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Improving law enforcement effectiveness and efficiency in protected areas using ranger-collected monitoring data

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Abstract

Protected areas are fundamental for conservation, yet are constantly threatened by illegal activities, such as cattle encroachment and wildlife poaching, which reduce biodiversity. Law-enforcement is an essential component of reducing illegal activities. Although necessary, law-enforcement is costly and its effectiveness in the field is rarely monitored. Improving ranger patrol efficiency is likely to decrease illegal activity occurrence and benefit biodiversity conservation, without additional resource implications. Using ranger-collected data, we develop a method to improve ranger patrol allocation, targeting different combinations of conservation priorities, and predict that detections of illegal activities can be greatly improved. In a field test in Queen Elizabeth Protected Area, Uganda, we increased detections of illegal activities in some cases by over 250% without a change in ranger resources. This easily implemented method can be used in any protected area where data on the distribution of illegal activities are collected, and improve law-enforcement efficiency in resource-limited settings.

Introduction

Illegal activities such as poaching are increasing and a major threat to biodiversity (Hilborn et al. 2006; Biggs et al. 2013). While policies such as trade restrictions, education and financial penalties can help reduce illegal activities (Rosen & Smith 2010; Treves & Bruskotter 2014), protected area conservation requires law enforcement policies at all levels, including ranger patrols, intelligence gathering and effective criminal justice systems (Challender & MacMillan 2014; Tranquilli et al. 2014; Rauset et al. 2015). Law enforcement in the field is fundamental for successful conservation because the rangers on the ground represent the primary deterrent that render higher-level legal policies effective (Leader-Williams & Milner-Gulland 1993; Rowcliffe et al. 2004). Population declines and

local extinctions, particularly of large mammals, continue, even within protected areas (Craigie et al. 2010; Laurance et al. 2012; Di Marco et al. 2014). Although law enforcement is crucial for reducing illegal activities (Geldmann et al. 2013) it represents the single largest expenditure in many protected areas (Jachmann 2008; Plumptre et al. 2014), suggesting that increasing the efficiency of ranger patrol activities should be a priority.

The efficiency of law enforcement is crucial to its success; when patrols are perceived to be more effective there is likely to be less illegal activity (Fischer et al. 2014), while simulations suggest increasing detection probability improves effective enforcement (Milner-Gulland & Leader-Williams 1992). However, effective management is often restricted by insufficient financial resources (Di Minin & Toivonen 2015). In criminology, spatial crime mapping is now being used to inform and improve the efficiency of law enforcement resources (Andresen 2005; Chainey et al. 2008). Despite the potential benefits, there have been few studies assessing the efficiency with which rangers are deployed in the field, though limited evidence available suggests efficiency may be low and targeting of patrols is necessary. For example, Plumptre *et al.* (2014) report that despite 60% of the Greater Virunga Landscape being visited by rangers, they only effectively patrol 22% of the landscape. Similarly, theoretical studies suggest that significant financial savings could be achieved through better allocation of law enforcement (Dhanjal-Adams et al. 2015).

Given the paucity of empirical studies of ranger efficiency, it is unsurprising that few methods for improving ranger patrols exist. Recently, theoretical work has explored security games (a branch of game theory) for allocating resources to protect wildlife and fisheries (Haskell et al. 2014; Yang et al. 2014; Nguyen et al. 2016), agent based models of poachers and rangers (Keane et al. 2012) and spatial models of optimal protected area design and patrolling (Albers 2010) as frameworks for thinking about optimising law enforcement. However, these methods, which rely on many assumptions, may struggle to cope with the complexity of illegal activities in practice: for example, we demonstrated that different illegal activities (e.g. poaching for high-value animal products versus

cattle encroachment) occur in different regions of a protected area, suggesting that the optimal ranger patrol strategies will differ for each threat (Critchlow et al. 2015).

