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Article

Optimal Monitoring Strategy to Detect Rule-breaking: A Power and Simulation Approach Parameterised with Field Data from Gola Rainforest National Park, Sierra Leone

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Abstract

Protected area designation aims to protect forests from illegal activities such as hunting. However, the effectiveness of protection and how this changes over time in response to protection measures is difficult to assess, including the design of monitoring programmes able to detect changes. We present new data on rule-breaking prevalence in Gola Rainforest National Park, Sierra Leone, and use these data in spatially explicit simulations to assess the survey effort and design required to detect change and assess the effect of rule-breaker behaviour to these designs. Despite being a protected area, rule-breaking (in the form of signs of hunting) occurred in almost 70% of 1 km survey squares but repeating this baseline survey of 53 survey squares would be insufficient to detect change. A much larger survey effort of 200-400 survey squares would be required to detect a 25% change in rule-breaking. Simulations highlight the extent to which rule-breaker behaviour, particularly hunter range size, influenced the likelihood of detecting change and importance of understanding this for survey design. A dedicated monitoring programme able to detect changes in the level of rule-breaking required an unrealistic level of resources, and we recommend combining monitoring with ranger patrol activities to reduce overall costs and employing questionnaire-based methods.

Keywords: Bushmeat hunting, protected area, power analysis, monitoring, rSPACE, rule-breaking, simulation, tropical forest

INTRODUCTION

On a global scale, tropical forests represent some of the most biodiverse and threatened habitats in the world. Their protection can be achieved through a range of approaches from global policy to small scale local action, but the establishment of protected areas remains a key tool (Di Marco et al. 2014). Gazettement or designation of protected status is often, though not always, accompanied by some form of action to deter and prevent 'rule-breaking' behaviour such as hunting (Bruner et al. 2001, Butchart et al. 2012, Laurance et al. 2012) and other anthropogenic pressures (Geldmann et al. 2013). Monitoring of rule-breaking provides protected area managers with knowledge of the distribution of threats in space and time, enabling more efficient targeting of resources, improving understanding of the drivers of threats (Gardner et al. 2010) and ultimately improving the success of conservation interventions (Danielsen et al. 2005; Geldmann et al. 2014; Legg and Nagy 2006; Plumptre et al. 2014).

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Bushmeat hunting is a widespread and significant threat to wildlife in tropical forests (Abernethy et al. 2013; Craigie et al. 2010; Fa and Brown 2009; Milner-Gulland and Bennett 2003). Despite a wealth of research on hunter behaviour (Kümpel et al. 2009), from market and household surveys (Coad et al. 2010; Kümpel et al. 2010; Fa et al. 2015; Foerster et al. 2012) and from modelling approaches (Bousquet et al. 2001; Rowcliffe et al. 2003; Damania et al. 2005; Ling and Milner-Gulland 2008; Iwamura et al. 2014), bushmeat hunting remains inadequately understood and quantified in Western Africa (Taylor et al. 2015), particularly in protected areas where hunting is illegal.

Systematic monitoring of rule-breaking behaviour such as hunting is challenging and costly, so assessment of the efficiency of survey design is valuable in ensuring resources are appropriately allocated (McDonald-Madden et al. 2010). The use of ranger patrols to monitor and prevent rule-breaking in protected areas can be a cost-effective approach to enable rapid responses and targeting of law enforcement efforts (Gray and Kalpers 2005, Stokes 2010; Plumptre et al. 2014). However, ranger based patrol data is often confounded by unknown sampling effort and encounter bias (Critchlow et al. 2015) and frequently requires validation using more robust and costly methods (Keane et al. 2011).

While some previous studies compare survey methods that assess rule-breaking (Jones et al. 2008, Gavin et al. 2010; Keane et al. 2011), few consider the statistical power of different methods and compare their ability to detect changes in rule-breaking occurrence (Seavy and Reynolds 2007). Power analyses have been extensively applied to improve the cost effectiveness of monitoring strategies for wildlife populations (Gerrodette 1987; Hadfield et al. 1996; Hatch 2003; McDonald-Madden et al. 2010, Meyer et al. 2010; Guillera-Arroita and Lahoz-Monfort 2012; Ellis et al. 2015), but are rarely applied to the design of monitoring rule-breaking activities (although, see Brashares and Sam 2005).

Here we investigate optimal surveying of rule-breaking occurrence in Gola Rainforest National Park, Sierra Leone, by collecting field data on the prevalence and variability of rule-breaking and using this to parameterise a spatially explicit power analysis. The aims were to (i) quantify the level of threat to the forest, measured as the frequency of occurrence of rule-breaking behaviour; (ii) estimate the level of survey effort, in terms of monitoring visit frequency and sample size, necessary to detect changes in rule-breaking; (iii) investigate whether monitoring efficiency could be improved by increasing or decreasing the area of each square surveyed; and (iv) understand the degree to which the ranging behaviour of rule-breakers (hunters) impacts on the level of survey effort required. Together these results provide a basis for developing an effective monitoring strategy.

