscape for extended durations, may be particularly difficult to diagnose (Dobson et al., 2019).

There is an urgent need to evaluate whether, how, and in what contexts patrols can be an effective means to reduce illegal activity, and to develop practical tools for assessing effectiveness which are accessible to patrol managers. If differenced plots are to become such a tool, the effects of different analytical decisions on the performance of this metric need to be explored using real datasets collected across a variety of contexts. Historically, aggregating patrol data from multiple protected areas was difficult as sites used inconsistent protocols and tools. Recent, broad-scale deployment of systems for standardized patrol monitoring, such as SMART (Cronin et al., 2021), provide a unique opportunity to apply differenced plots across contexts.

Here, to inform development of evaluative tools, and to improve the evidence base for use of patrols, we trialled application of differenced plots to real patrol data, and explored methods for applying the metric in practice. We assembled SMART patrol data from four diverse

protected areas in which wildlife is threatened by illegal activity, and used differenced plots to test whether we find evidence of deterrence, using two different indicators of illegal activity with contrasting landscape persistence. We also explored the consequences of data processing decisions, including the effects of a small set of plausible time intervals on the strength of the association between patrol effort and illegal activity, and two alternative methods for aggregating observations of illegal activity.

2 | METHODS

2.1 | Site selection and patrol data

We selected four, terrestrial parks situated in four countries across tropical Africa and Southeast Asia in which: (1) illegal activity had been identified as a major threat to wildlife; (2) rangers on patrol recorded their routes and observations of illegal activity using SMART; and (3) records of illegal activity occurred throughout the monitoring period, the timing and duration of which varied by site (Table 1). We chose sites with relatively high levels of patrol effort (Table 1), in which deterrence might be more likely to operate, and be more detectable. We also selected sites representing a range of habitat densities, which, in theory, could be important for identifying deterrence, although we did not have strong a priori hypotheses about the direction of these effects (e.g. open grassland habitats could enhance deterrence by increasing the visibility of rangers, or providing fewer refuges for rule-breakers, while dense forest habitats could also enhance deterrence by channeling rule-breakers through predictable trails). Consequently, we stratified our sample across two forest-dominated sites and two grassland-dominated sites.

All sites were government-managed, and were designated as either Wildlife Sanctuaries (sites 1 & 2) or National Parks (sites 3 & 4), with government rangers responsible for conducting patrols and gathering data, but the sites varied in other respects (e.g. ranger density; Table 1). To encourage participation, the sites' identities were anonymised by removing identifying features (e.g. name, location, and area) and assigning arbitrary number IDs.

We assembled patrol data from the four study sites. SMART-enabled rangers used handheld GPS units to record the time and location at the beginning and end of patrols, when they observed signs of illegal activity or wildlife, and at regular intervals in-between. All data were collected between June 2013 and October 2017. The combined dataset consisted of 200,035 position records from 7082 ground-based ranger patrols.

TABLE 1 Monitoring period, average patrol coverage (measured as percentage of unique 1 km cells visited by patrols per timestep), and ranger density for the four study sites

Site ID	Monitoring period			Spatial patrol coverage (% per timestep)						Ranger density (/100 km ²)
	Start month	End month	Duration (years)	14-day		28-day		42-day		
				Mean	SD	Mean	SD	Mean	SD	
<i>Forest-dominated</i>										
1	Jul-15	Jun-17	1.86	16.4	7.9	28.2	7.6	36.4	8.9	17.0
2	Oct-13	Dec-15	2.23	20.2	5.4	30.5	5.7	37.6	5.9	1.7
<i>Grassland-dominated</i>										
3	Jun-13	Oct-17	4.38	19.7	12	30.5	16	37.7	18	2.4
4	May-15	Mar-17	1.91	10.1	3.6	17.1	5.1	22.2	6.4	1.6

2.2 | Analysis

To assess whether presence of patrols deterred illegal activity we used patrol data to generate differenced plots for each study site and inspected the plots for signals of deterrence.

First, we calculated differenced patrol effort (i.e., change between consecutive observations of patrol effort), as given by Equation (1), where E_t is the patrol effort (e.g. proportion of protected area covered by patrols) at time t :

$$E_t - E_{t-1} \quad (1)$$

Second, we calculated differenced CPUE illegal activity (i.e., change between consecutive observations of an index of illegal activity) in the subsequent timestep, as given by Equation (2), where D_t is the number of illegal activities detected by patrols (e.g. number of snares encountered) and D_t / E_t is the number of illegal activities detected per unit of patrol effort (i.e., CPUE) at time t :

$$(D_{t+1}/E_{t+1}) - (D_t/E_t) \quad (2)$$

Finally, we plotted differenced CPUE over differenced patrol effort. We fitted linear regression models to the data to assess the significance of the relationship and to obtain a measure of model fit (r^2), and plotted regression lines with 95% confidence intervals. In the presence of deterrence, we expected differenced plots to display a significant negative correlation, with higher r^2 -values indicating a clearer relationship (Dobson et al., 2019). All data were processed and analyzed within the R software environment (R Core Team, 2020).

We trialled methods for generating differenced plots from real data, as follows:

2.2.1 | Time lag

We assumed a time lag between cause and effect corresponding to one timestep. That is, we assumed the rate of appearance of illegal activities changed in response to change in patrol effort over the preceding timestep. In theory, rulebreakers may make decisions based upon information on patrol presence from the preceding timestep, or from across multiple prior timesteps. In the absence of evidence for what lag to specify, we assumed the simplest model – one timestep – in line with previous deterrence studies.

2.2.2 | Indicators of illegal activity

We used two indicators: observations of (1) snares, and (2) people. We selected two indicators, as different activity types persist in the landscape for varying durations and thus differ in terms of their detectability by rangers (e.g. a poached carcass may persist for days or weeks, while a gunshot is only detectable for a few seconds after the event). Differenced plots for more persistent types can display weaker negative relationships, as changes in patrol effort can have impacts beyond the consecutive time-step (Dobson et al., 2019). Different activity types may also be influenced by distinct deterrence processes (e.g. operate over differing spatiotemporal scales). Aggregating across types may thus render differenced plots difficult to interpret (Dobson et al., 2019). Consequently, to inform evaluation of differenced plots, we selected two indicators, at either extreme of the persistence spectrum, and only aggregated data within type.