Here we develop a method to i) identify the efficiency of ranger patrol strategies in relation to illegal activities patterns; ii) determine an improved patrol strategy for any given set of conservation priorities using the existing patrol resources and iii) assess the impact of improved strategies on the effectiveness of illegal activity detection. We apply this law enforcement allocation method to ranger-collected data from the Queen Elizabeth Protected Area (QEPA), south-western Uganda, and test it by changing patrol strategies at three ranger posts. This spatial crime mapping approach is applicable to any area that records the spatial occurrence of illegal activities, and can inform site-level patrol strategies.

Methods

Improving existing patrol effort:

The starting point for any method to improve allocation of rangers is at least one geographical map of illegal activity occurrence within the area of interest and a map of the current ranger effort. Here we used 500m resolution maps of six classes of illegal activity (e.g. encroachment and non-commercial animal poaching as defined in Critchlow et al. 2015) identified within the QEPA (Figure 1a). These data were collected over 15 years by Uganda Wildlife Authority rangers and entered into software designed to manage ranger-collected law enforcement data: MIST (Management Information SysTem) and SMART (Spatial Monitoring and Reporting Tool; <http://smartconservationtools.org>). These software are now used across many protected areas (Hötte et al. 2016). Our maps show the probability of illegal activity occurrence (Figure 1b) estimated using Bayesian, spatially explicit generalised additive models that explicitly account for detection biases (Critchlow et al. 2015), and these biases must be accounted for when producing accurate

occurrence maps (Stokes 2010; Keane et al. 2011). Full details of this method can be found in Critchlow et al. (2015) and are provided in the Supplementary Material.

With maps of occurrence and patrol effort, an improved patrol strategy for maximizing the detection of any given class of illegal activity is the strategy that places maximum effort in areas with maximum probabilities of occurrence of that class of activity (Ratcliffe 2004; Kennedy et al. 2010). (If detection probabilities vary spatially as a function of, e.g. visibility, improving patrols might be a balance between actual occurrence probability and detectability but in our mapping process we assume that the probability of detecting an illegal activity on any one visit to a cell is constant across space, with only effort (the number of visits to a cell) varying spatially). This can be implemented by arranging existing ranger patrol effort according to the ranked probabilities of each activity occurring per cell, such that the highest probability cells receive the greatest effort (Figure 1c). We use ranks to allocate effort, not direct proportions (which would be optimal) because we sought to maintain the actual realised distribution of ranger effort in order to maintain realism, but without this constraint improvements could be greater. Technical details and R code to implement all analyses are provided as Supplementary Material.

To identify the patrol strategy that simultaneously improves the detection of multiple classes of activity (e.g. maximise efficiency of detecting all six illegal activities simultaneously, or focus mainly on commercial animal poaching, but also include encroachment and other illegal activities as lower priorities) is more complex and requires managers to decide *a priori* on relative weightings for each class of activity. These weightings determine not the number of detections desired for each activity, but the proportion of overall resource that should be allocated to each problem activity, a decision that needs to be carefully considered by managers. Here, we illustrate three different strategies: one representing an even weighting of all six, a second focussing only on commercial and subsistence animal poaching (50% each), and one representing different proportional weightings (Proportional mix) to the two animal poaching categories and encroachment (40%, 40%, 20% respectively). If it

were decided that ranger resources should be evenly allocated between each illegal activity type irrespective of relative abundance of each activity, ranger effort should target all illegal activities simultaneously ('Evenly mixed strategy'). To calculate this we normalised the occurrence probability between classes such that the maximum was one and minimum zero, set cell values to the maximum normalised probability of any of the six illegal activities and used the rank of these probabilities to order existing ranger effort as before. For the three different strategies, we first weighted the normalised probability values for each illegal activity of interest according to the conservation priorities assigned to them and then selected the maximum as before. It is important to normalise probabilities before combining them, because different activities occur at different rates which, if ignored, will result in solutions that effectively sample only the commonest illegal activities, when rarer activities may be more important (Table S2 shows an alternative allocation targeting all illegal activities using raw probabilities, resulting in decreased detection of the majority of illegal activities, but an overall increase of total detections by 3.9%).