MATERIALS AND METHODS

Field collected data

We surveyed 53 squares 1 km in area within Gola Rainforest National Park (GRNP) for signs of rule-breaking activity by hunters using a stratified random approach. GRNP is located in Sierra Leone, between 7°18' - 7°51' N and 10°37' - 11°21' W and comprises 70,000 ha of Upper Guinea rainforest in three non-contiguous forest blocks surrounded by villages and a community forest buffer zone. Squares surveyed were sampled within the park in four distance bands from the park boundary:0-0.5 km (n=20); 0.5-1.5 km (n=11); 1.5-2.5 km (n=14); and >2.5 km (n=8). Each square was visited once between March and August 2012 and searched for signs of rule-breaking activities by walking a 'V' shaped path of least resistance across the square without retracing any part of the route. Routes taken in each square were recorded using a GPS (mean transect length was 2.86 km, range 2.16-3.65 km). Observed signs of rule-breaking were recorded for four categories: marked human trails, wire snares or snare lines, spent shotgun cartridges and overnight camps. As few observations were made for some categories, all four categories were then pooled, with rule-breaking considered to have occurred in a square if any sign was recorded.

Current level of threat: frequency of occurrence and spatial pattern of rule-breaking

We modelled the occurrence of rule-breaking signs as a binary response variable using a generalised linear model (GLM) with quasibinomial errors and logit link function in R (R Development Core Team 2014). We fitted a global model that included linear and quadratic terms describing altitude of the square centroid (derived from a 30 m resolution Digital Elevation Model), and distance from square centroids to the nearest village and to the nearby international border with Liberia. We also included an interaction term between distance to the nearest village and altitude, and included the log of transect length as an offset term. A variable describing the distance to the edge of the national park was omitted because it was strongly correlated with distance to nearest village (Pearson's product-moment correlation = 0.87; $t = 12.9$; $df = 51$; $p < 0.001$).

To identify the most important factors influencing rule-breaking to use in subsequent simulations we identified the best ranked model from all possible subsets of the global model based on quasi Akaike Information Criterion adjusted for small sample size (QAICc). Model ranking by QAIC was performed in R using the package MuMIn (Barton 2011).

Simulation models

An overview of all steps used in the simulation process for the spatially explicit power analysis is shown in Figure 1. We investigated power to detect one-off changes in rule-breaking using a simulation approach with the R package rSPACE (Ellis et al. 2015). This analytical framework treats rule-breaking as analogous to a wildlife population whereby a population of individual hunters are each assigned an activity centre and unique centre-weighted movement distribution (an area across which hunting takes place, or home-range). This simple spatial model allowed us to manipulate the number of activity centres. We use the term 'hunter population' to refer to the number of hunter activity centres in the landscape. Hunter activity centres were added or removed to simulate change in rule-breaking activity between survey periods. The composite home-range movement distributions of the hunter population resulted in a map of utilisation probability for each survey period, with a new utilisation map created for each new simulation iteration. At each iteration, rSPACE creates a unique hunter utilisation surface with probability values for before and after a change in the hunter population. To simulate monitoring, a 1 km square fishnet grid was overlaid over the utilisation map and squares randomly sampled, with the probability of detecting rule-breaking in a square taken as the probability of use by a hunter. For all simulation models the response variable was binary (detection or non-detection of rule-breaking), with imperfect detection accounted for by repeating visits to squares each survey period. The proportion of simulation iterations where a change at $p<0.05$ was correctly identified provided our estimate of power for each simulated scenario.

Parameters defined in the spatial simulation

We used the coefficients of spatial variation from the top ranked model of the field data to predict relative rule-breaking probability in all 1 km-squares across GRNP, and generated a raster map containing these values. Cell size was then disaggregated to 0.25 km so squares were smaller than the simulated sample units to meet requirements of rSPACE. This map of rule-breaking probability was used in all scenarios to determine the spatial distribution of hunter activity centres (for the details of how rSPACE distributes activity centres see Ellis et al. 2015). We set the minimum distance between hunter activity centres to 0.1 km to ensure hunter ranges substantially, but not directly, overlapped each other.

For each hunter activity centre we specified a movement home-range of 4 km radius, except where the effect of hunter range size was explicitly tested when it was varied to 1.5, 2, 4, 6 and 8 km. We assumed 4 km radius was realistic based on personal observations and published figures of bushmeat hunting in west and central Africa (Kümpel et al. 2009; Gill et al. 2012; Coad et al. 2013,). Ranging by hunters was set to 90% within this home-range radius, and 10% beyond the home-range radius, allowing for the realistic possibility of some longer movements. Ranges were constrained to prevent them extending outside the GRNP boundary. The probability that individual squares in each hunter's range were utilised was based on a bivariate normal distribution, so hunters were more likely to use squares near the centre of their range (for details of how rSPACE estimates use see Ellis et al. 2015).

