Analysing trends of illegal activities from ranger-collected data in the Queen Elizabeth National Park

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1 Introduction

In this report we provide a draft manuscript of how our method can be applied to analyse illegal activities using Management Information System (MIST) data from a single national park: the Queen Elizabeth National Park (QENP), Uganda. In addition, we detail: how we have gone about this process, any problems encountered, the key results from the initial analysis, and finally the immediate plans and future steps.

The aims of this primary analysis were to develop a method to use ranger-based monitoring data (1) map the spatial distribution of illegal activities, (2) identify the influential drivers of these activities, and (3) assess the spatial and temporal trends of illegal activities. Our current approach can be applied across multiple protected areas, and importantly accounts for observation effort. With accurate knowledge of the locations and processes that drive different types of illegal activities, rangers can more effectively target problems.

Existing methods to assess patterns of illegal activities from ranger based monitoring include analysis of raw patterns or use of encounter rates. However, these simple methods give highly biased results as the statistics used are developed for situations where survey data is random or evenly spread across a protected area, and ranger-based monitoring is focussed on areas where illegal activities are expected to be highest. Encounter rates or catch per unit effort (CPUE) are an improvement on analysis of raw or uncorrected data, but have their own additional biases. For example, CPUE may not reflect the underlying trends of illegal resource use if the efficiency of ranger patrols improves over time. Additional pitfalls of the CPUE method are that it assumes reporting of illegal activity is proportional to patrol effort and that observing illegal activities is constant across space and time. This is unlikely because ranger patrols will rarely perfectly cover a survey area, and proportionally more effort will be needed to detect remaining illegal activity (Keane, Jones & Milner-Gulland 2011). Depending on the particular assumptions made, the consequences of these biases may lead to systematic over- or under-estimate of illegal activities with little information on the scale of the bias, and always lead to uncertain trends.

Recognising this problem, we have taken an analysis approach that accounts for surveillance effort by estimating the probability of reporting an illegal activity independently from assessing the biotic and abiotic drivers of illegal activities. This type of analysis is based on an approach used to analyse volunteer-based records of bird distributions and change in regions with highly variable observer effort in space and time (Beale *et al.* 2013) and is fully described in a recent paper describing species distribution modelling (Beale, Brewer & Lennon 2014).

2 What the process has involved

Our initial step was to identify the types of illegal activity as reported in the MIST database and re-classify these to six broad categories; Encroachment, Fishing, Plant Commercial, Plant Non-Commercial, Animal Commercial, Animal Non-Commercial (Table 1).

Table 1. Classification of illegal activities within the Queen Elizabeth National Park

Classification	Example of values in MIST database[1]	Number of records
Encroachment	Livestock grazing, mining, trespassing	1570
Fishing	Fishing	443
Plant Commercial	Pitsawing, cultivation	260
Plant Non Commercial	Medicinal Plants, grass harvesting	605
Animal Commercial	Hippo, Elephant, Buffalo	241
Animal Non Commercial	Snares, other animal hunting, honey harvesting	1589

The next step was to manually check the MIST data, firstly by plotting the geographic locations to identify unlikely and incorrect records, for example those with locations hundreds of kilometres away from the protected area. Then secondly, searching through each patrol for incorrect times and dates, such as patrols dates across multiple years or months, or repeated times throughout the patrol. Although time consuming, this process was important because calculating

[1] From Observation or Observation_Code columns within the MIST database

ranger patrol effort across the QENP relies on accurate date, time and location information. This data cleaning resulted in the removal of about 7% (*n* = 6485) of the records. This data was then aggregated to a 500m resolution grid (~11000 cells).

A measure of observer effort is a crucial for the modelling process, but because ranger locations are recorded by rangers up to 30 minutes apart, we do not know the exact route of all patrols. Using the ranger patrol locations, we estimated the spatial distribution of patrol routes to determine observer effort using two methods. Firstly we calculated a probability density (utilisation distribution (UD)) based on the time and movement of each ranger patrol on a 500m grid (Papworth *et al.* 2012). The UD is derived by estimating the likely trajectory between known points as reported during ranger patrols. This method identifies cells, across the full grid, that are likely to have been passed through by rangers during their patrols. Secondly we generated a density surface, again on a 500m grid, based on the raw count of the number patrols that have passed through a grid cell given the trajectory of each patrol. All statistical models were run twice, i.e., for each measure of ranger patrol effort. However, the models run using the raw counts per grid cell (the second effort measure) were poor and many models did not converge or complete unlike the models using the UD. For future analyses, not running the models using the second patrol effort measure (raw counts) on a similar sized dataset and across a similar sized spatial area, we anticipate this would save more than 800 hours of computer and analysis time.

We identified a number of variables that are likely to influence movements of ranger patrols and poachers, and the distribution of natural resources, including measures of primary productivity, terrain wetness and habitat type (Table 2). The methods for obtaining these data, such as downloading and converting Net Primary Productivity (NPP) satellite imagery from MODIS (http://reverb.echo.nasa.gov), are now automated and can be applied across other protected areas with minimal changes to the current scripts.

Table 2. Variables hypothesised to influence patterns of illegal resource use in Queen Elizabeth National Park (QENP).

Variable	Data Source	Predicted effect	Summary	Range of values
Net Primary Productivity (NPP)	MODIS (MOD17A3)	+/-	Mean biomass productivity between 2000 and 2010	0 - 1.72 (kg C/m^2)
Topographic wetness	ASTER (ASTGTM2)	+	Index of soil moisture	-6.4 – 8.2 units
Distance from roads	Global GIS Database: Africa	-	Distance from centroid of grid cell to the nearest road	0.001 - 11872.57 (km)
Distance from rivers	Global GIS Database: Africa	-	Distance from centroid of grid cell to the nearest river	0.37 – 6079.47 (km)
Slope	ASTER (ASTGTM2)	-	Mean slope	0 – 0.74
Wildlife density	WCS surveys	+	Animal density	0 – 123.75 (2.5 km^2)
Habitat	MODIS (MCD12Q1)	+/-	Forest/Savannah/ Other	
Travel cost	Rivers, Roads, wetness, habitat	+	Index of accumulated travel cost from villages and towns to centroid of grid cell	0 – 1500 units

Measures of productivity and vegetation indices, such as NPP, are associated with the distribution of wildlife (Loarie, van Aarde & Pimm 2009; Duffy & Pettorelli 2012; de Boer *et al.* 2013) and suitability for grazing, with higher density of animals in areas of high productivity (Pettorelli *et al.* 2009). Areas of high wetness and areas in close proximity to water are also likely to predict areas with higher density of animals (Redfern *et al.* 2003; Becker *et al.* 2013). We expected evidence of illegal activities to occur closer to roads, since roads improve access and have been shown to predict illegal activities in previous work (Wato, Wahungu & Okello 2006; Watson *et al.* 2013). In addition, habitat variation will influence resource density and travel cost, with illegal activity more probable closer to human habitation and on areas of open savannah (Hofer *et al.* 2000; Plumptre *et al.* 2014).

In addition to these variables we created a surface of travel cost, for poachers, from villages and towns to obtain a measure of accessibility to all areas within the QENP. Calculating an accurate travel cost map from multiple variables was a very time consuming process, but we wanted to get a realistic measure of accessibility. For example, crossing large rivers or travelling through dense forest habitats is likely to be more dependent on roads and bridges across such terrain. Using the digital sources identified in **Error! Reference source not found.**, each of these variables was extracted at 500 m resolution grid, with finer-scale data aggregated using the mean value.

Additional predictor variables could be used in future analyses. In an initial analysis we included measures of human and livestock densities, but these were poorly correlated with locations of reported illegal activities, perhaps because these were derived from global datasets (Gridded Livestock of the World and Gridded Population of the World). Information on these variables at a finer scale may be useful in future. In addition, employment and income levels have been linked to illegal resource use (Kaltenborn, Nyahongo & Tingstad 2005; Knapp 2012; Nuno *et al.* 2013), and a fine scale measure of household employment or income levels could provide other useful predictor variables.

3 Statistical Analyses

To analyse these data and identify spatial and temporal patterns in illegal activities we fitted a series of Bayesian, spatially explicit occupancy models (see Beale *et al.* 2014 for full details of this method). The models have three components: (1) a process model defining the relationship between covariates and illegal activities, (2) a component to account for spatial autocorrelation and (3) a model to explicitly account for temporal and spatial heterogeneity in detection of illegal activities by ranger patrols (i.e., ranger patrol effort as described above). Together, these three components allow estimation of the underlying patterns of illegal activities independently of the probability of detecting such activity. We fitted separate models to each class of activity across the entire time period as well as for annual and monthly subsets.

Although multiple statistical models can be run at the same time, for example across multiple years, not all models completed successfully using the basic model structure: these are complicated models and the data on some activities are relatively rare year on year (Table 3). After identifying those that did not complete, we tried couple of methods at getting the models to converge, by altering the prior information provided to each model. Understanding the issues with the statistical models, such as suitable prior information and imputation of data where data is missing was a time consuming processes, but there is now a suitable protocol in place for future analysis of other protected areas.