Predicting efficiency changes:

Because our occurrence maps are based on models which include an estimate of detectability (Critchlow et al. 2015)), we could estimate the expected number of detections of each activity type for any given spatial arrangement of ranger effort. To estimate number of detections (and associated uncertainty) for any given strategy, the improved patrol strategy is substituted in place of existing ranger effort (Figure 1d). For details on predicting changes in patrol efficiency, see Supplementary Methods.

Differences between current and improved strategies:

To identify areas where current patrol effort is either too high or too low relative to improved strategies we subtracted the two values. As a further step we recognised that there may be cells for which recommended patrol effort should always increase or decrease irrespective of conservation

priorities. Cells where increased effort is recommended were identified where current patrol strategy is below the minimum recommended effort when prioritising any of the five terrestrial classes of illegal activity (i.e. excluding fishing), cells where decreased effort is recommended indicate where current effort is always greater than the maximum recommended effort.

Field testing of improved patrol strategy:

Both control and test sites (Figure 2) were selected based on the quantity of ranger-collected data (MIST/SMART) from the previous two years and where there were a high number of patrols in the surrounding 5-8km of the patrol post. Control sites represented all remaining standard posts in the north of the QEPA that showed similar threats and had recorded at least 50km of patrols within 5km of the site prior to and during the testing period. The three ranger posts where patrol strategies would be manipulated were chosen based on ease of access, allowing regular data downloading, and because these are in known areas of high illegal activity occurrence (i.e. high occurrence of cattle encroachment, snares and firewood collection).

All data were collected from May to September 2015. Comparison data (MIST/SMART) was from January 2014 to April 2015 for the same patrol areas (i.e. 5km around each ranger patrol post) to ensure sufficient effort data was available for comparison of CPUE from both periods.

Across the test patrol posts, given the high probability of encroachment, plant harvesting and non-commercial animal poaching, the improved patrol strategy aimed to simultaneously target these three priorities. The improved patrol strategy was implemented using weightings of 40% encroachment, 40% non-commercial animal and 20% non-commercial plant (Figure S2).

To generate improved patrol strategies, all areas within 5km of the patrol posts within the jurisdiction of the post were assigned to a 500m grid (Figure 2b). A 5km area was because the majority of patrols already occur within 5km of patrol posts (Plumptre et al. 2014). For each patrol

post, coordinates within the grid cells were selected with a probability proportional to the improved patrol strategy, such that more coordinates fell in areas requiring high effort than elsewhere.

During the testing period rangers were given up to three coordinates to reach during their regular foot patrols each day. Fifteen coordinates were issued each month, reflecting the frequency of patrol activity. Rangers were asked to patrol as normal, including searching water holes, visiting areas of known previous illegal activity and walking animal tracks, while aiming towards the given coordinates. Rangers were asked not to travel directly from their ranger post to the coordinates. Once close to the coordinates (within 250m) rangers were encouraged to search more actively for evidence of illegal activities within a 500m radius of the location. Data was collected using CyberTracker and SMART software on CAT B15 Q mobile phones.

Assessing patrol effectiveness:

To assess patrol effectiveness we calculated catch per unit effort (CPUE) for each ranger post by dividing the number of illegal activities detected per kilometre walked. Because testing coordinates were restricted to within 5 km of a ranger post, CPUE was also restricted to data collected only within 5 km of each ranger post. CPUE was then calculated for the preceding 16 months from the same patrol areas, i.e. 5km around each ranger patrol post. Monthly variation in illegal activity occurrence is low (see Supplementary Material).

To test the effect of patrol strategy manipulation, we used Generalized Linear Models with a Gaussian error structure; the CPUE ratio was the response, with patrol post and the interaction between time (pre/post-testing) and patrol post type (control/test) as explanatory variables. All analyses were conducted in R 3.2.2 (www.r-project.com).