We used a baseline hunter population of 205. This value was determined by creating hunter utilisation surface landscapes under a range of hunter population sizes (10-600) with the home-range radius set at 4 km. For each landscape we generated 53 simulated datasets, equal to our field data survey square sample size. We then identified the hunter population size most likely to return the number of hunting signs we observed in the field data. Simulated datasets were a random sample of the 53 survey squares, with each of these 1 km

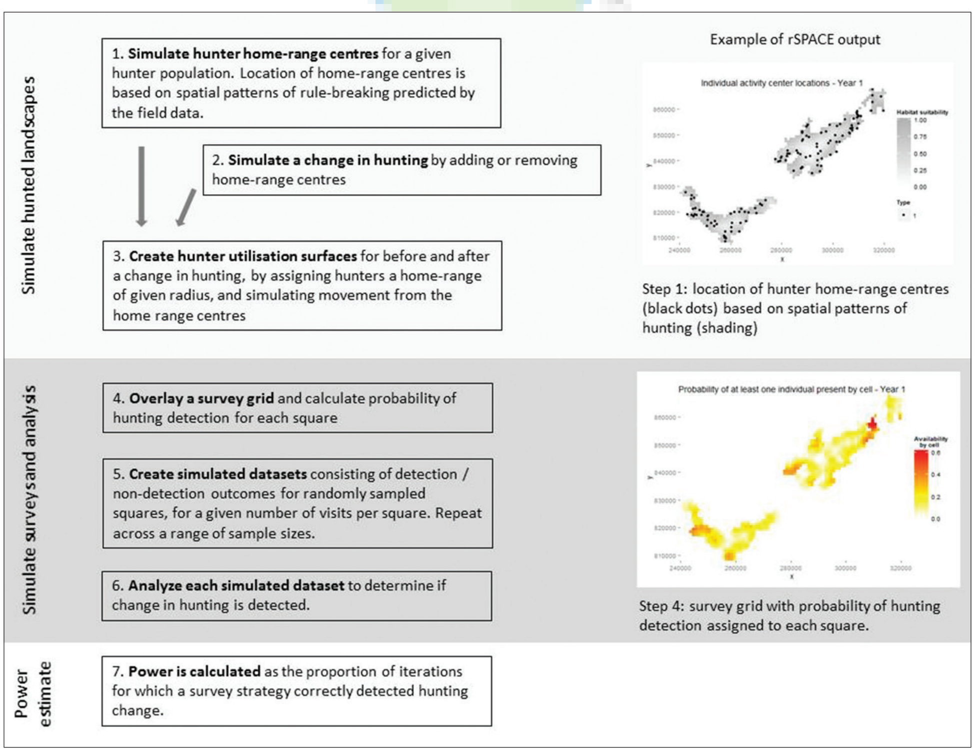

Figure 1
Overview of the simulation process used for spatially explicit power analysis

squares having an outcome of 1 (detection) or 0 (non-detection) based on the hunter utilisation probability for the respective square. This was repeated for 100 landscapes at each value of hunter population size, with the mean number of squares with hunting presence calculated for each landscape. To identify which value of hunter population size most closely matched the observed frequency of finding snares from our field data, we fitted a GLM including a quadratic term for hunter population to the simulated results, with the number of squares with signs of hunting modelled as a function of hunter population. We calibrated our simulations to snares rather than all signs combined in order to assess a monitoring strategy that measured hunting within a defined period of time (snares could be most reliably aged in the field) and targets types of rule-breaking separately.

Calculating the power to detect changes in rule-breaking

We applied the single-season occupancy modelling framework of Mackenzie et al. (2002) for the analysis of simulated data. This framework enables assessment of use or occupancy of a sampling unit (in our case evidence of rule-breaking in a surveyed square) while addressing the problem of imperfect detection. This is achieved by estimating the detection probability and adjusting the estimate of occupancy to take into account the likely proportion of squares where rule-breaking was present but not detected. Estimation of detection probability requires repeated visits to squares within a survey season, with the assumption that the real state of rule-breaking does not vary between visits. Observed differences between visits are due to imperfect detection, which is estimated and incorporated into the overall estimate of rule-breaking occurrence.

For each scenario a fishnet grid was overlaid over the utilisation probability map in which each cell was assigned a probability of hunter utilization. Cell size was 1 km except where survey square area was explicitly being tested when it was set to 0.25, 0.5, 1 or 2 km. We generated binary detection data for a given number of visits at each square from a Bernoulli process, with probability of detection equal to the utilisation probability within that square. This was repeated six times for each square, both before and after the population had been increased or decreased, to simulate a maximum of six visits per square per survey season. Detection histories were generated for every square in the sample grid for two survey seasons (before and after population change) which were then randomly sub-sampled for a given sample size and number of visits.