For snares, we included all snare observations in our analysis, except for one site (#1), in which snare condition was also recorded (as “new” vs. “old”), where we

restricted our analysis to new snares. Ideally, only new snares would be included for all sites, as older snares will have persisted in the landscape undetected, further weakening any relationship with patrolling. However, snare age was only recorded in one site. For people, we included all direct observations of people within park boundaries. In theory, this could include people engaged in illegal or legal activity. However, >90% of observations of people in three of the study sites were recorded in association with illegal activity (e.g. poaching) and/or a patrol action in response to illegal activity (e.g. an arrest), and for the remaining observations these fields were inconsistently completed. For the remaining site (#1), whether people were engaged in illegal activity or not was not recorded. Consequently, for consistency, and as nearly all observations of people were associated with illegal activity where this was recorded, we included all observations in our analysis.

When generating indicators, we explored the effect of two different methods for aggregating catch data: (1) a count of unique 1 km² grid cells in which any observations of the activity type were recorded within the analysis area (henceforth, occurrence method); and (2) a sum of all snares or people observed within the analysis area (henceforth, sum method). We used a 1 km² cell size as this is the default in SMART software, and thus commonly used by managers.

When calculating CPUE, we assumed that detectability – the probability of rangers detecting a sign of illegal activity per unit of patrol effort – was constant over time within sites. In reality, detectability can change in response to multiple factors (e.g. changing capacity of personnel), but these relationships are poorly understood, so we assumed the simplest model.

2.2.3 | Patrol effort measure

For our effort measure, we used the percentage of each site's study area covered by ground-based ranger patrols per timestep (henceforth, spatial coverage). Over longer time intervals, a spatial coverage measure can miss important variation in magnitude of patrol effort within areas. However, alternative measures that capture magnitude of effort more accurately (e.g. distance patrolled) ignore that rangers often repeatedly patrol the same locations (e.g. near patrol posts [Plumptre et al., 2014]); activity which may have little additional impact on deterrence. Consequently, we considered spatial coverage appropriate for use over short time intervals. We constructed a grid of 1 km² cells corresponding to the study area and calculated spatial coverage as the percentage of unique cells through which patrol routes passed at least

once. We estimated patrol routes by assuming the shortest route between successive position records.

2.2.4 | Monitoring period

We included records from the entire time period of available SMART monitoring data, except for the first 3 months following implementation of SMART, and the final timestep. Excluding the first 3 months of data allowed a period to ensure all patrols were monitored using SMART, as it is common for patrol teams to be trained and equipped successively during initial implementation.

2.2.5 | Study area

For our study area, we used each site's core patrol area, which we defined as the intersection between (1) a minimum convex polygon surrounding 99% of patrol position records closest to the centroid of all points, and (2) each site's boundary (i.e., we excluded 1% of points farthest from the centroid and all those outside the boundary). We used core patrol area rather than the broader protected area boundary, as in some contexts rangers only routinely patrol part of a site, providing little or no consistent monitoring outside of this area. In practice, the study sites' core patrol areas were broadly consistent with their official boundaries, but we used core patrol area for consistency.

2.2.6 | Spatial aggregation

We treated each site as one analytical unit, aggregating data from and assessing deterrence across the entirety of a site's study area.

2.2.7 | Temporal aggregation

Understanding of the temporal scales over which deterrence operates in protected areas is poor. Studies examining effects at annual scales have garnered mixed results (Beale et al., 2018; Moore et al., 2018), and few analyses have assessed deterrence over alternative intervals. Yet establishing appropriate scales using observational data is challenging, as searching for deterrence at multiple intervals risks generating spurious correlations by chance, while confining analyses to one interval risks missing effects operating at alternative timescales. In non-protected area contexts, deterrence effects have been

found across a range of temporal scales, from weeks to years (Braga et al., 2014, 2019). Notably, reappraisals of annual scale analyses have found effects at multiple shorter intervals (Chamlin et al., 1992). Consequently, we explored the effect of a small set of short intervals over which to aggregate data, including 14-, 28- and 42-day intervals, and divided monitoring data into discrete temporal subsets according to these intervals. Intervals <14 days generated a high proportion of timesteps with zero observations.

3 | RESULTS

3.1 | Summary

Increased patrol effort was associated with reduced CPUE occurrence of illegal activity in three out of four protected areas, including reduced snaring in one site, and reduced presence of people in two sites. The temporal resolution over which the effect operated varied between sites and illegal activity types, across 14-, 28-, and 42-day timesteps. In two out of the three cases, the association between patrolling and illegal activity was not apparent when using the sum method for aggregation instead of the occurrence method. In the third case, the association was evident using both methods, but the sum method returned a weaker correlation (see Supporting Information). Two of the sites in which the associations were apparent were grassland-dominated and one was forest-dominated.

3.2 | Snares

Differenced ($t-1$) plots of snare occurrence returned a significant negative correlation for one of four sites (#3, a grassland-dominated site) over the 28-day timestep (Figure 1; Table 2). While the effect was strong, with a 1% increase in patrol effort predicting a reduction in CPUE snare occurrence of 0.010 ± 0.003 (*SE*) occupied grid cells per unit effort (vs. mean CPUE rate of 0.014), the relationship was weak ($r^2 = 0.14$).

3.3 | Direct observations of people

Differenced ($t-1$) plots of people occurrence returned significant negative correlations for two of four sites: one forest-dominated site over the 42-day timestep (#2), and one grassland-dominated site over the 14-day timestep (#4) (Figure 2; Table 3). In both cases, the effect was strong, with a 1% increase in patrol effort predicting a

reduction in CPUE people occurrence of 0.064 ± 0.027 (*SE*) and 0.039 ± 0.015 (*SE*) occupied grid cells per unit effort, respectively (vs. mean CPUE rates of 0.084 and 0.034), but the relationships were weak ($r^2 = 0.30$ and 0.15, respectively).