4 Results

4.1 Locations of illegal activities and distribution of ranger patrols

There has been an increase in the raw reporting rates of all illegal activities between 1999 and 2012 (Table 3; Figures 1-14). The peak reporting of Encroachment and Non-Commercial animal poaching was in 2009 and both have since decreased. Records of illegal fishing have continually increased. Commercial animal poaching was greatest in 2007 and has been reported few times annually until 2012. Locations recorded outside the national park boundary (Figures 1-14) were not included in the statistical analyses. These raw data show primarily the increase in reporting activity via the MIST database rather than genuine changes in rates of illegal activity, demonstrating the importance of accurate modelling.

Table 3. Annual records of illegal activities in the Queen Elizabeth National Park classified in to six separate categories and annual variation in reporting effort. Ranger reporting effort includes all recorded positions and records of illegal activities.

	Encroachment	Fishing	Plant Commercial	Plant Non-Commercial	Animal Commercial	Animal Non-Commercial	Ranger reporting effort[2]
1999	5	0	0	0	0	27	533
2000	3	1	0	1	4	18	353
2001	3	3	1	12	13	27	835
2002	10	14	1	15	24	79	1385
2003	58	22	6	4	2	78	1716
2004	67	20	1	12	4	109	3175
2005	79	33	10	37	10	95	4803
2006	259	59	22	50	15	176	8479
2007	188	26	29	90	40	109	6078
2008	184	16	24	72	24	178	8582
2009	271	31	49	97	23	248	10421
2010	198	43	32	102	30	179	12623
2011	142	95	51	58	32	109	12691
2012	103	80	34	55	20	157	12634

[2] Number of locations reported each year from the MIST database

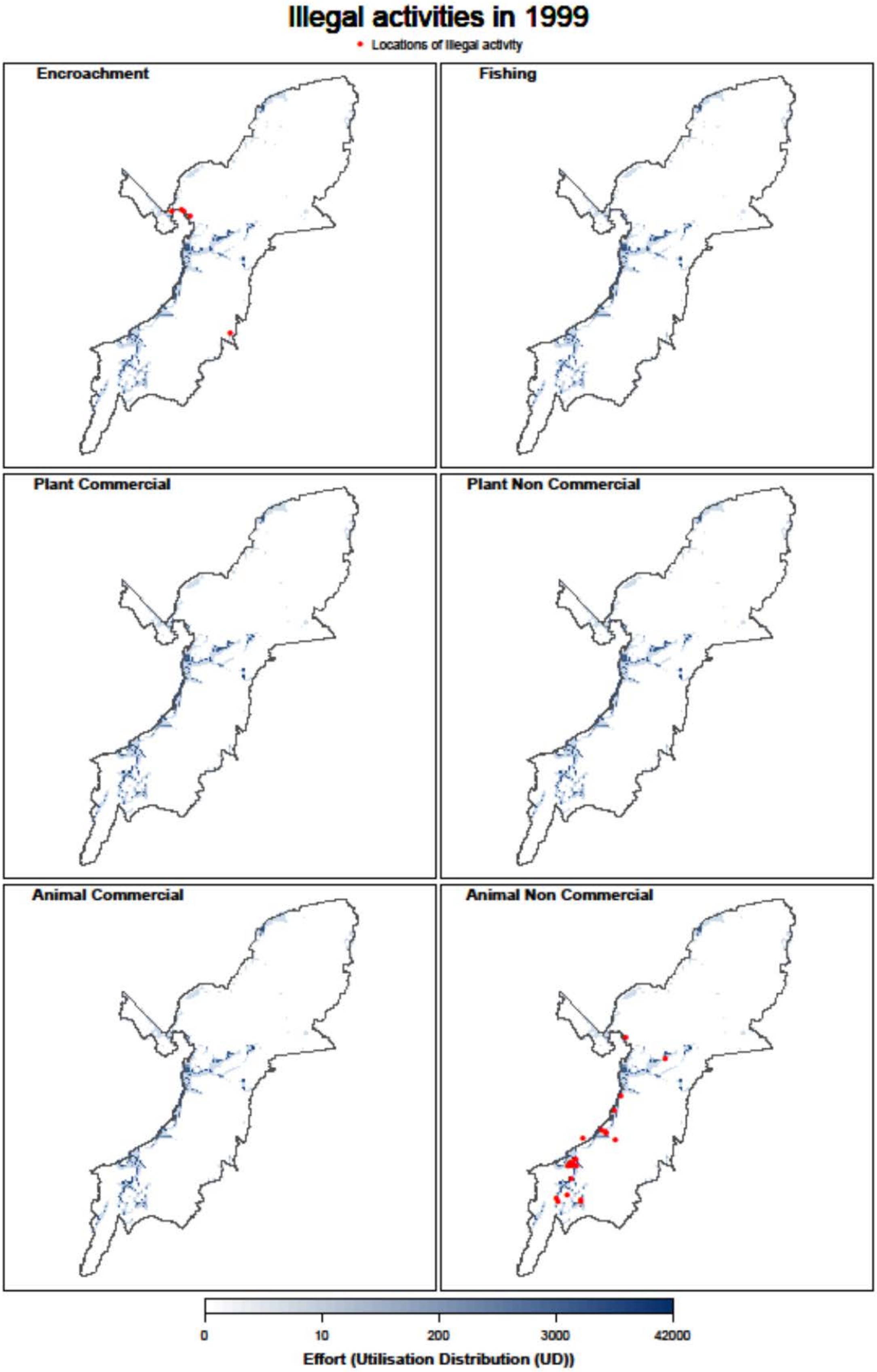

Figure 1. Distribution of ranger patrol effort and locations of illegal activity in 1999

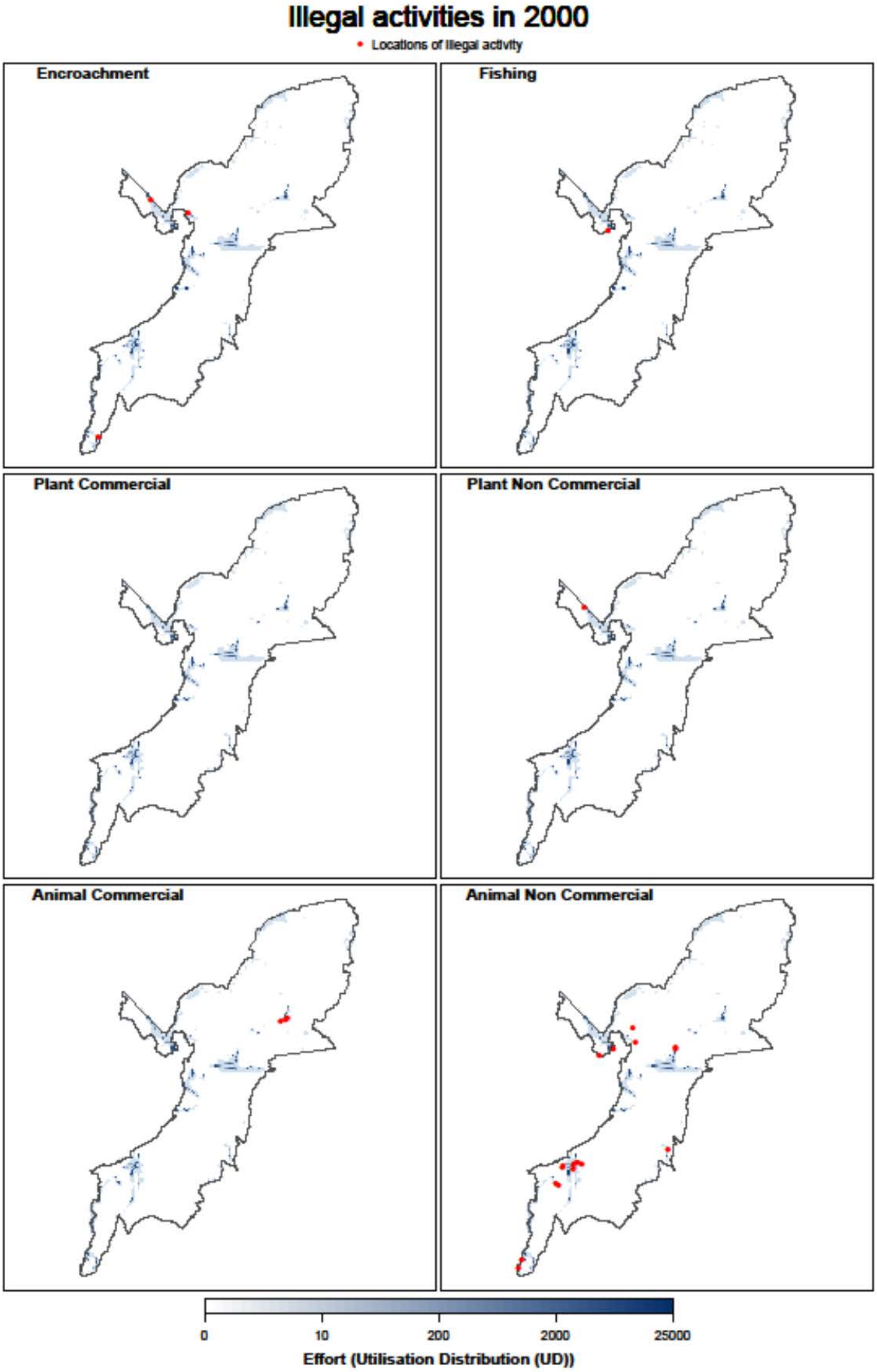

Figure 2. Distribution of ranger patrol effort and locations of illegal activity in 2000