Detection histories were analysed with a single-season occupancy model using the R package 'unmarked' (Fiske and Chandler 2011). A model was fitted to each dataset, with survey season as a covariate to identify responses before and after a change in hunter population. A model successfully identified a change in rule-breaking occurrence (the measure and consequence of change in the hunter population) if the survey season coefficient was significantly different from zero at $p<0.05$. No covariates were included in estimation of the detection probability.

For each simulated scenario, the power to detect a change in rule-breaking between two surveys was the proportion of iterations for which models indicated a statistically significant difference. 1000 iterations were performed under each scenario, and runs in which models failed to converge were discarded. The number of iterations, excluding models with computational problems, are shown in the Supplementary Information, Table S1. For all scenarios, power was calculated for six areas that encompassed 5, 15, 25, 35, 45 or 55% of the study area, equivalent to 34-380 1 km-squares, for simulation scenarios of three and six survey visits per square.

Detecting a change in hunter population

To investigate the power to detect an increase or decrease in rule-breaking we next varied the number of hunter activity centres to simulate decreases in the hunter population of 25 and 50% and increases of 50, 75 and 100%. For all these simulations hunter home-range radius was 4 km, and survey square area 1 km^2.

We explored two aspects of survey design likely to influence the power to detect change, the number of visits per square and the size of survey squares. Standard errors associated with estimates of detection probability can be reduced by increasing the number of repeated visits to each square (Mackenzie and Royle 2005), therefore we evaluated power with three and six visits for all scenarios. Three can be considered the minimum number of visits required to estimate detection probabilities, while six represents the maximum possible at GRNP given logistical constraints.

Survey square area defines the sample unit in which hunters are recorded. Larger squares are closer in area to hunter's ranges, and therefore provide a more sensitive measure of change in the number of hunters. However, more effort is required to survey larger squares. Survey effort can therefore be allocated either to fewer larger squares, or more smaller squares, to give the same overall coverage. We investigated changes in the survey design by varying square size to 0.5 and 2 km^2 from our baseline of 1 km^2 and compared survey effort that gave the same overall percentage coverage of the study area. For survey square areas of 0.5 and 2 km^2, we tested power at sample sizes that gave coverage of 5, 15, 25, 35, 45 and 55% of the study area, for scenarios of a 50% decrease and a 100% increase in hunter population.

The area over which hunters are active (home-range) is a key parameter likely to affect monitoring power, but is usually unknown. To investigate the effects of hunter range size finally we considered five different home-range size radii: 1.5, 2, 4, 6 and 8 km in simulations of a 50% decrease and 100% increase in the hunter population with a 1 km^2 survey square area. An 8 km radius is within the upper range recorded from central Africa (Noss 1998; Wilkie et al. 1998; Gill et al. 2012; Coad et al. 2013).

RESULTS

Frequency of occurrence and spatial pattern of rule-breaking

Rule-breaking signs were found in 35 of the 53 surveyed squares. Snares and shotgun cartridges were each found in 13 squares, with 8 squares containing both, and marked trails in 17 squares. The highest ranked model predicting rule-breaking occurrence only included distance to the nearest settlement as a predictor, which showed a negative relationship with the presence of rule-breaking signs (n=53; coefficient = -0.001; standard error = 0.0002; z= -2.72; p<0.01, Table 1).

Power to detect change

Detecting changes in the rule-breaking occurrence required a relatively large number of squares to be surveyed and for the smallest change simulated, a 25% decrease, power was low even with large sample sizes (200-400 squares, approximately 30-50% of the study area, Figure 2).

There was considerable improvement in power if squares were surveyed six times compared to three. For example, detecting a 75% increase in hunter population required surveying approximately 200 squares six times, compared to >300 squares surveyed three times. Power was also improved by optimising the size of survey squares (Figure 3). For simulations with six survey visits per square the best strategy was to survey many squares of a smaller size. A survey of 0.5 km^2 squares with six visits required a sample size covering 15% of the study area (n=210 squares) to detect a doubling in the population at a power of >0.8. By contrast 35% coverage was needed to achieve the same power with squares of 1 or 2 km^2 (n=241 and 139 squares, respectively). For scenarios with three visits per square, there was an inconsistent pattern. At large sample sizes (>20% coverage of the study area), the best strategy was to survey squares of 2 km^2, with 1 km^2 being the least efficient strategy. However, at smaller sample sizes the best approach was to sample a greater number of small (0.5 km^2) squares.

Hunter home-range size had a large effect on the estimated power required to detect a doubling or halving of the hunter population (Figure 4). When hunter home-ranges were large (>4 km), power to detect changes in the hunter population was small (<0.8), even when 55% of the study area (or 380 squares) was surveyed. By contrast, when hunter home-ranges were small (<4 km) power to detect change was much higher, with a sample coverage of 15% (100 squares) sufficient to detect a doubling or halving of the hunter population with six survey visits per square.