4 | DISCUSSION

We trialled application of differenced plots – a recently proposed metric of deterrence (Dobson et al., 2019) – to patrol data collected in four protected areas. We report evidence of significant associations between increased patrol effort and reduced illegal activity within patrolled areas in the subsequent timestep in three sites, over shorter timescales than observed hitherto, including 14-, 28- and 42-day intervals. In contrast, previous deterrence studies in conservation contexts have typically been conducted at annual scales (Beale et al., 2018; Linkie et al., 2015; Moore et al., 2018). The finding of associations in some but not all sites is in line with existing evidence, which is mixed, with studies focused on individual protected areas reporting presence of deterrence in some circumstances (e.g. Sumatra [Linkie et al., 2015], Rwanda [Moore et al., 2018], and Uganda [Xu et al., 2020]), and its absence in others (e.g. South Africa [Barichiev et al., 2017] and Tanzania [Beale et al., 2018]).

We report effects of patrolling on both the presence of snares and people. Deterrence studies using snare detections as an indicator of illegal activity observed effects using the measure in isolation (Linkie et al., 2015) and in aggregate with other indicators (Moore et al., 2018). This is the first quantitative evidence of increased patrol presence being associated with reduced people presence in patrolled areas. We found more evidence for effects on ephemeral than persistent illegal activity types, with associations between patrolling and snares observed in one site, and with people presence in two sites, potentially because indicators that persist in the landscape can have impacts beyond the consecutive time-step, blurring the relationship between patrolling and rule-breaking and thus rendering deterrence harder to detect (Dobson et al., 2019). Analyses using detections of poached animal carcasses, which are more persistent than people but perhaps less persistent than snares, have found mixed effects (Barichiev et al., 2017; Beale et al., 2018).

The associations between patrolling and illegal activity that we report are consistent with the operation of deterrence over the spatiotemporal scales assessed. However, whether patrolling reduced overall illegal activity levels or merely led to its displacement was unclear from differenced plots, nor could the metric conclusively

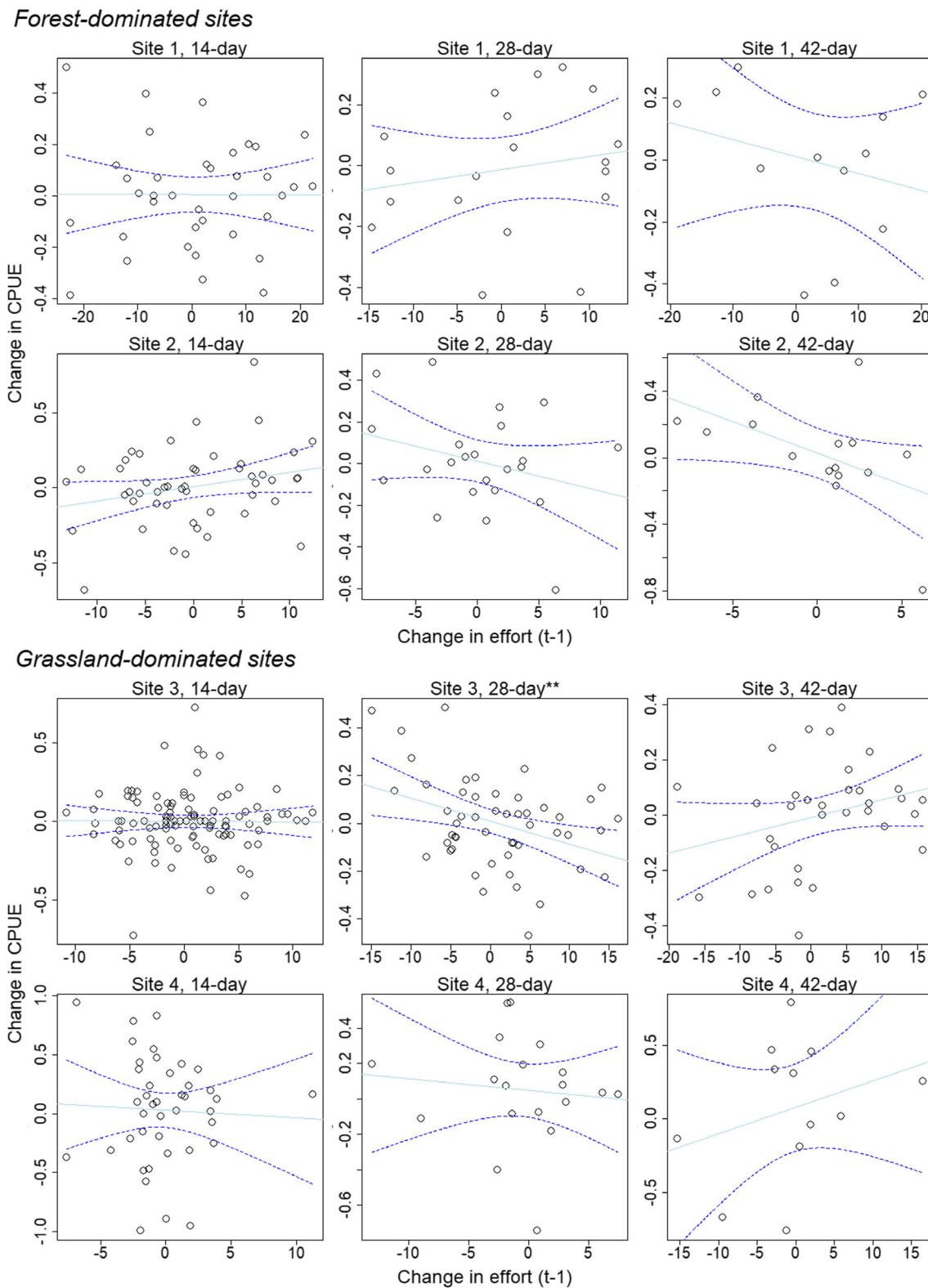


FIGURE 1 Differenced ($t-1$) plots of CPUE snare occurrence over patrol effort applied to patrol data collected in four protected areas, with data aggregated into 14-, 28- and 42-day intervals. A significant, negative slope, indicative of deterrence, was evident for one site (#3, a grassland-dominated site), over one time resolution (28 days). Significance at .01 level = ** and .05 level = *. Light blue line = linear regression line. Dotted blue lines = 95% confidence intervals

TABLE 2 Regression output for differenced ($t-1$) plots of CPUE snare occurrence over patrol effort applied to patrol data collected in four diverse protected areas, with data aggregated into 14-, 28- and 42-day intervals