Results

Improved patrol strategies:

Improving patrol allocation for each activity is expected to increase the number of cells where illegal activities are detected (Table 1). The current patrol strategy visits between 28.9% and 62.4% of the cells with illegal activities that would be identified using strategies improved for each activity in turn. Improving effort allocation for any activity resulted in an increase in detections of most other categories of activity with respect to the current patrol strategy.

The evenly mixed strategy suggests effort should be directed to the periphery of the QEPA and near water channels (Figure 3a). It would result in around a 50% increase in detections in most illegal activities with respect to current detections, and should detect a minimum of 80% of the improved strategy for each class in turn (Table 1). Arranging patrols to focus different proportions of effort on illegal activities results in slightly different improved strategies, (Figure 3b) and detecting a minimum of 90% of the improved strategy for each class in turn (Table 1).

Irrespective of conservation priorities, areas where current patrol effort is too high, relative to the current patrol effort, are mostly in the south and central regions of the QEPA, whilst areas where current effort is too low are dominated by large areas in the north and south-east of the QEPA (Figure 3d).

Comparison of CPUE from test and control ranger posts:

Two of the test sites (Kahendero and Kabirizi) had a vastly greater CPUE in the 5 month testing period than CPUE in the preceding 16 months while at the third test site (Nymugasani) CPUE values were more similar from the two periods (Figure 4; Table S3). More illegal activities were recorded from the test posts during the testing period than prior to the testing period (Table S3). Across the three test ranger posts, altering patrol strategies had a significant effect on CPUE ($F_{1,9} = 6.61$, $P = 0.033$).

Discussion

We described a simple method using maps of illegal activity occurrence to improve the effectiveness of ranger patrols. We found that current patrol strategies in the QEPA may be sub-optimal, predicting increases of around 50% in cells where illegal activities are detected if allocation of existing patrols improved. In a field trial, we showed that detections of illegal activities can be substantially increased by directing ranger effort using our allocation strategy. These results are directly comparable to successful implementation of spatial crime mapping systems in urban environments (Chainey et al. 2008; Delle Fave et al. 2014) and support the suggestions of Linkie *et al.* (2010) and Dhanjal-Adams *et al.* (2015) that the efficiency of law enforcement effort can easily be improved. Whilst the overall results are therefore unsurprising, the scale of the potential benefits is notable.

Implementation of our allocation method and field test makes some assumptions and could be improved. For example, rearranging effort in proportion to occurrence ignores the fact that rangers operate out of fixed bases and follow linear patrol routes. Similarly, due to constraints on the degree to which rangers could be directed by us, control and treatment posts were not randomly allocated. Consequently we are not certain that increases in CPUE at test sites were due to improved allocation per se, or simply from increased vigilance of rangers when applying new methods (the Hawthorne effect - McCambridge et al. 2014).

At the Nymugasani patrol post there was little change in CPUE. This post differs from the other two test sites because encroachment for cattle grazing is the dominant illegal activity here (Supplementary material; Critchlow et al. 2015) and allocating effort towards animal poaching may have simultaneously reduced detections of encroachment. This suggests that practical improvements may be possible through first improving effort allocation across the area as a whole, then enhanced within sectors based on local priorities.

Further testing of altered patrol allocation in more sites and for longer periods is needed to address the wider impact of these patrol strategies, especially because poacher behaviour is likely to alter in

relation to the changes in patrols (Keane et al. 2008). Although illegal activity patterns in QEPA are relatively constant over time (Critchlow et al. 2015), short-term spatio-temporal changes do occur and continuously updating recommended patrol effort allocation using the most recent data (e.g. SMART) is important. To enable this, monitoring of low probability areas must be built into patrol responsibilities to provide early detection of spatio-temporal changes, such as planning daily routes to ensure a varied patrol distribution while still targeting areas with high occurrence probability.