In all scenarios of hunter ranging, power was lower for surveys with only three visits per square compared to six visits. However, when hunter ranges were small, there was only a slight advantage to be gained by monitoring six times rather than three. Detection of a 100% increase in hunting with power >0.8 could be achieved with similar sample sizes for three visits as for six visits, where hunter range size was small (1.5 or 2 km). Therefore, the required sample effort both in terms of number of squares, and number of visits per square, was considerably lower when hunters have restricted ranges.

Table 1
Ranked models predicting factors influencing rule-breaking occurrence according to AICc values and AICc differences

Model rank	Model parameters	K	AICc	*ΔAICc*
1	Village	2	63.19	0.00
2	Village+village∩	3	64.58	1.39
3	Village∩	2	64.87	1.68
4	Altitude∩+village	3	65.13	1.94
5	Altitude+village	3	65.20	2.01
6	Liberia+village	3	65.26	2.07
7	Liberia+village+village∩	4	66.69	3.50
8	Altitude∩+village∩	3	66.69	3.50
9	Altitude+village+altitude*village	4	66.79	3.59
10	Altitude+village∩	3	66.80	3.61

K indicates the number of parameters, AICc the Akaike's Information Criterion for small samples and ΔAICc the scaled AICc relative to the top ranked model. Model terms included linear and quadratic (∩) altitude and distance to the nearest village terms, a linear term for distance to the international border with Liberia, and an interaction term altitude*village and included the log of transect length as an offset term. Models were GLMs with quasibinomial errors and used a logit link function

DISCUSSION

The power analyses presented here, and the field data upon which they are based, were designed to help develop a programme for monitoring rule-breaking activities, such as hunting, in a protected forest national park in Sierra Leone. We present baseline field data of prevalence of rule-breaking behaviour, and used simulation-based models to explore the way in which basic elements of monitoring design, such as size of sampling units and number of survey visits, and behaviour of hunters, such as ranging, may influence the likelihood of detecting changes. We show hunting to be relatively widespread in GRNP despite its protected status and demonstrate that repeating the baseline survey of 53 survey squares in a 690 km^2 area would be insufficient to detect any changes in hunting activity. Monitoring could be improved by increasing the number of visits to squares and by optimising the survey square area, with the highest power achieved for survey strategies of many, small squares, visited at least six times each. Finally, the simulations show that the spatial aspects of rule-breaking behaviour in terms of how far individual hunters range can have substantial consequences for monitoring efficiency. We conclude that repeating the methods applied in our baseline survey would be impractical and ineffective as a monitoring strategy, due to the large survey effort required and the risk of uninformative results if hunters operate over large ranges.

The new field data presented here suggest that rule-breaking activity in GRNP is mainly associated with bushmeat hunting, and is widespread with signs found in 66% of 1 km-squares

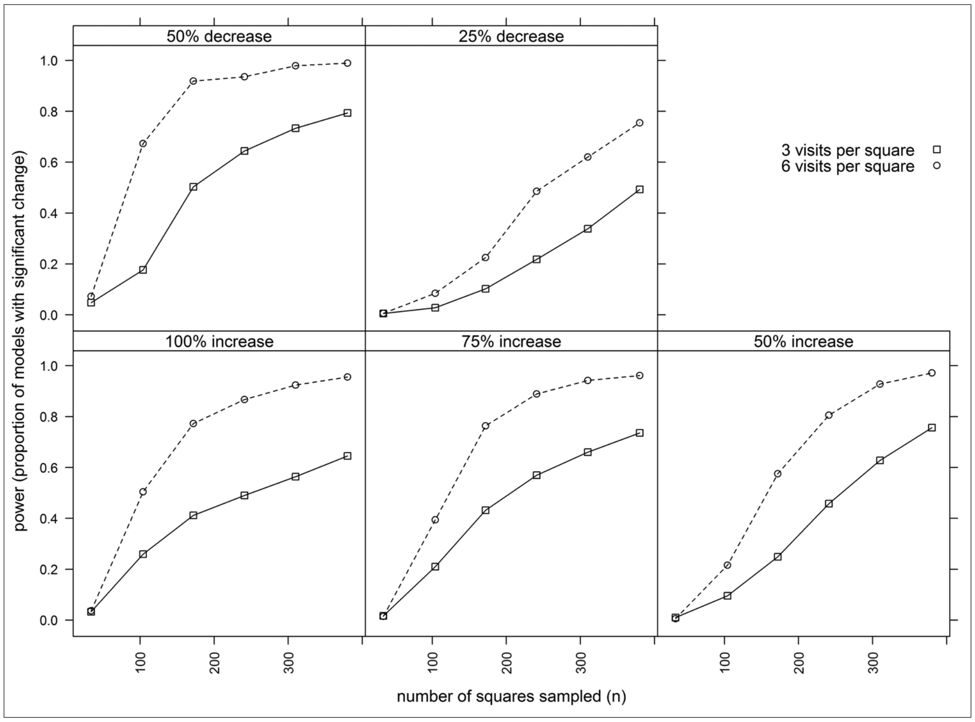

Figure 2
Power to detect change in rule-breaking based on an occupancy model
Note: Three visits and six visits per surveyed square for 50% and 25% decreases (upper panels) and 100%, 75% and 25% increases (lower panels) in hunter population size