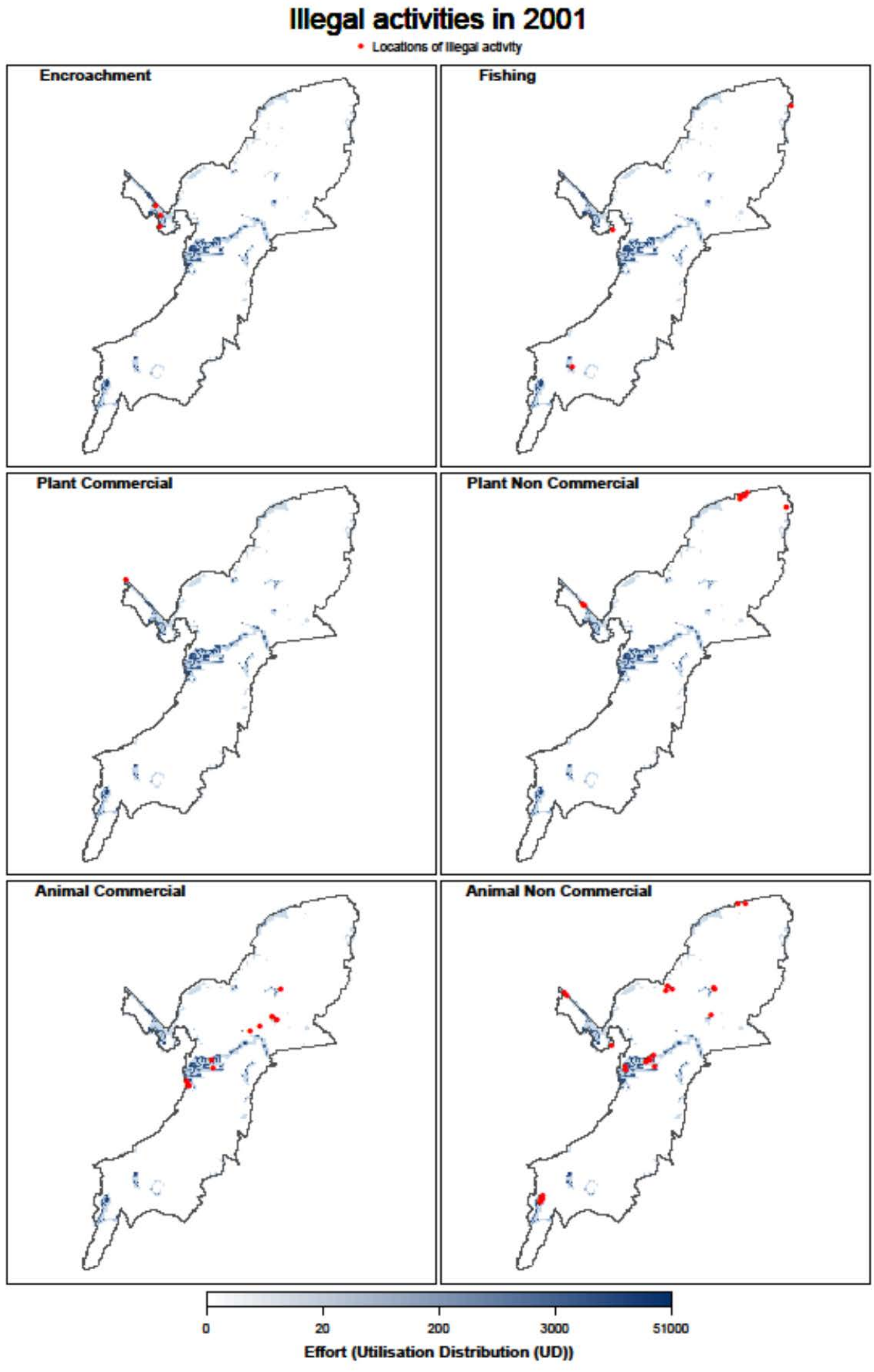

Figure 3. Distribution of ranger patrol effort and locations of illegal activity in 2001

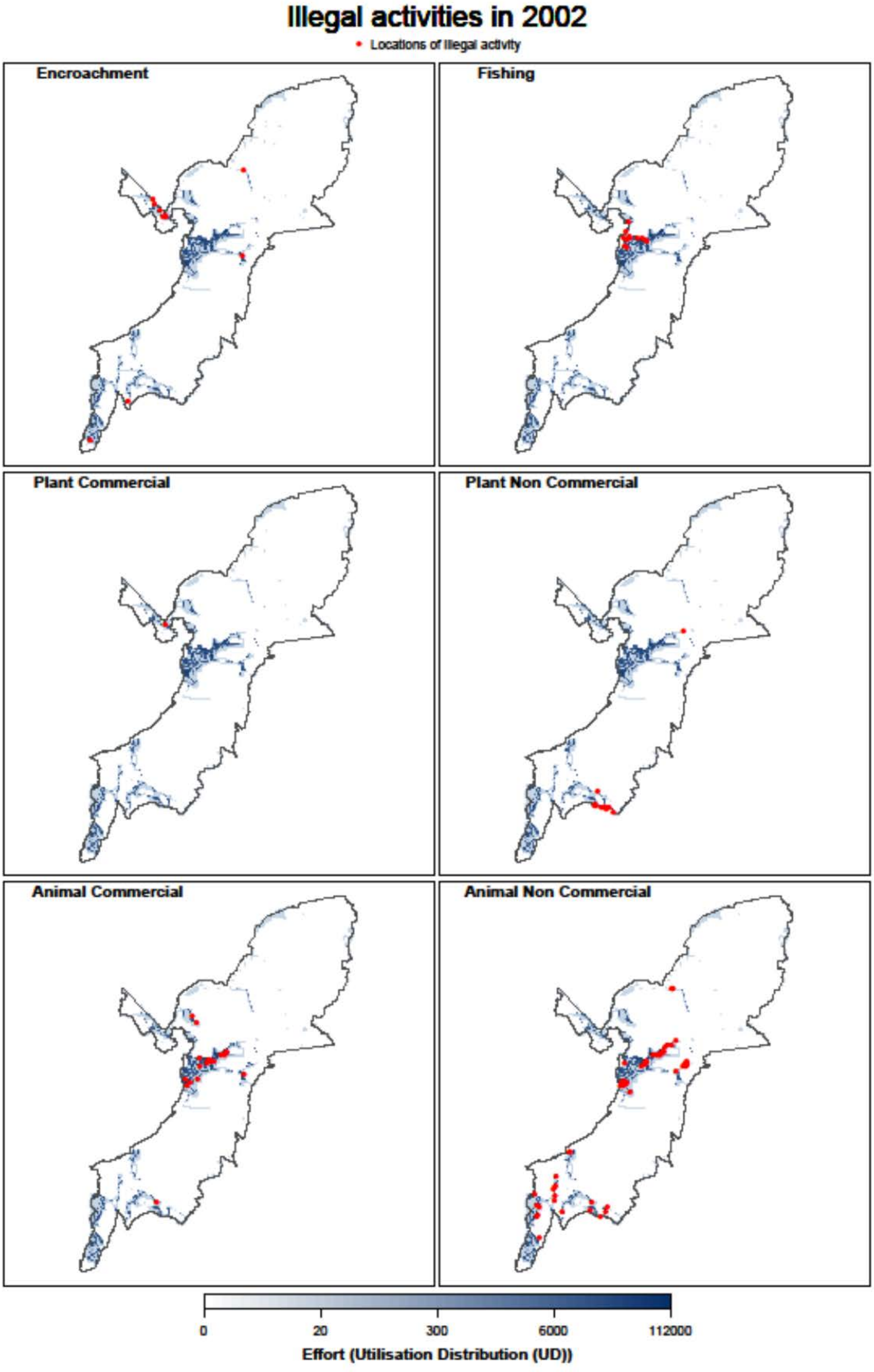

Figure 4. Distribution of ranger patrol effort and locations of illegal activity in 2002