Game theoretic models (Haskell et al. 2014) and community interviews (Fischer et al. 2014; Harrison et al. 2015) suggest deterrence has a key role in determining law-enforcement efficiency. Empirical data on deterrence is rare, although a recent study suggests deterrence effects resulted in lower poaching levels (Linkie et al. 2015). Areas with currently low probabilities of occurrence may reflect the deterrent effect of relatively high patrol coverage, yet our effort allocation method suggests these areas are over patrolled. It is unclear whether ranger effort should be directed primarily towards the areas where illegal activities currently occur, or towards preventing activities from occurring in core zones. Resource allocation methods used in conservation planning (e.g. Marxan) could also be used to achieve an optimum deployment of rangers, aiding the design of effective strategies (Plumptre et al. 2014). Furthermore, optimal allocation of patrols can only be determined when the relative importance given to each illegal activity is explicit and is an area that needs research.

Despite these uncertainties, our methods identify areas to which ranger patrols can be directed with positive impacts in the field. By analogy with work on spatial crime mapping, we consider that our method offers potential for improving law enforcement within protected areas without increasing the resources required for patrols.

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Table 1. Expected mean number of cells with detections of illegal activities within the Queen Elizabeth Protected Area, Uganda, assuming the improved patrol strategies for each illegal activity type. Patrol strategies are defined by matching patrol effort according to cells with high probability of illegal activity. Values in bold represent the number of expected cells recorded with each illegal activity that the improved strategy would report. Values in brackets represent the percent of the improved strategy achieved for each alternative strategy.

		Expected number of cells with detections of:					
		Animal Non-commercial	Animal Commercial	Encroachment	Fishing	Plant Commercial	Plant Non-commercial
Effort focused on:	Animal Non-commercial	1511 (100%)	130 (47.4%)	696 (62.1%)	302 (57.6%)	150 (55.6%)	358 (64.4%)
	Animal Commercial	733 (48.5%)	274 (100%)	396 (35.3%)	238 (45.4%)	70 (25.9%)	202 (36.3%)
	Encroachment	965 (63.7%)	109 (39.7%)	1121 (100%)	304 (58.0%)	175 (64.8%)	376 (67.6%)
	Fishing	881 (58.3%)	146 (53.3%)	629 (56.1%)	524 (100%)	110 (40.75)	286 (51.45)
	Plant Commercial	827 (54.7%)	98 (35.8%)	623 (55.6%)	261 (49.8%)	270 (100%)	362 (65.1%)
	Plant Non-commercial	966 (63.9%)	111 (40.5%)	729 (65.0%)	300 (57.3%)	207 (76.7%)	556 (100%)
Patrol strategies - expected number of cells with detections of:	Current	763 (50.5%)	171 (62.4%)	583 (52.0%)	205 (39.1%)	78 (28.9%)	257 (46.2%)
	Evenly mixed	1209 (80.0%)	219 (79.9%)	958 (85.5%)	449 (85.7%)	240 (88.9%)	484 (87.1%)
	50% each animal poaching	1398 (92.5%)	250 (91.2%)	615 (54.9%)	296 (56.5%)	121 (44.8%)	317 (57.0%)
	Proportional mix	1357 (89.8%)	243 (88.7%)	932 (83.1%)	308 (58.8%)	130 (48.1%)	343 (61.7%)

Figure Legends

Figure 1. Example of process to determine improved effort allocation for commercial animal poaching in the Queen Elizabeth Protected Area, Uganda (a). (b) Current estimated probability of occurrence; (c) Improved ranger patrol strategy; (d) Expected number of detections of animal poaching with current effort and using an improved strategy.