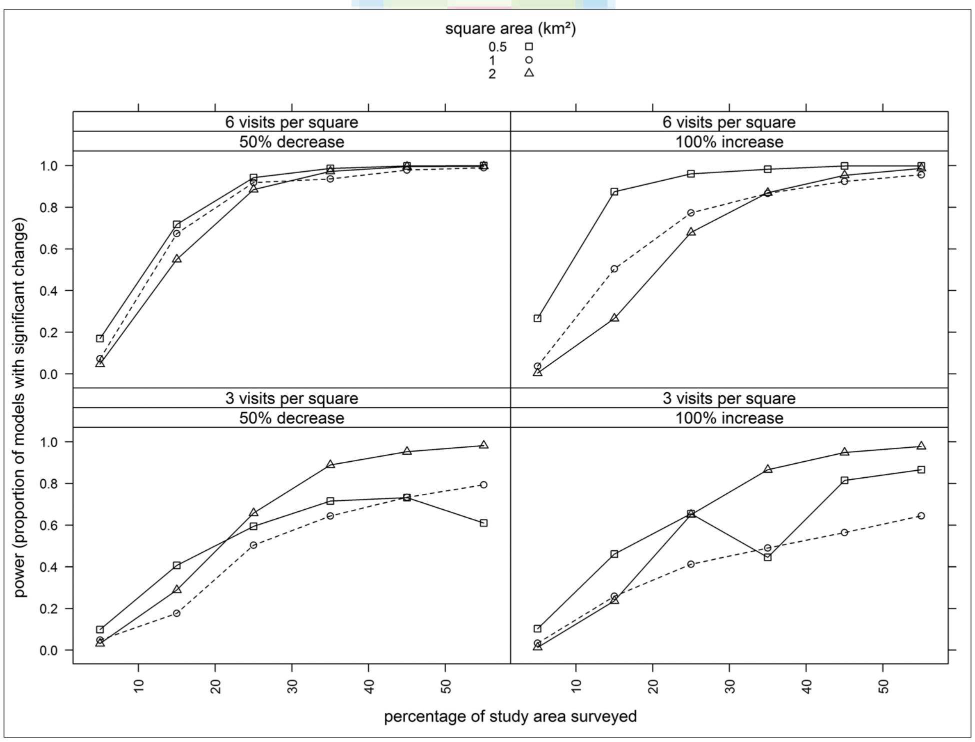

Figure 3
Power to detect a 50% decrease and 100% increase in rule-breaking under different scenarios of survey square area
Note: Three alternative scenarios of survey square area, 0.5, 1 and 2 km, under a sampling strategy of three and six visits per square

at encounter rates of one sign per 0.5 ± 0.7 km. Comparing this threat level with other protected forests in western Africa is difficult due to differences in survey methods, but they are broadly comparable with those recorded for forests in