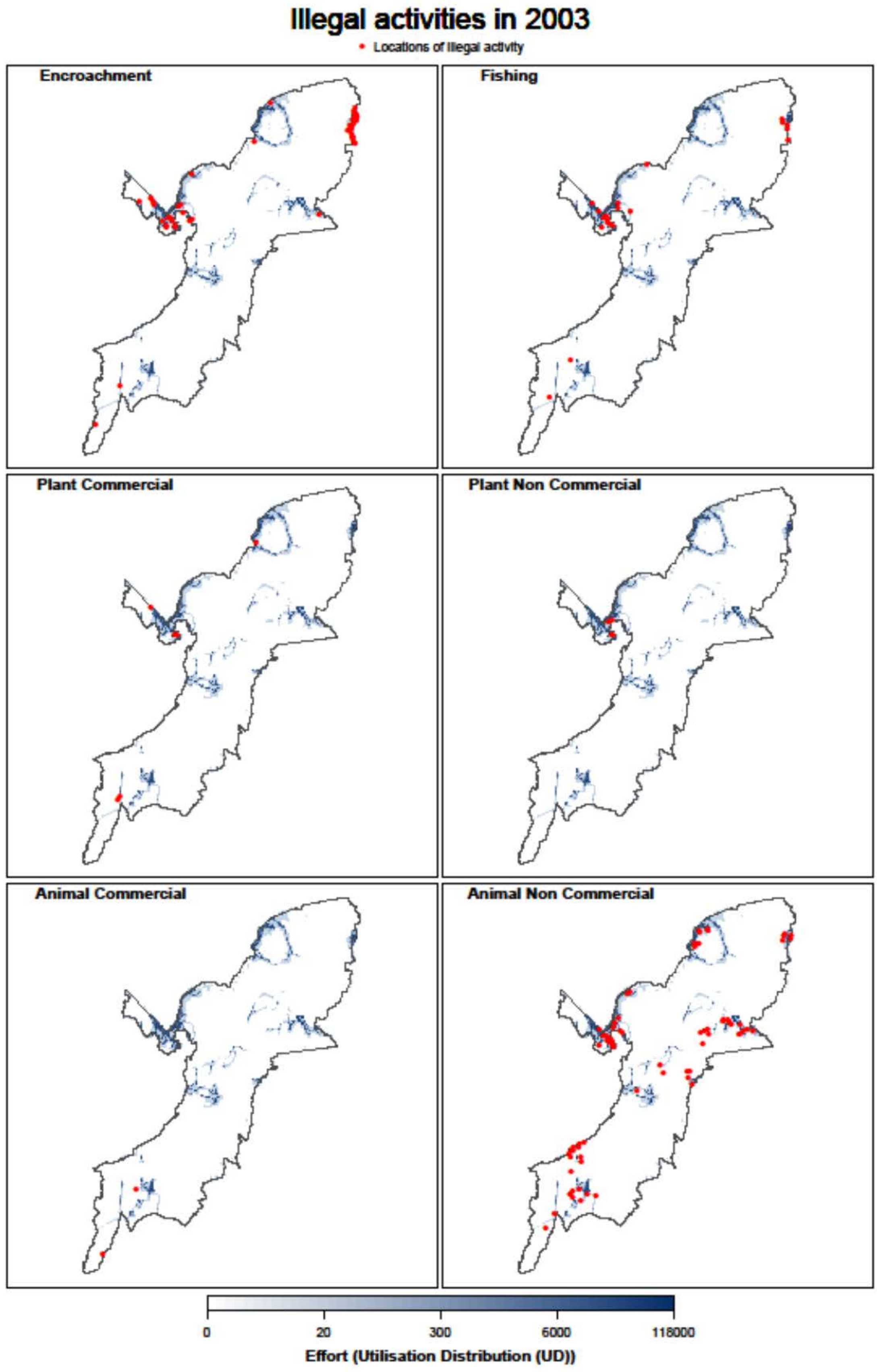

Figure 5. Distribution of ranger patrol effort and locations of illegal activity in 2003

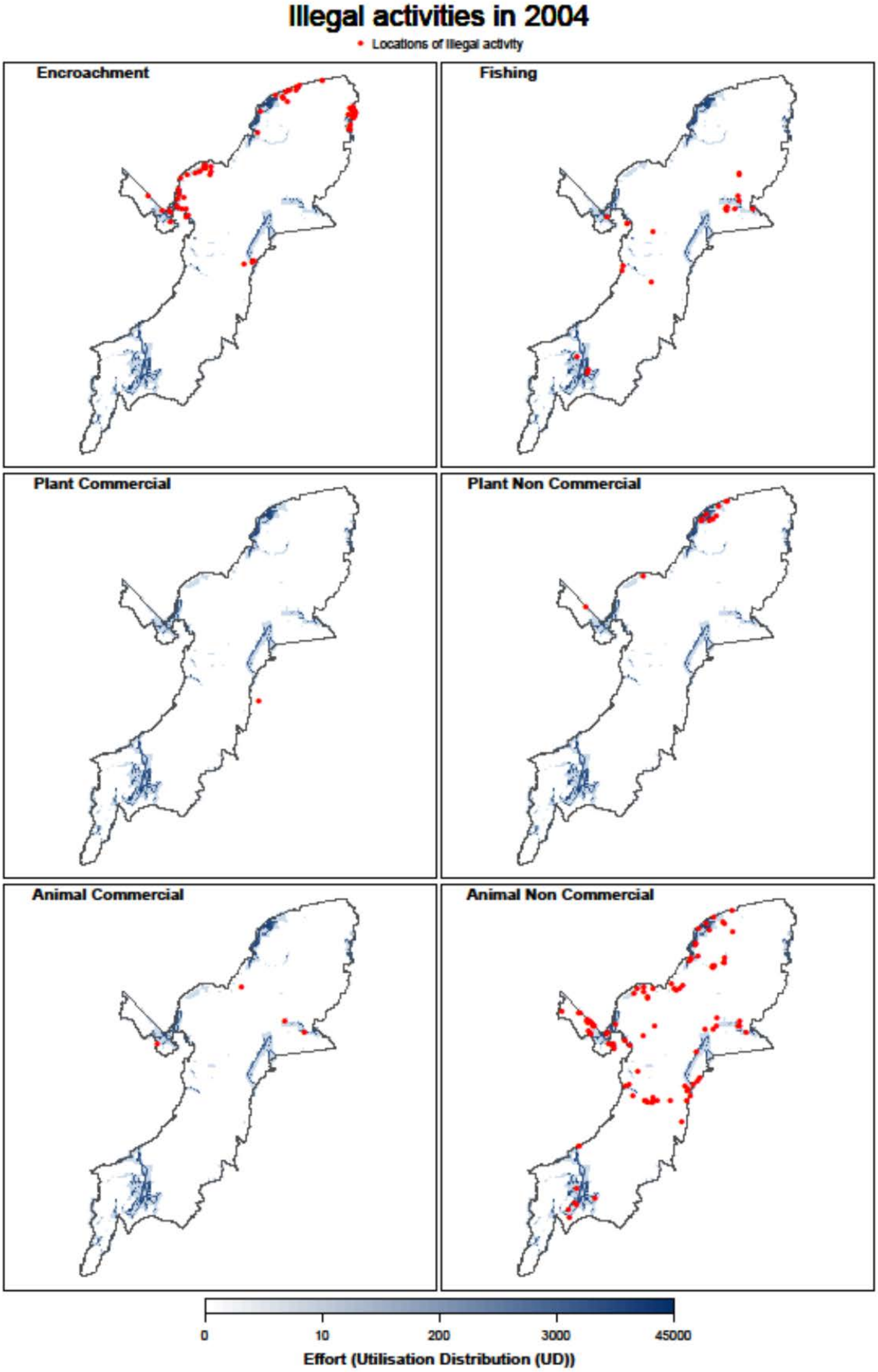

Figure 6. Distribution of ranger patrol effort and locations of illegal activity in 2004