Site	Interval	Slope	SE	F	DF	p	r ²
<i>Forest-dominated sites</i>							
1	14	0.000	0.003	0.000	(1,36)		0.00
	28	0.004	0.005	0.639	(1,17)		0.04
	42	-0.005	0.006	0.812	(1,10)		0.08
2	14	0.010	0.005	3.147	(1,47)		0.06
	28	-0.014	0.010	1.931	(1,21)		0.08
	42	-0.038	0.018	4.637	(1,13)		0.26
<i>Grassland-dominated sites</i>							
3	14	0.000	0.004	0.005	(1101)		0.00
	28	-0.010	0.003	7.869	(1,49)	**	0.14
	42	0.006	0.004	2.663	(1,31)		0.08
4	14	-0.006	0.023	0.075	(1,39)		0.00
	28	-0.007	0.015	0.185	(1,17)		0.01
	42	0.018	0.018	1.005	(1,10)		0.09

Note: **Significance at $p = .01$ level.

confirm absence of deterrence, raising questions for future applications.

Differenced plots can detect effects of patrolling on illegal activity in subsequent timesteps within areas monitored by patrols. However, deterrence could have been operating in the study sites but with spatial displacement of pressure to unpatrolled areas surrounding sites, or with temporal displacement of illegal activity to later time periods, such that the overall pressure on biodiversity was unchanged. Similarly, pressure would not be reduced if rule-breakers switched methods (e.g. if poachers switched from snaring to gun hunting). Such spatial, temporal and typological displacement is a common phenomenon in policing in general (Hesseling, 1994), although understudied in conservation settings. Fundamentally, differenced plots cannot tell us whether presence of patrols leads to potential rulebreakers implementing tactics to avoid patrols (i.e., situational deterrence; Cusson, 1993), or reduces rule-breaking entirely.

The absence of an association between patrolling and illegal activity in differenced plots is also not conclusive evidence that deterrence is absent. We found no evidence of an effect of patrolling on snaring in three study sites, on people presence in two sites, and on either indicator in one site. The lack of a consistent signal could be due to lack of deterrence, or because differenced plots – or our application of the metric – failed to detect it, for multiple reasons. Firstly, generation of differenced plots necessitated selection of spatiotemporal scales over which we assume deterrence operates (Dobson et al., 2019).

However, the effect may operate over entirely different scales to those chosen. Evidence generated here and in previous conservation research suggests deterrence functions at a wide range of temporal scales, from weeks to years (Linkie et al., 2015; Moore et al., 2018). Yet the effect may also operate at even shorter intervals, with rule-breakers making decisions based upon presence of patrols within minutes or hours (which would be beyond the analytical limits of patrol data). Furthermore, our analysis found effects operating over different choices of temporal resolution in each case, suggesting that selection of an appropriate interval is crucial for identification of deterrence. Yet, at present, understanding of deterrence is too poor to provide clear guidance on what scales to apply, indicating a need for research to develop a better qualitative understanding of how deterrence operates. Similarly, deterrence could also have been operating at finer spatial scales. Our analysis would detect an effect if patrolling led to an overall reduction in illegal activity throughout a monitored area. Yet if deterrence were operating at finer scales, but with internal displacement within sites such that the overall frequency of activities remained unchanged, no effect would be detected. The ultimate aim of patrolling is generally to reduce illegal activity within a protected area, and we assessed whether this goal had been achieved, but deterrence at finer scales can be satisfactory in some circumstances (e.g. parks with priority areas).

Secondly, our measure of patrol effort may ignore aspects of patrolling which are important for deterrence.