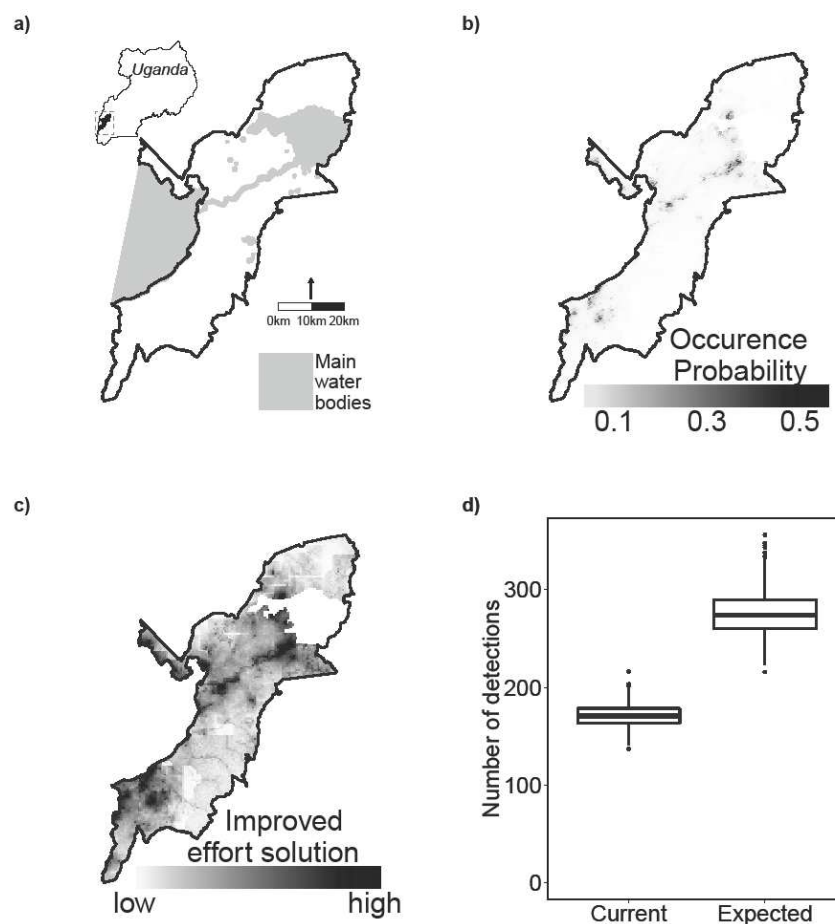


Figure 2. Selected ranger posts in the Queen Elizabeth Protected Area. a) Locations of test and control posts; b) area around each test patrol posts (boxed areas - 500m grid cells) used to compare data collected pre and during testing period.