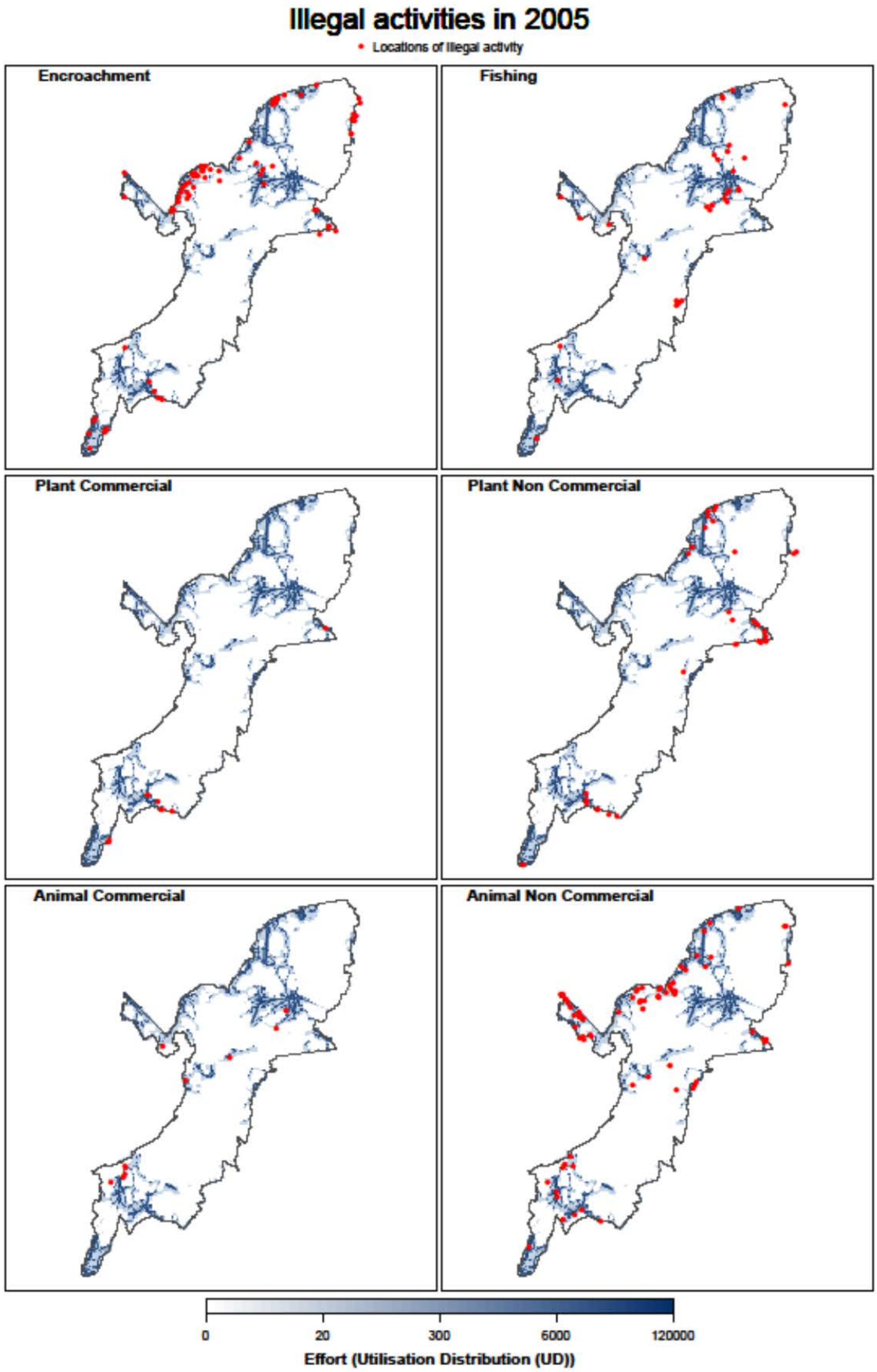

Figure 7. Distribution of ranger patrol effort and locations of illegal activity in 2005

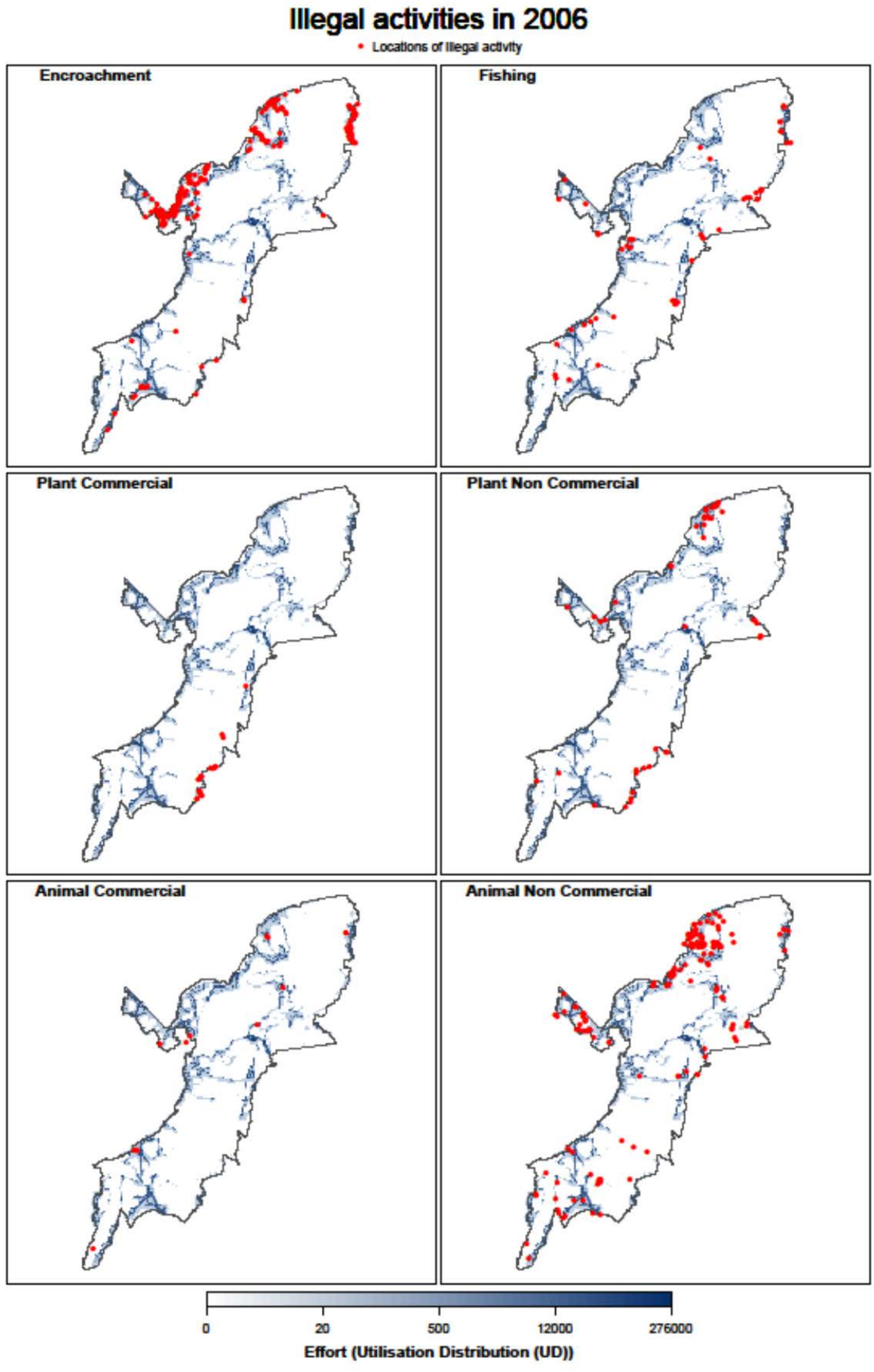

Figure 8. Distribution of ranger patrol effort and locations of illegal activity in 2006