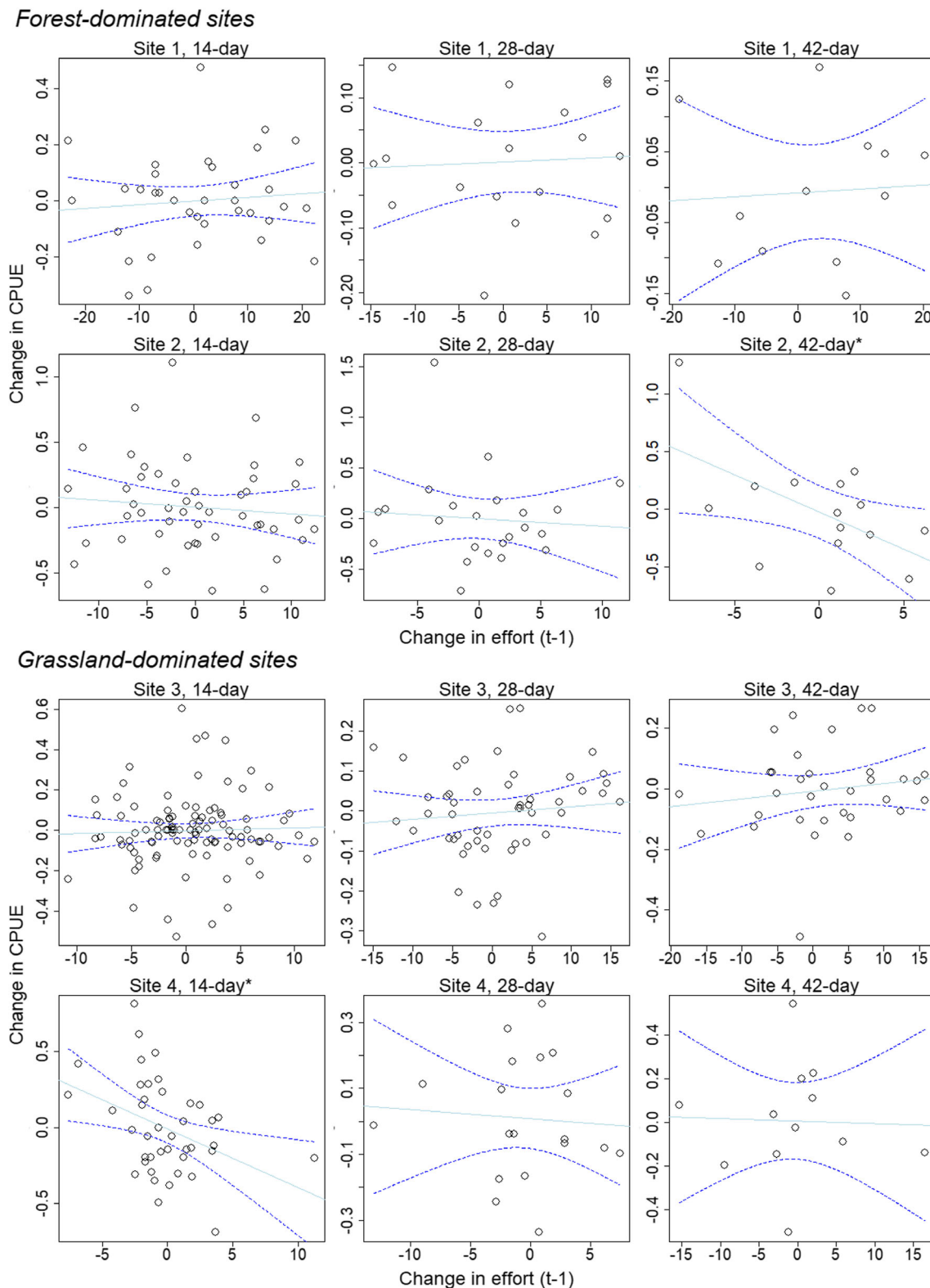


FIGURE 2 Differenced ($t-1$) plots of CPUE people occurrence over patrol effort applied to patrol data collected in four protected areas, with data aggregated into 14-, 28- and 42-day intervals. A significant, negative slope, indicative of deterrence, was apparent in one forest (#2) and one grassland (#4) site, over single, different time resolutions (42 and 14 days, respectively). Significance at .01 level = ** and .05 level = *. Light blue line = linear regression line. Dotted blue lines = 95% confidence intervals

TABLE 3 Regression output for differenced ($t-1$) plots of CPUE people occurrence over patrol effort applied to patrol data collected in four diverse protected areas, with data aggregated into 14-, 28- and 42-day intervals

Site	Step	Slope	SE	F	DF	p	r ²
Forest-dominated sites							
1	14	0.001	0.002	0.372	(1,36)		0.01
	28	0.001	0.002	0.061	(1,17)		0.00
	42	0.001	0.003	0.046	(1,10)		0.00
2	14	-0.005	0.008	0.461	(1,47)		0.01
	28	-0.008	0.020	0.142	(1,21)		0.01
	42	-0.064	0.027	5.683	(1,13)	*	0.30
Grassland-dominated sites							
3	14	0.001	0.004	0.148	(1101)		0.00
	28	0.002	0.002	0.499	(1,49)		0.01
	42	0.003	0.003	0.715	(1,31)		0.02
4	14	-0.039	0.015	6.897	(1,39)	*	0.15
	28	-0.003	0.009	0.086	(1,17)		0.01
	42	-0.001	0.011	0.012	(1,10)		0.00

Note: *Significance at $p = .05$ level.

For example, we focused exclusively on patrolling conducted inside park boundaries, but patrols conducted outside of boundaries could deter entry and thereby reduce illegal activity. In practice, almost all patrolling in the study sites was conducted within boundaries but future analyses should consider extending catchment areas as needed. Our measure of patrol effort was also relatively crude, capturing only spatial coverage of sites by patrols per timestep and ignoring variation in magnitude of activity within that space (e.g. rangers may have visited an area briefly, or for an extended period), which may be important for deterrence. As we were considering relatively short time periods, we considered spatial coverage appropriate, but there is a clear need for development of patrol effort measures which account for both coverage and magnitude of activity simultaneously.

Thirdly, differenced plots test for deterrence operating linearly, with a greater reduction in illegal activity depending on the magnitude of change in effort. Yet deterrence may also operate in a way that is undetectable by differenced plots; for example, being present where there is any quantity of patrolling and absent where there is none, which would result in a flat plot (Dobson et al., 2019). Illegal activity was a persistent issue throughout the monitoring period in all study sites, so if deterrence was operating non-linearly it was insufficient to deter rule-breaking entirely, but the effect would still have been missed.

Finally, differenced plots are reliant upon data collected by rangers on patrol and derived CPUE indices, which are subject to numerous uncontrolled biases, including non-random distribution of sampling effort, inaccurate reporting, variable catchability, and nonlinear relationships between abundance and CPUE (Keane et al., 2011). Apparent changes in CPUE measures may thus reflect sampling biases rather than underlying trends in the abundance of illegal activity, rendering interpretation of differenced plots challenging. To mitigate issues associated with patchy or inconsistent sampling effort, we selected sites with relatively high spatial and temporal patrol coverage, but other biases are less easily controlled. Robust methods for accounting for biases in patrol survey effort exist (e.g. using Bayesian hierarchical models [Critchlow et al., 2015]) but their application is non-trivial. Similarly, predictions derived using machine learning methods, which are increasingly common in these contexts (e.g. Fang et al., 2019), can be especially hard to interpret (Wearn et al., 2019). Importantly, all existing methods for modeling illegal activity from patrol data may require high levels of patrol effort and coverage, which are not the norm (Plumptre et al., 2014).

Overall, our findings provide some weak support for the assumption that presence of patrols can discourage illegal activity within patrolled areas for at least short periods, suggesting short-term decisions around patrol deployment may be important for patrol effectiveness. However, there are reasons to expect that the deterrent effect of patrolling in protected areas may sometimes be weak or ephemeral. Firstly, while deterrence theory suggests that risk of punishment following detection should inhibit future rule-breaking (Pratt & Cullen, 2005), in practice the risk of detection by rangers in some sites may be too low to deter crime. We selected SMART-monitored protected areas with relatively high patrol effort, but their large size meant that patrols still provided low presence in space and time, providing ample opportunity for rule-breakers to go undetected, suggesting that deterrence may be even harder to identify in less well-patrolled sites. Secondly, perceptual deterrence theory suggests that would-be offenders' perceptions of the certainty, severity, and celerity of punishment following detection will have a negative influence on their decisions to commit crime (Cullen & Wilcox, 2015); yet these factors may be too weak in some protected area contexts to have an effect (Wilson & Boratto, 2020). For example, rangers can lack the capacity or sufficient incentive to arrest rule-breakers (Ogunjinmi et al., 2009) or may seek to avoid potentially lethal situations (Moreto, 2016). In addition, justice systems in the global south do not always have a vested

interest in punishing arrested wildlife offenders (Moreto & Gau, 2017). Compliance with rules may also depend on individuals' perceptions of legitimacy and fairness, which may be undermined in countries where authorities are complicit in illegal activity (Kahler & Gore, 2012).