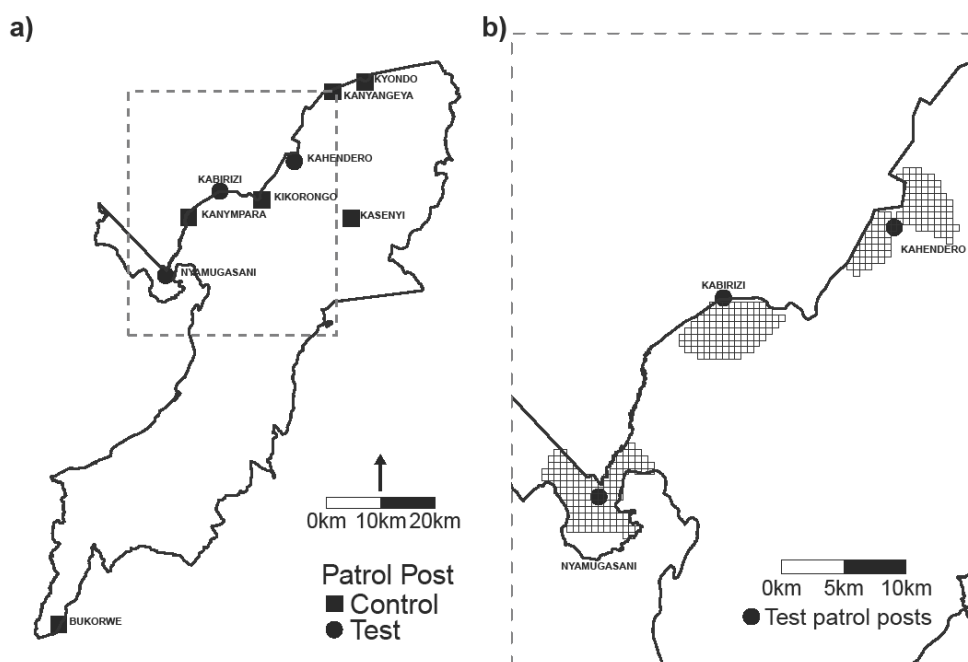


Figure 3. Patrol strategy recommendations in Queen Elizabeth Protected Area; (a-c) improved patrol strategy scenarios to increase efficiency of detecting illegal activities; (d) recommended changes in patrol effort with respect to current patrol strategy irrespective of conservation priorities within the QEPA.

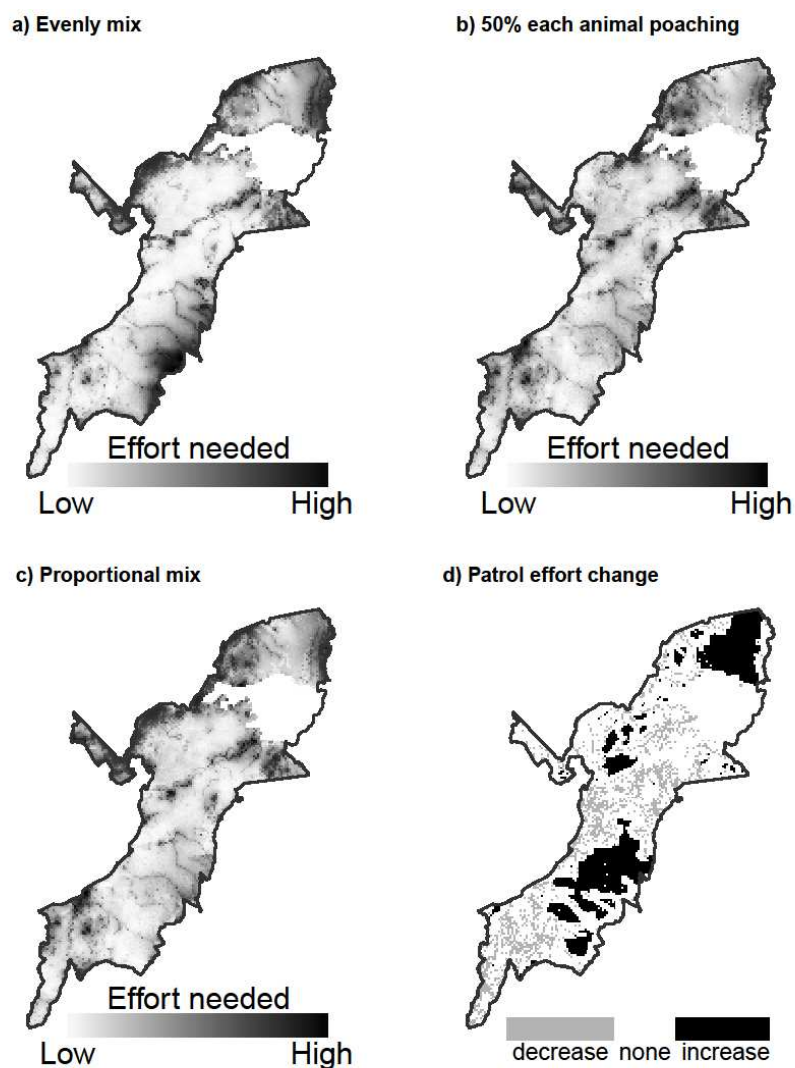


Figure 4. Comparison of catch per unit effort (CPUE) between the three ranger patrol posts where patrols were manipulated (test sites) and the seven patrol posts where no changes to patrol strategies were made (control sites). Error bars represent standard error of the mean.