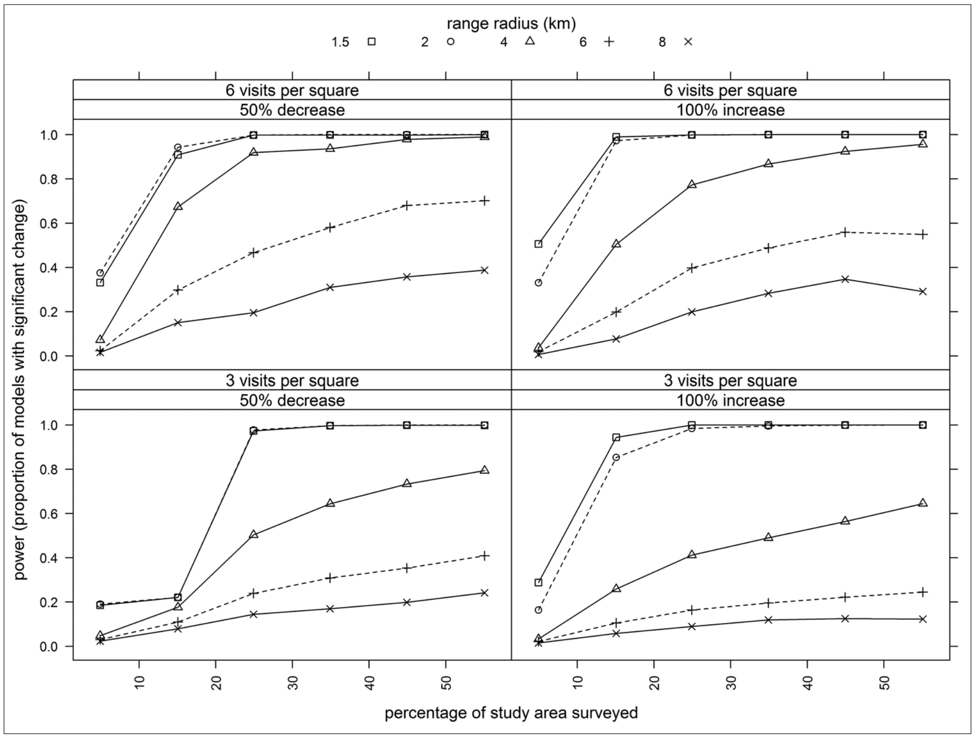

Figure 4

Power to detect a 50% decrease and 100% increase in rule-breaking under different scenarios of hunter range size

Note: Alternative scenarios of hunter ranging behaviour with a hunter range radius of 1.5, 2, 4, 6 and 8 km under a sampling strategy of three and six visits per square

adjacent Liberia, 0.5 ± 1.3 per km (Tweh et al. 2014) and 0.11-0.81 per km (Vogt 2011). The spatial distribution of rule-breaking signs was positively related to proximity to human settlements, but this relationship was relatively weak. For instance, we found hunting signs in 74% of squares within 1.5 km of the boundary and 50% of squares more than 2.5 km from the boundary. Accessibility is a known correlate of hunting pressure in protected areas (Wato et al. 2006, Watson et al. 2013) but at GRNP, access appears to be only a minor deterrent to hunting. This may be due in part to the shape of the park itself, which is formed of three non-contiguous forest blocks (the maximum distance to the nearest settlement from anywhere in the park is 8.3 km).

There is growing recognition that bushmeat hunting is a critical and widespread threat for tropical forest wildlife, particularly in Africa (Abernethy et al. 2013), yet hunting remains poorly understood and quantified. Our baseline survey describes hunting pressure across a relatively long time-frame, in a protected area that has been actively protected for several years. We measured signs that may have accumulated over many years, but were difficult to age in the field, such as spent shotgun cartridges (observed in 24% of squares). Law enforcement resources at GRNP are high relative to many protected forests and in the three years since the baseline survey was conducted, ranger patrols have increased in frequency, with effort now targeted using the spatial monitoring and reporting tool SMART (SMART Conservation Software 2013) to analyse patrol data on a monthly basis. Forest monitoring is undertaken within the context of significant livelihood interventions amongst forest-edge communities from which both subsistence and commercial hunters have been known to operate (Davies and Richards 1992). That hunting is illegal is widely known but the results of this work; showing widespread low levels of hunting, suggest more proactive approaches may be required to reduce these levels.

Our simulations demonstrate that at GRNP simply replicating the baseline survey of 53 survey squares (representing 8% of the study area) would be insufficient to detect change under any scenario. Detecting even large changes in rule-breaking occurrence would require a considerable increase in survey effort in terms of the number of squares surveyed and the number of visits per square. For example, the total survey effort required to detect a 75% increase or a 50% decrease in hunting was approximately 20 times the effort of our baseline, under our parameters for hunter behaviour. Detecting smaller, arguably more realistic changes, such as a 25% decline in hunting, would require a sample almost 50 times the baseline, visiting at least 400 squares six times each.

There were limited opportunities to improve efficiency of the survey design. We manipulated two aspects of survey strategy, the number of visits and the survey square area. Power was greatly improved through increasing the number of survey visits from three to six per square. This was expected because increasing the number of visits reduces uncertainty in detection probability, and therefore reduces the standard errors of hunting estimates. In practice however, carrying out six visits to squares may be as costly as surveying additional squares, and the optimal strategy will depend on relative costs.

Survey square area also had an effect on power to detect change. When we compared alternative survey designs that gave the same overall spatial coverage (i.e. fewer, larger squares versus many, smaller squares), we found that reducing the square size in favour of surveying more squares improved power in scenarios with six visits per square. By contrast, with only three visits per square, the most effective approach was to survey larger squares provided the sample size was above a minimum threshold. Larger squares gave higher overall detection probability and provided a more sensitive measure of the number of hunter's ranges (which themselves are large in size). Therefore, if we ignore the extra effort required to survey a larger area, then larger square sizes give the better power to detect change than the same number of small squares. However, when sample effort was measured in terms of total area surveyed, this advantage was generally outweighed by the higher sample size obtained from monitoring many small squares. The exception to this was for scenarios with only three visits per square, when the uncertainty in the detection estimate meant the advantage of larger squares reliably detecting hunter ranges outweighed the benefits of increased sample size. In practise, basic information about the spatial and temporal variability in hunting signs would allow managers to identify the most appropriate square size, given the specific aims of monitoring.