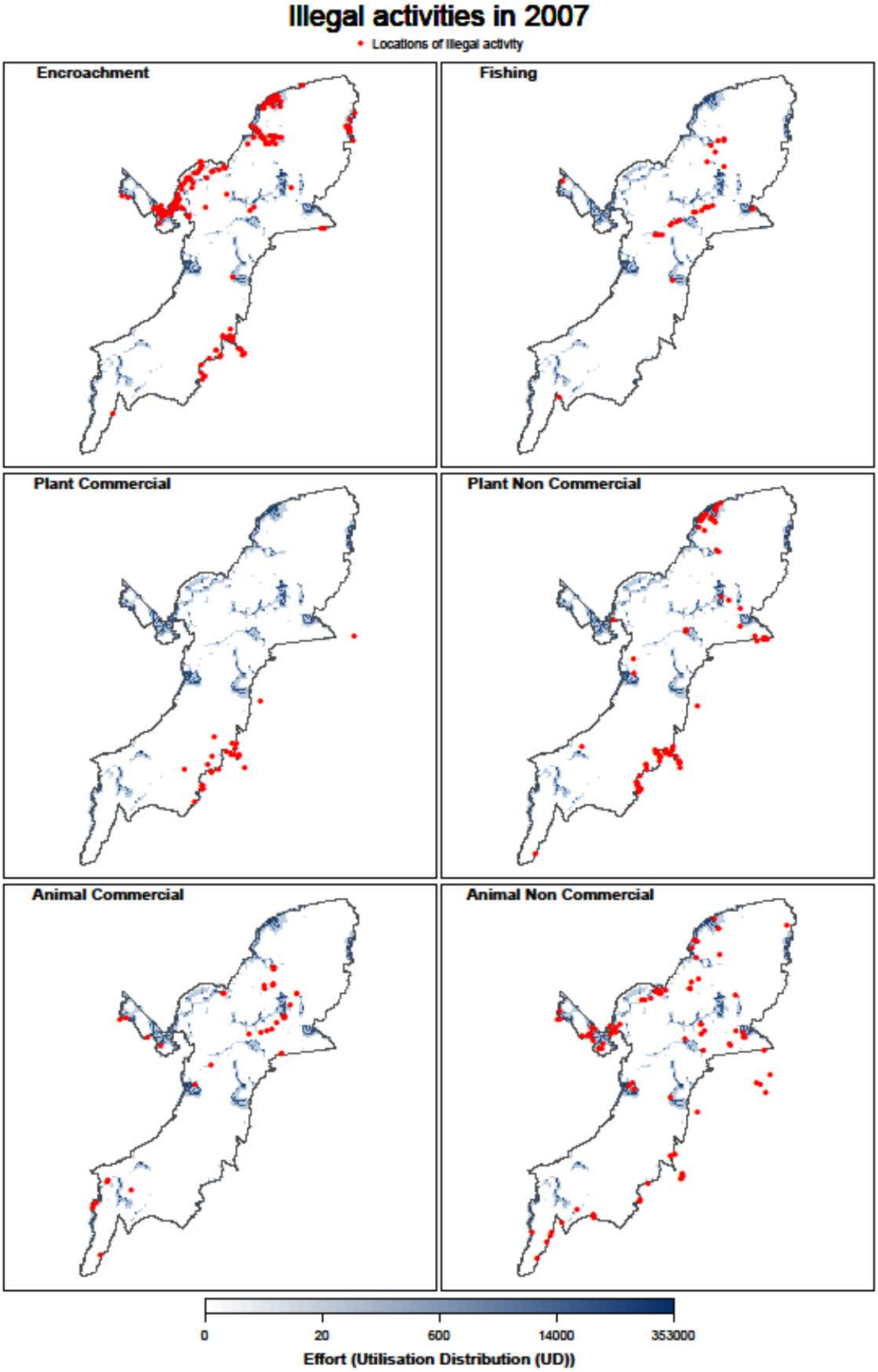

Figure 9. Distribution of ranger patrol effort and locations of illegal activity in 2007

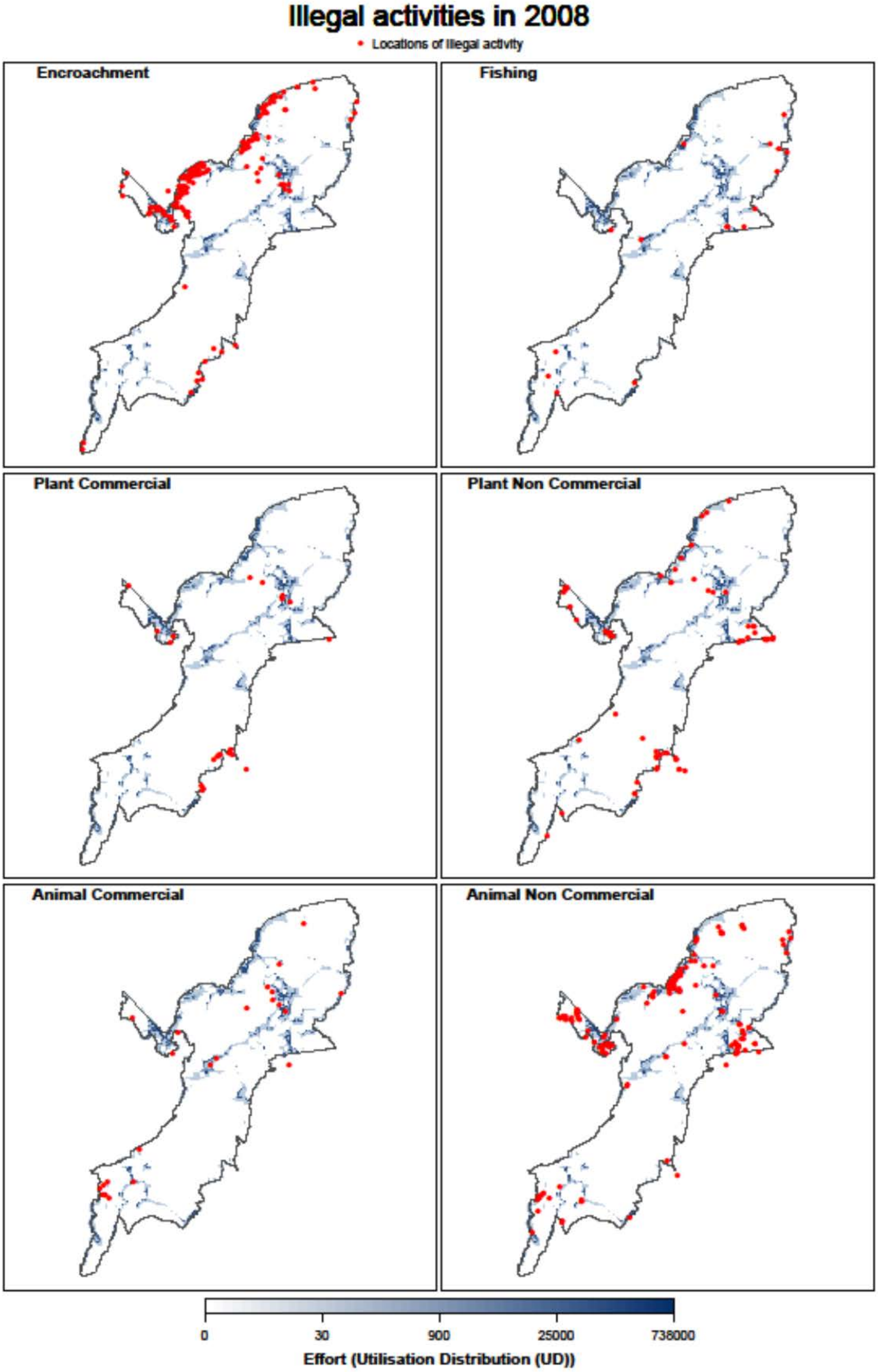

Figure 10. Distribution of ranger patrol effort and locations of illegal activity in 2008

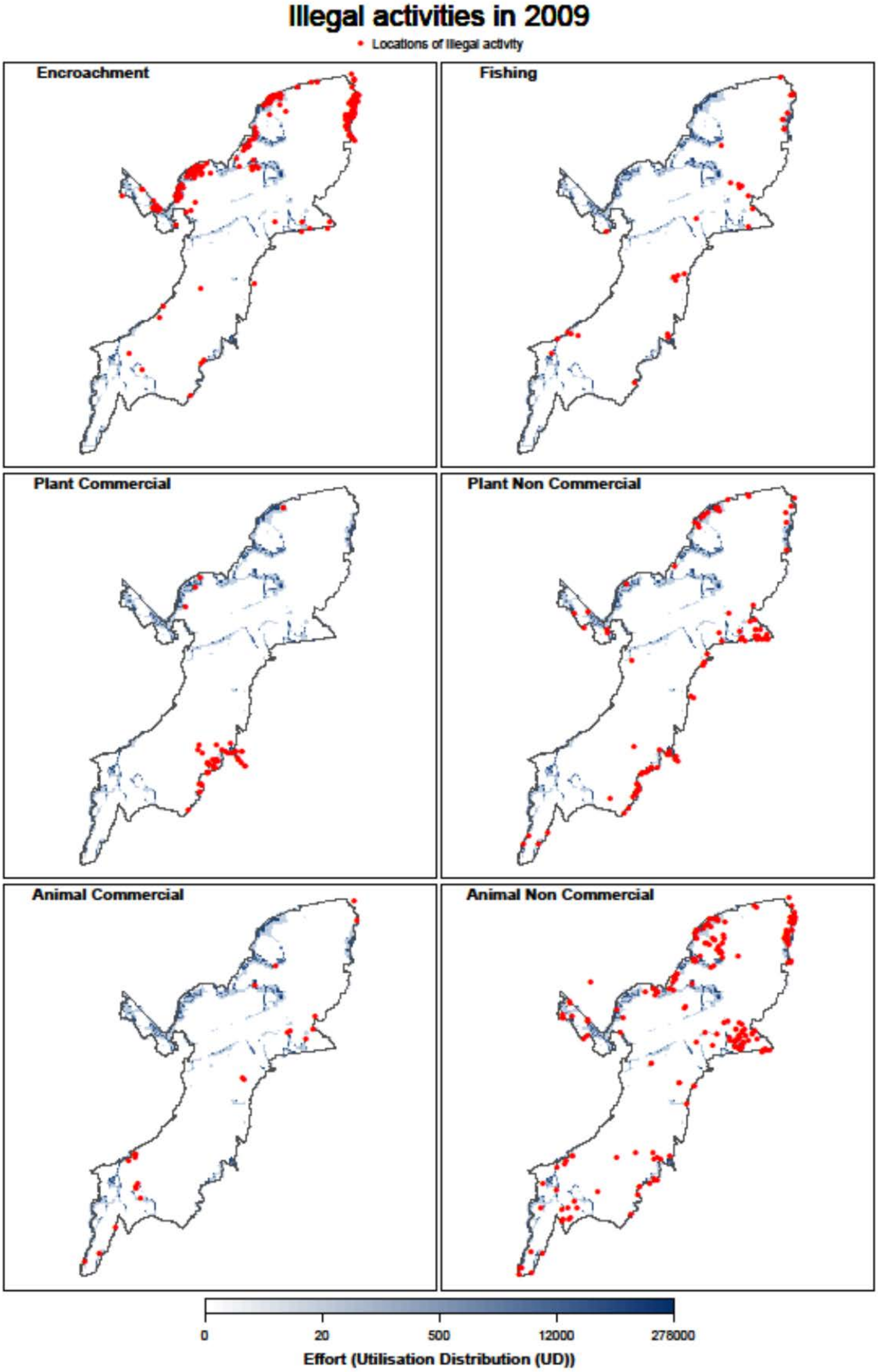

Figure 11. Distribution of ranger patrol effort and locations of illegal activity in 2009