Ultimately, confirming presence or absence of deterrence requires good understanding of the reality underlying patrol-illegal activity relationships, which is currently lacking. Critically, evaluating why people offend or re-offend in the presence of patrols requires understanding of offenders' perceptions of the likelihood of being caught and punished, which cannot be determined from patrol data alone, pointing to a need for in-depth study of crime in protected areas, drawing on alternative data sources (e.g. community interviews, offender interviews).

4.1 | Future application of differenced plots

While differenced plots cannot be used to discern whether patrolling truly reduces rule-breaking, nor to definitively confirm absence of deterrence, our trial suggests that the metric can still be a useful tool for informing patrol management, although the method should be applied and interpreted with care. Similar to common deterrence metrics, such as CPUE-time and CPUE-effort plots, differenced plots enable managers to evaluate the effects of patrolling on illegal activity, using a simple method, which is crucial for uptake, and which only requires patrol data, the most common source of information on illegal activity in protected areas. However, in contrast to common metrics, differenced plots are robust to confounding temporal effects and autocorrelation (Dobson et al., 2018), and thus represent an improvement in evaluation methods, despite the metric's shortcomings.

In practical applications, the presence of a negative slope in a differenced plot is indicative that patrolling may work to suppress illegal activity within the study area over the spatiotemporal scales assessed. Additional monitoring and evaluation will be needed, however; particularly to assess if illegal activity persists despite regular patrols, which may indicate displacement. The absence of a negative slope across a variety of scales is indicative that assessed areas may need more attention – and resource allocation – to evaluate why evidence for deterrence is lacking. For example, managers could implement additional monitoring to assess whether different poaching methods are being used, or vary patrol strategies, such as routes or timing, to attempt to elicit a

measurable deterrent effect. Where the deterrent effect is truly weak, and its absence is validated through non-patrol data, managers might explore refining and evaluating alternative enforcement strategies, such as targeting patrols towards illegal activity hotspots (via robust threat monitoring) or intelligence-led policing (Moreto, 2015), or implementing enforcement alongside activities to strengthen prosecution systems and increase compliance (e.g. by tackling corruption; Hauenstein et al., 2019).

The metric may have specific utility for comparing variation in deterrence across space and through time within sites. We applied the metric across the entirety of each sites' patrolled area and since monitoring began, but it could also be applied separately across multiple spatial or temporal subsets. For example, differenced plots could be applied to data from different regions or patrol posts within a protected area, or to different seasons throughout the year, enabling managers to identify periods and places where deterrence appears relatively weak or strong, and to plan monitoring and enforcement activities accordingly. Similarly, differenced plots could be used to evaluate displacement effects within sites, by comparing movement of effects across contiguous areas or sequential time periods (Xu et al., 2020).

The methods we trialled for generating differenced plots from real data can be used to guide future applications. Some processing decisions, such as choice of illegal activity measure and level of temporal aggregation, have already been discussed. Importantly, no single temporal resolution was favored across contexts, suggesting that the scale of deterrence may be context-dependent and should be assessed on a case-by-case basis, drawing on alternative lines of evidence (e.g. poacher interviews). We also explored the effect of two alternative methods for aggregating observations of illegal activity. Our findings suggest that aggregating observations of illegal activity data using a unique grid cell occurrence approach may be more effective for identifying deterrence than a simple observation sum method, because infrequent records of very high observation counts – representing clustering of observations in the landscape (e.g. caches of snares) – may skew relationships between patrolling and illegal activity when using a sum method.

Our results lend some weak support to the conjecture that presence of patrols can deter illegal activity in certain contexts, for short periods. However, whether such an effect is sufficient to reduce threats to wildlife in the long-term is still unclear. Determining whether and how patrols deter illegal activity is of critical importance, and we demonstrate how differenced plots can be a practical tool for exploring deterrence using the most common

source of data on illegal activity in protected areas – rangers themselves – but the metric should be used with care, and there is still an urgent need for methods which can reliably diagnose deterrence. Ultimately, this will likely require in-depth study of systems with independent data on illegal activity, and in which some confounding factors are accounted for.

AUTHOR CONTRIBUTIONS

Anthony Dancer led the work, including analysis and writing. Aidan Keane, Colin M. Beale, and Andrew D. M. Dobson contributed to conception of the work, design of the methods, and interpretation of the results. Inaoyom Imong, Matthew Linkie, Barney Long, Francis O. Okeke, Andrew J. Plumptre, Emma J Stokes, and Elsabé van der Westhuizen contributed to acquisition of data. Rajan Amin, Robin Freeman, Kate Jones, J. Marcus Rowcliffe, and Ben Collen provided supervision. All authors provided critical feedback on the manuscript.

ACKNOWLEDGMENTS

Anthony Dancer and Aidan Keane were supported by the Natural Environment Research Council [grant number NE/L002485/1]. Robin Freeman and J. Marcus Rowcliffe were supported by Research England funding to the Institute of Zoology. Andrew J. Plumptre was supported by various MacArthur Foundation, US Fish and Wildlife Service and USAID grants, and the Wildlife Conservation Society. We would like to thank the protected area staff and partners who contributed data, and individuals representing the SMART Partnership who facilitated the research. We would also like to thank E.J. Milner-Gulland and Harriet Ibbett for their input into the design of the analysis, and for reviewing an early manuscript draft.