Importantly, the simulations demonstrate that hunter behaviour is a key consideration in the design of monitoring strategies. As home-range size of hunters increases, the ability to detect changes in their number declines. This result is not unexpected, occupancy will tend to provide a relatively insensitive measure of rule-breaking in scenarios where hunters have large, overlapping ranges because the addition of new hunters does not greatly alter the overall spatial extent of hunting. We found that a relatively small change in hunter behaviour produced substantial differences in the level of survey effort required. For example, if hunter home-range size was >6 km^2 rule-breaking changes could not be detected at even the largest sample sizes of >300 squares (55% of the study area), but at range sizes of <2 km^2 there was an 80% chance of detecting a doubling or halving of the hunter population if only 100 squares (15% of the area) were surveyed. This suggests that under plausible scenarios of hunter behaviour, monitoring based on presence of hunting in 1 km-squares may be relatively uninformative. There is little empirical data describing hunter ranging patterns. Informal interviews with hunters operating within the (unprotected) Liberian part of the Gola forest, suggest that a 6-8 km range radius will likely be at the upper limits of most hunter's ranges, with travel times of 3-4 hours generally considered the maximum distance a hunter will walk from a camp. This is supported by published studies from central Africa, which document mean trapping distances from camps of 2-3 km (Kümpel 2006, Rist et al. 2008) although larger distances are recorded for trappers operating from villages of 6.5-15 km (Abernethy et al. 2013, Coad et al. 2013).

The influence of movement parameters on monitoring sensitivity may make some forms of rule-breaking easier to monitor. For example, subsistence hunting could be more spatially structured compared to commercial hunting, making changes easier to detect (Jachmann 2008). Differences in ranging behaviour linked to types of hunting have been described elsewhere, although data are lacking for western Africa. Kumpel et al. (2010) distinguish between three typical hunter profiles in Sendje, Equatorial Guinea, showing that low-impact hunters operate closer to the village than high-impact hunters (average distances of 5.5 km and 32.4 km respectively). In addition, changes in hunter behaviour through time could have significant consequences for monitoring efficiency. For example, Coad et al. (2013) document changes in spatial behaviour of hunters across a six year interval, linked to hunter demography and local economic opportunities. A number of studies find evidence that hunters increase distances travelled in response to local prey depletion (Gill et al. 2012; Coad et al. 2013). Our results indicate that where possible, managers should consider behavioural attributes of rule-breakers in the design of monitoring strategies to avoid wasting resources. Greater efficiency may be achieved by tailoring survey design for specific types of rule-breaking, while adaptive monitoring strategies can be used to account for shifts in behaviour through time.

Our simulations provide only approximate and relative estimates of required sample effort and are subject to various caveats. First, we greatly simplify hunter movement patterns, whereas true hunter behaviour is likely to vary between individuals and may be influenced by many factors including prey distribution (Critchlow et al. 2015), local features such as watercourses (Kümpel 2006), or law enforcement efforts (N'Goran et al. 2012). Second, we assume hunter effort is constant, regardless of range size, and so an increase in range results in the detection probability in any one square within the range decreasing. Although this seems a reasonable assumption, if violated (e.g. if hunters increase effort per km when operating across larger areas), monitoring efficiency would not show such a dramatic decline with increasing range size of hunters. Third, we assumed that hunter home-ranges can overlap extensively. If they do not then monitoring power would be higher than our estimated values under all scenarios tested. Unfortunately, no information is available to assess the likelihood of this assumption. However, informal interviews with hunters in Liberia suggest hunters have loosely defined territories based on semi-permanent camps, but that these frequently overlap to some degree depending on the number of hunters. Finally, our sample effort estimates are taken from the extreme case of detecting a change between just two surveys, rather than considering regular, repeated surveys through time. In practice, long-term monitoring efforts will be more sensitive to detecting trends in hunting and in this regard our estimates are conservative.

Taken together, the power simulations indicate the methodology used in our baseline survey will be unsuitable as a monitoring strategy to detect changes in prevalence of rule breaking and that this will require alternative monitoring approaches. These could include assessing density of signs using distance monitoring approaches rather than spatial prevalence (Thomas et al. 2010), combining monitoring with ongoing research or ranger patrol activities to reduce overall costs and employing questionnaire-based methods (Jones et al. 2008). Recent developments in the latter that effectively anonymise incriminating responses to sensitive questions have been shown to be a valuable tool for assessing rule-breaking behaviour and provide better insight into socio-economic drivers of change that cannot be gained from direct questioning (St. John et al 2010, Nuno and St. John 2015). Some of the poorly understood parameters relating to hunting behaviour could be uncovered using such methods.

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