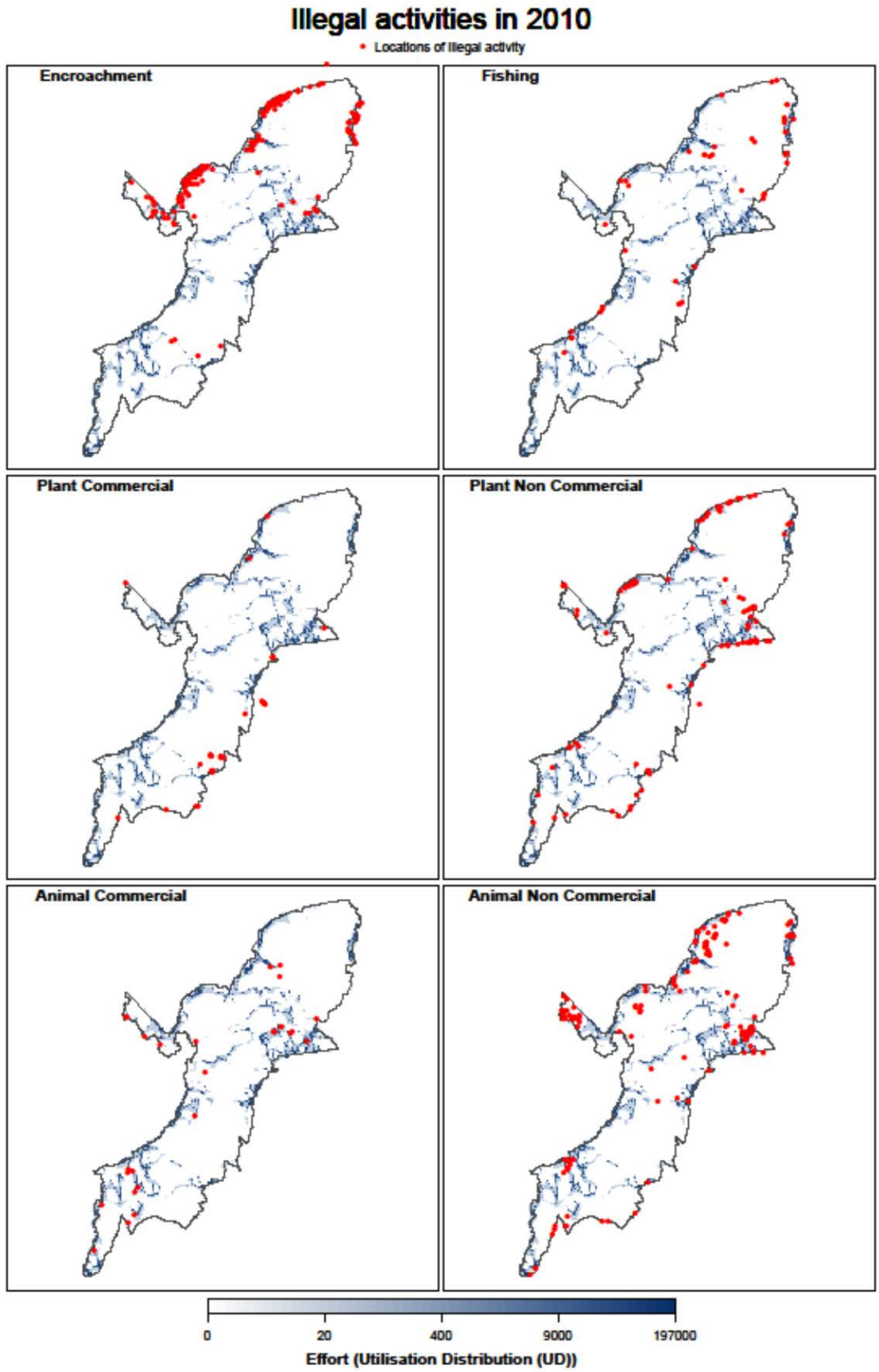

Figure 12. Distribution of ranger patrol effort and locations of illegal activity in 2010

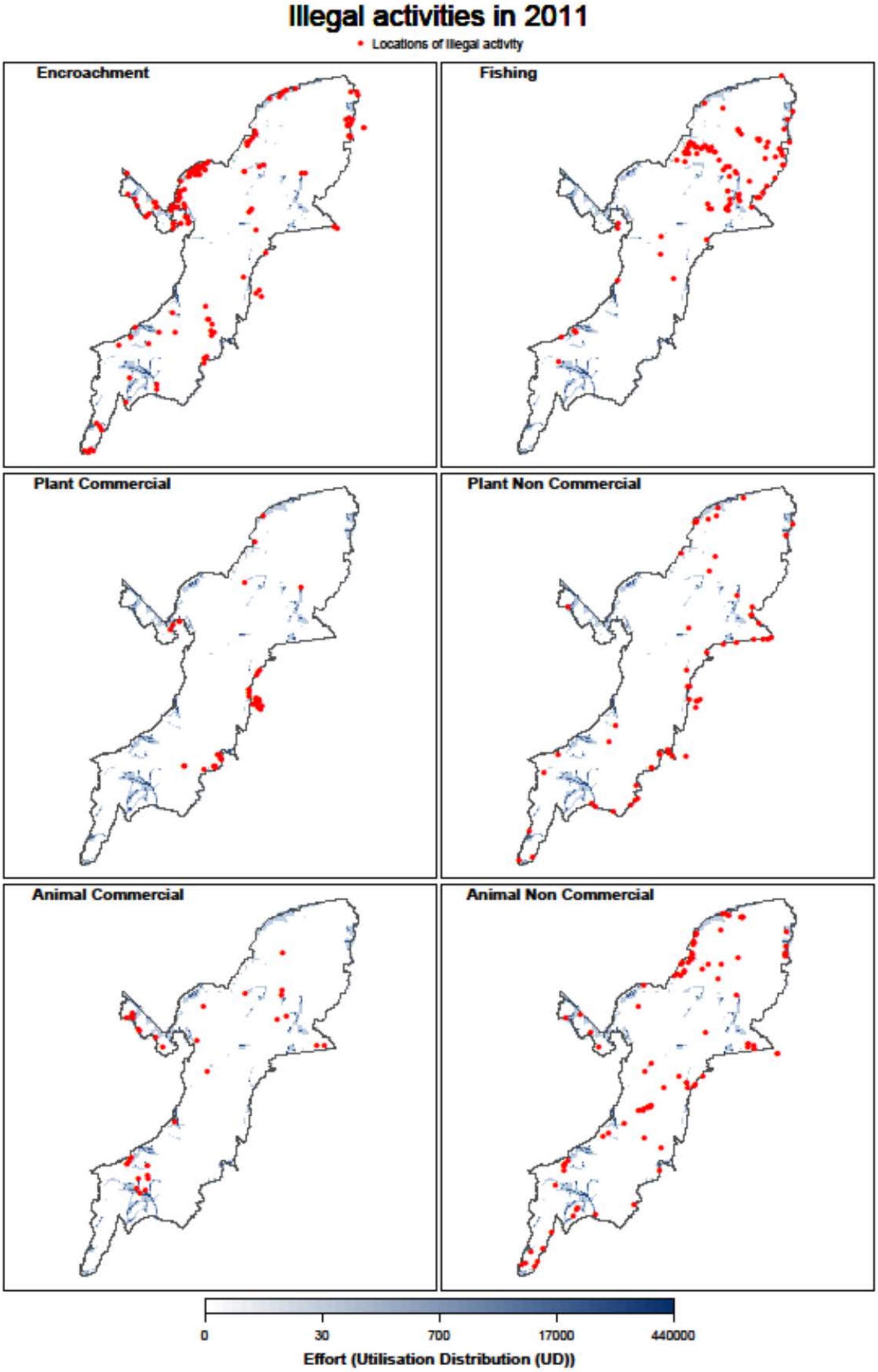

Figure 13. Distribution of ranger patrol effort and locations of illegal activity in 2011