CONFLICT OF INTEREST

The authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

Due to the sensitive nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

ORCID

Anthony Dancer  <https://orcid.org/0000-0002-3322-2502>

Aidan Keane  <https://orcid.org/0000-0002-9704-5576>

Andrew J. Plumptre  <https://orcid.org/0000-0002-9333-4047>

REFERENCES

Barichiev, C., Munro, L., Clinning, G., Whittington-Jones, B., & Masterson, G. (2017). Do armed field-rangers deter rhino

poachers? An empirical analysis. *Biological Conservation*, 209, 554–560. <https://doi.org/10.1016/J.BIOCON.2017.03.017>

- Beale, C. M., Hauenstein, S., Mduma, S., Frederick, H., Jones, T., Bracebridge, C., Maliti, H., Kija, H., & Kohi, E. M. (2018). Spatial analysis of aerial survey data reveals correlates of elephant carcasses within a heavily poached ecosystem. *Biological Conservation*, 218, 258–267. <https://doi.org/10.1016/J.BIOCON.2017.11.016>
- Benítez-López, A., Alkemade, R., Schipper, A. M., Ingram, D. J., Verweij, P. A., Eikelboom, J. A. J., & Huijbregts, M. A. J. (2017). The impact of hunting on tropical mammal and bird populations. *Science (New York, N.Y.)*, 356(6334), 180–183. <https://doi.org/10.1126/science.aaj1891>
- Braga, A. A., Papachristos, A. V., & Hureau, D. M. (2014). The effects of hot spots policing on crime: An updated systematic review and meta-analysis. *Justice Quarterly*, 31(4), 633–663.
- Braga, A. A., Weisburd, D., & Turchan, B. (2019). Focused deterrence strategies effects on crime: A systematic review. *Campbell Systematic Reviews*, 15(3), e1051.
- Bruner, A. G., Gullison, R. E., Rice, R. E., & da Fonseca, G. A. (2001). Effectiveness of parks in protecting tropical biodiversity. *Science (New York, N.Y.)*, 291(5501), 125–128. <https://doi.org/10.1126/science.291.5501.125>
- Chamlin, M. B., Grasmick, H. G., Bursik, R. J., & Cochran, J. K. (1992). Time aggregation and time lag in macro-level deterrence research. *Criminology*, 30(3), 377–396. <https://doi.org/10.1111/j.1745-9125.1992.tb01109.x>
- CITES. (2010). Monitoring of illegal hunting in elephant range states. In *Fifteenth Meeting of the Conference of the Parties Doha (Qatar)* 13–25 March 2010, 2, 27. Wiley. <https://cites.org/sites/default/files/eng/prog/MIKE/CoP/E-CoP15-44-02.pdf>
- Critchlow, R., Plumptre, A. J., Driciru, M., Rwetsiba, A., Stokes, E. J., Tumwesigye, C., Wanyama, F., & Beale, C. M. (2015). Spatiotemporal trends of illegal activities from ranger-collected data in a Ugandan national park. *Conservation Biology*, 29(5), 1458–1470. <https://doi.org/10.1111/cobi.12538>
- Cronin, D. T., Dancer, A., Long, B., Lynam, A. J., Muntifer, J., Palmer, J., & Bergl, R. A. (2021). Application of SMART software for conservation area management. In S. A. Wich & A. K. Piel (Eds.), *Conservation technology*. Oxford University Press.
- Cullen, F. T., & Wilcox, P. (2015). *The Oxford handbook of criminological theory*. Oxford University Press.
- Cusson, M. (1993). Situational deterrence: Fear during the criminal event. In R. Clarke (Ed.), *Crime prevention studies, Volume 1* (pp. 55–68). Willow Tree Press.
- Dobson, A. D. M., Milner-Gulland, E. J., Aebischer, N. J., Beale, C. M., Brozovic, R., Coals, P., Critchlow, R., Dancer, A., Greve, M., Hinsley, A., & Ibbett, H. (2020). Making messy data work for conservation. *One Earth*, 2(5), 455–465.
- Dobson, A. D. M., Milner-Gulland, E. J., Beale, C. M., Ibbett, H., & Keane, A. (2019). Detecting deterrence from patrol data. *Conservation Biology*, 33, 665–675. <https://doi.org/10.1111/cobi.13222>
- Fang, F., Tambe, M., Dilkina, B., & Plumptre, A. J. (2019). *Artificial intelligence and conservation*. Cambridge University Press <https://www.cambridge.org/us/academic/subjects/computer-science/artificial-intelligence-and-natural-language-processing/>

- artificial-intelligence-and-conservation?format=PB&isbn=9781108464734
- Gray, M., & Kalpers, J. (2005). Ranger based monitoring in the Virunga-Bwindi region of east-Central Africa: A simple data collection tool for park management. *Biodiversity and Conservation*, 14(11), 2723–2741. <https://doi.org/10.1007/s10531-005-8406-x>
- Hauenstein, S., Kshatriya, M., Blanc, J., Dormann, C. F., & Beale, C. M. (2019). African elephant poaching rates correlate with local poverty, national corruption and global ivory price. *Nature Communications*, 10(1), 2242. <https://doi.org/10.1038/s41467-019-09993-2>
- Henson, D. W., Malpas, R. C., & D'Udine, F. A. C. (2016). Wildlife law enforcement in sub-Saharan African protected areas: A review of best practices. *IUCN International Union for Conservation of Nature*. <https://doi.org/10.2305/IUCN.CH.2015.SSC-OP.58.en>
- Hesseling, R. (1994). Displacement: A review of the empirical literature. *Crime Prevention Studies*, 3(1), 97–230.
- Hilborn, R., Arcese, P., Borner, M., Hando, J., Hopcraft, G., Loibooki, M., Mduma, S., & Sinclair, A. R. E. (2006). Effective enforcement in a conservation area. *Science*, 314(5803), 1266. <https://doi.org/10.1126/science.1132780>
- Holmern, T., Muya, J., & Røskaft, E. (2007). Local law enforcement and illegal bushmeat hunting outside the Serengeti National Park, Tanzania. *Environmental Conservation*, 34(1), 55–63. <https://doi.org/10.1017/S0376892907003712>
- Hötte, M. H. H., Kolodin, I. A., Bereznuik, S. L., Slaght, J. C., Kerley, L. L., Soutyrina, S. V., Salkina, G. P., Zaumyslova, O. Y., Stokes, E. J., & Miquelle, D. G. (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>
- Isaac, N. J. B., van Strien, A. J., August, T. A., de Zeeuw, M. P., & Roy, D. B. (2014). Statistics for citizen science: Extracting signals of change from noisy ecological data. *Methods in Ecology and Evolution*, 5(10), 1052–1060. <https://doi.org/10.1111/2041-210X.12254>
- Kahler, J. S., & Gore, M. L. (2012). Beyond the cooking pot and pocket book: Factors influencing noncompliance with wildlife poaching rules. *International Journal of Comparative and Applied Criminal Justice*, 36(2), 103–120.
- Keane, A., Jones, J. P. G., & Milner-Gulland, E. J. (2011). Encounter data in resource management and ecology: Pitfalls and possibilities. *Journal of Applied Ecology*, 48(5), 1164–1173. <https://doi.org/10.1111/j.1365-2664.2011.02034.x>
- Linkie, M., Martyr, D. J., Harihar, A., Risdianto, D., Nugraha, R. T., Maryati, Leader-Williams, N., & Wong, W.-M. (2015). Safeguarding Sumatran tigers: Evaluating effectiveness of law enforcement patrols and local informant networks. *Journal of Applied Ecology*, 52(4), 851–860. <https://doi.org/10.1111/1365-2664.12461>
- Moore, J. F., Mulindahabi, F., Masozera, M. K., Nichols, J. D., Hines, J. E., Turikunkiko, E., & Oli, M. K. (2018). Are ranger patrols effective in reducing poaching-related threats within protected areas? *Journal of Applied Ecology*, 55, 99–107. <https://doi.org/10.1111/1365-2664.12965>
- Moreto, W. D. (2015). Introducing intelligence-led conservation: Bridging crime and conservation science. *Crime Science*, 4(1), 15. <https://doi.org/10.1186/s40163-015-0030-9>
- Moreto, W. D. (2016). Occupational stress among law enforcement rangers: Insights from Uganda. *Oryx*, 50(4), 646–654. <https://doi.org/10.1017/S0030605315000356>
- Moreto, W. D., & Gau, J. M. (2017). Deterrence, legitimacy, and wildlife crime in protected areas. In *Conservation criminology* (pp. 45–58). John Wiley & Sons. <https://doi.org/10.1002/9781119376866.ch3>
- Nagin, D. S. (2013). Deterrence in the twenty-first century. *Crime and Justice*, 42(1), 199–263. <https://doi.org/10.1086/670398>
- Ogunjinmi, A., Umunna, M., & Ogunjinmi, K. (2009). Factors affecting job satisfaction of rangers in Yankari game reserve, Bauchi, Nigeria. *Journal of Agriculture and Social Research (JASR)*, 8(2). <https://doi.org/10.4314/jasr.v8i2.43332>
- O'Kelly, H. J., Rowcliffe, J. M., Durant, S. M., & Milner-Gulland, E. J. (2018). Experimental estimation of snare detectability for robust threat monitoring. *Ecology and Evolution*, 8(3), 1778–1785. <https://doi.org/10.1002/ece3.3655>
- Paternoster, R. (2010). How much do we really know about criminal deterrence. *Journal of Criminal Law and Criminology*, 100(3), 765–823. <https://scholarlycommons.law.northwestern.edu/jclc/vol100/iss3/6>
- Plumptre, A. J., Fuller, R. A., Rwetsiba, A., Wanyama, F., Kujirakwinja, D., Driciru, M., Nangendo, G., Watson, J. E., & Possingham, H. P. (2014). Efficiently targeting resources to deter illegal activities in protected areas. *Journal of Applied Ecology*, 51(3), 714–725. <https://doi.org/10.1111/1365-2664.12227>
- Pratt, T. C., & Cullen, F. T. (2005). *Assessing macro-level predictors and theories of crime: A meta-analysis*. The University of Chicago Press. <https://doi.org/10.2307/3488363>
- R Core Team. (2020). *R: A language and environment for statistical computing*. Author <https://www.r-project.org/>
- Schulze, K., Knights, K., Coad, L., Geldmann, J., Leverington, F., Eassom, A., Marr, M., Butchart, S. H., Hockings, M., & Burgess, N. D. (2018). An assessment of threats to terrestrial protected areas. *Conservation Letters*, 11, e12435. <https://doi.org/10.1111/conl.12435>
- Stokes, E. J. (2010). Improving effectiveness of protection efforts in tiger source sites: Developing a framework for law enforcement monitoring using MIST. *Integrative Zoology*, 5(4), 363–377. <https://doi.org/10.1111/j.1749-4877.2010.00223.x>
- Tranquilli, S., Abedi-Lartey, M., Abernethy, K., Amsini, F., Asamoah, A., Balangtaa, C., ... Sommer, V. (2014). Protected areas in tropical Africa: Assessing threats and conservation activities. *PLoS One*, 9(12), e114154. <https://doi.org/10.1371/journal.pone.0114154>
- Tranquilli, S., Abedi-Lartey, M., Amsini, F., Arranz, L., Asamoah, A., Babafemi, O., Barakabuye, N., Campbell, G., Chancellor, R., Davenport, T. R., & Dunn, A. (2012). Lack of conservation effort rapidly increases African great ape extinction risk. *Conservation Letters*, 5(1), 48–55. <https://doi.org/10.1111/j.1755-263X.2011.00211.x>
- Wearn, O. R., Freeman, R., & Jacoby, D. M. P. (2019). Responsible AI for conservation. *Nature Machine Intelligence*, 1(2), 72–73. <https://doi.org/10.1038/s42256-019-0022-7>
- Wilson, L., & Boratto, R. (2020). Conservation, wildlife crime, and tough-on-crime policies: Lessons from the criminological

literature. *Biological Conservation*, 251, 108810. <https://doi.org/10.1016/j.biocon.2020.108810>

Xu, L., Perrault, A., Plumptre, A., Driciru, M., Wanyama, F., Rwetsiba, A., & Tambe, M. (2020). Game theory on the ground: The effect of increased patrols on deterring poachers. In *AI for Social Good Workshop*. International Joint Conferences on Artificial Intelligence.

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: Dancer, A., Keane, A., Beale, C. M., Dobson, A. D. M., Amin, R., Freeman, R., Imong, I., Jones, K., Linkie, M., Long, B., Okeke, F. O., Plumptre, A. J., Rowcliffe, J. M., Stokes, E. J., van der Westhuizen, E., & Collen, B. (2022). Evidence of deterrence from patrol data: Trialling application of a differenced-CPUE metric. *Conservation Science and Practice*, e12746. <https://doi.org/10.1111/csp2.12746>