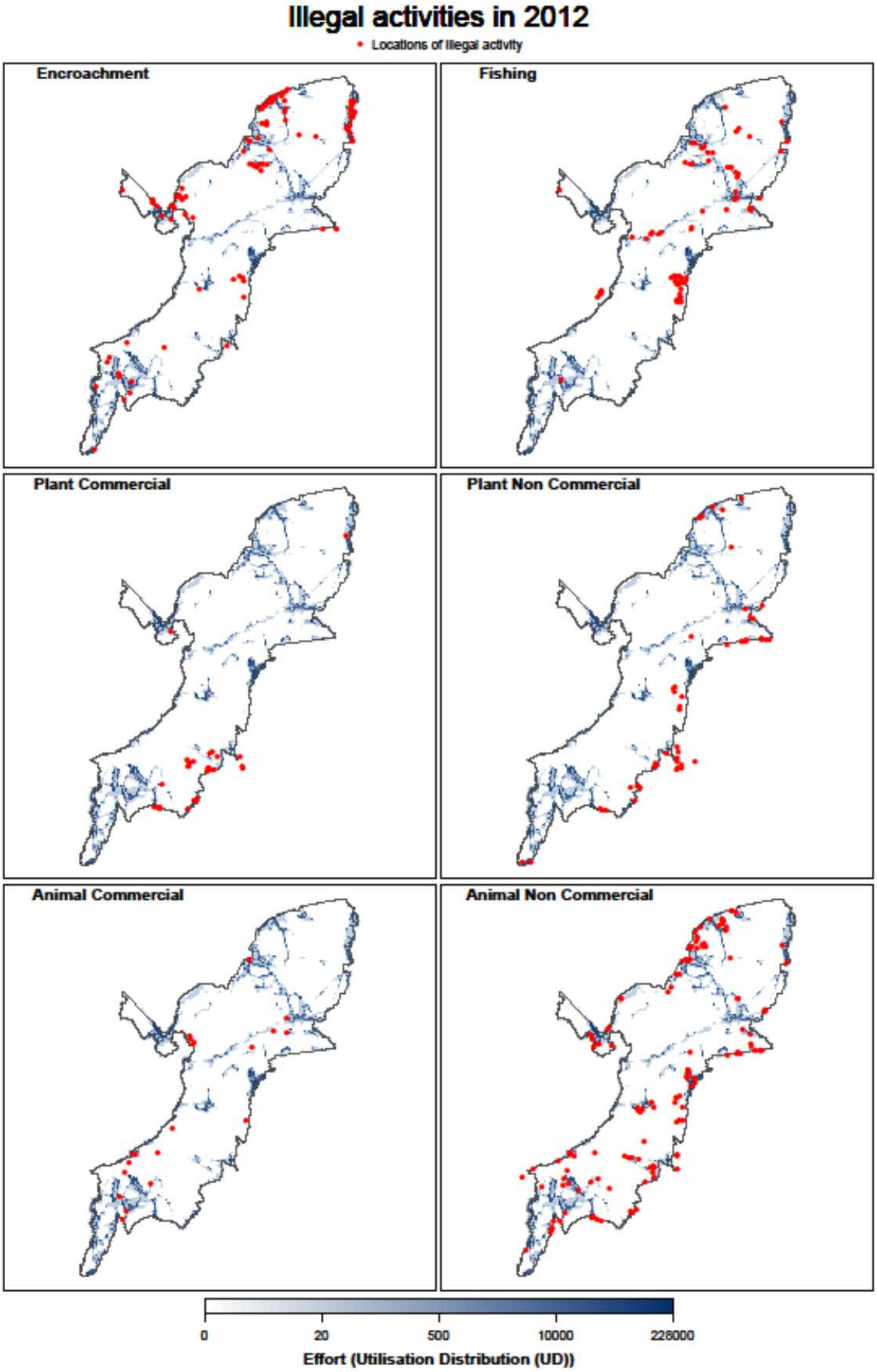

Figure 14. Distribution of ranger patrol effort and locations of illegal activity in 2012

4.2 Probability of reporting illegal activities

The spatial distribution of illegal resource use differed among the six categories for the full time period data were collected (Figure 15). Overall, there were differences in the distribution patterns of the six classifications of illegal activity. Encroachment (mostly cattle herding) was most common at the boundary of the QENP, especially in the North-west where there is a high cattle population density outside the QENP. Commercial plant activity (timber and charcoal) was most likely to occur in a restricted area in the South-east of the QENP where the Maramagambo Forest is located. This was also an area where the probability of non-commercial plant harvesting is high. The highest probability of commercial animal poaching is concentrated at lake edges and rivers (because it includes hippopotamus as well as buffalo and elephant that can often be found near the water's edge. In addition, in the South of QENP there are areas with high probability of illegal animal poaching. In comparison to the other classifications, high probabilities of non-commercial animal poaching (mostly snaring) were widely distributed across the QENP.

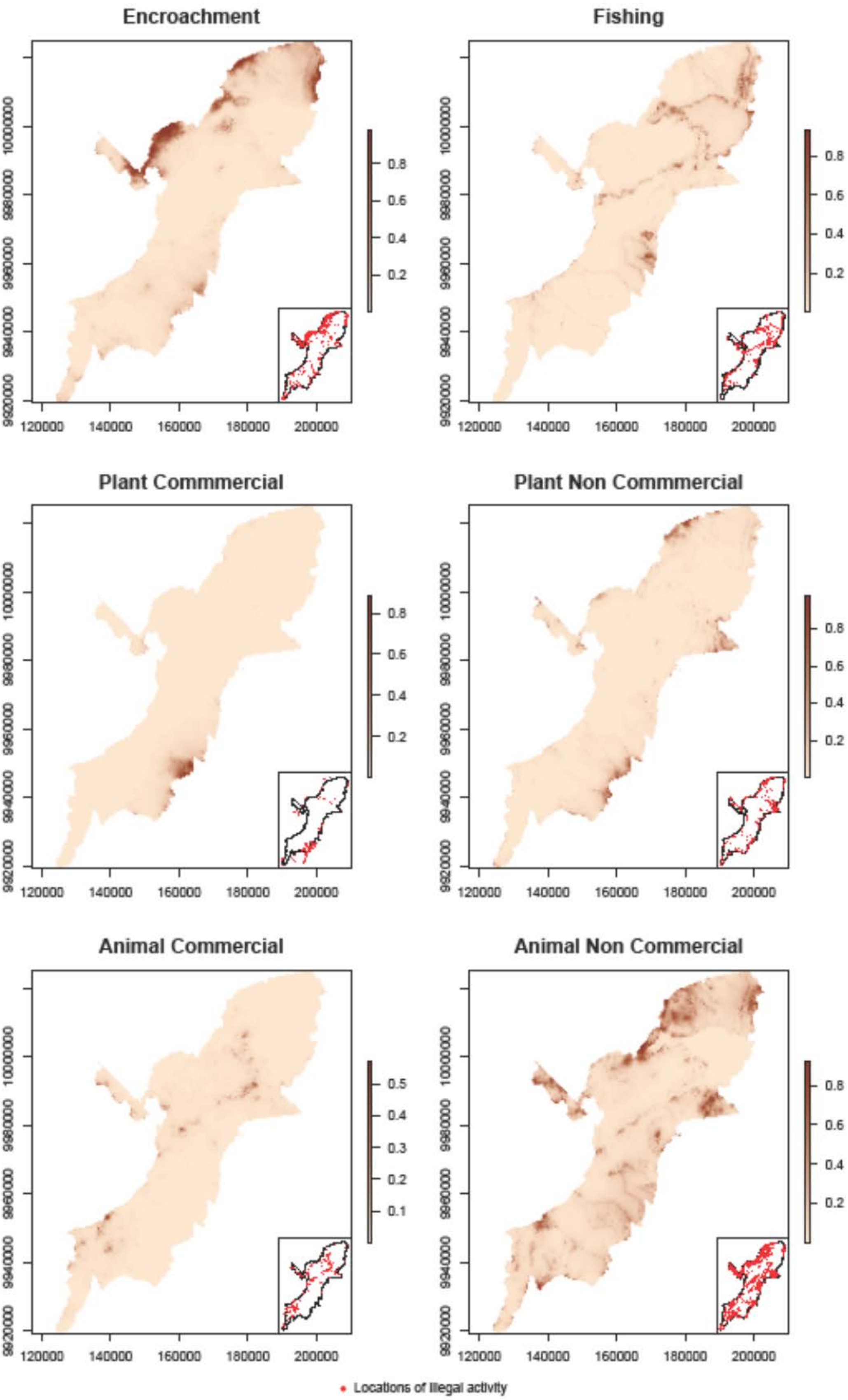

Figure 15. Occurrence probabilities of illegal activities in the Queen Elizabeth National Park

4.3 Drivers of illegal activities

Different variables were responsible for driving the different spatial patterns of different illegal activities (Figure 16). Animal density had a strong influence on the occurrence of commercial animal poaching, but not on non-commercial poaching. Habitat was also influential on animal poaching; the probability of poaching was greater in savannah habitats, and forest habitats had a strong positive effect on non-commercial poaching. Distance to roads did not have a strong effect on illegal activities, whereas an increase in the distance to rivers had a negative effect on fishing, non-commercial plant harvesting and non-commercial animal poaching. Travel cost also had an influence on non-commercial plant harvesting and commercial animal poaching; an increase in travel cost was associated with a lower probability of illegal activity.

For Net Primary Productivity (NPP) and topographic wetness there are two parameter estimates; the pattern of the two estimates represents the direction of the effect each variables has on illegal activities. For example, the effect of NPP on commercial and non-commercial animal poaching was opposite from each other (Figure 16); an increase in non-commercial animal poaching was associated with a higher NPP, whereas Commercial animal poaching was associated with lower levels of NPP.

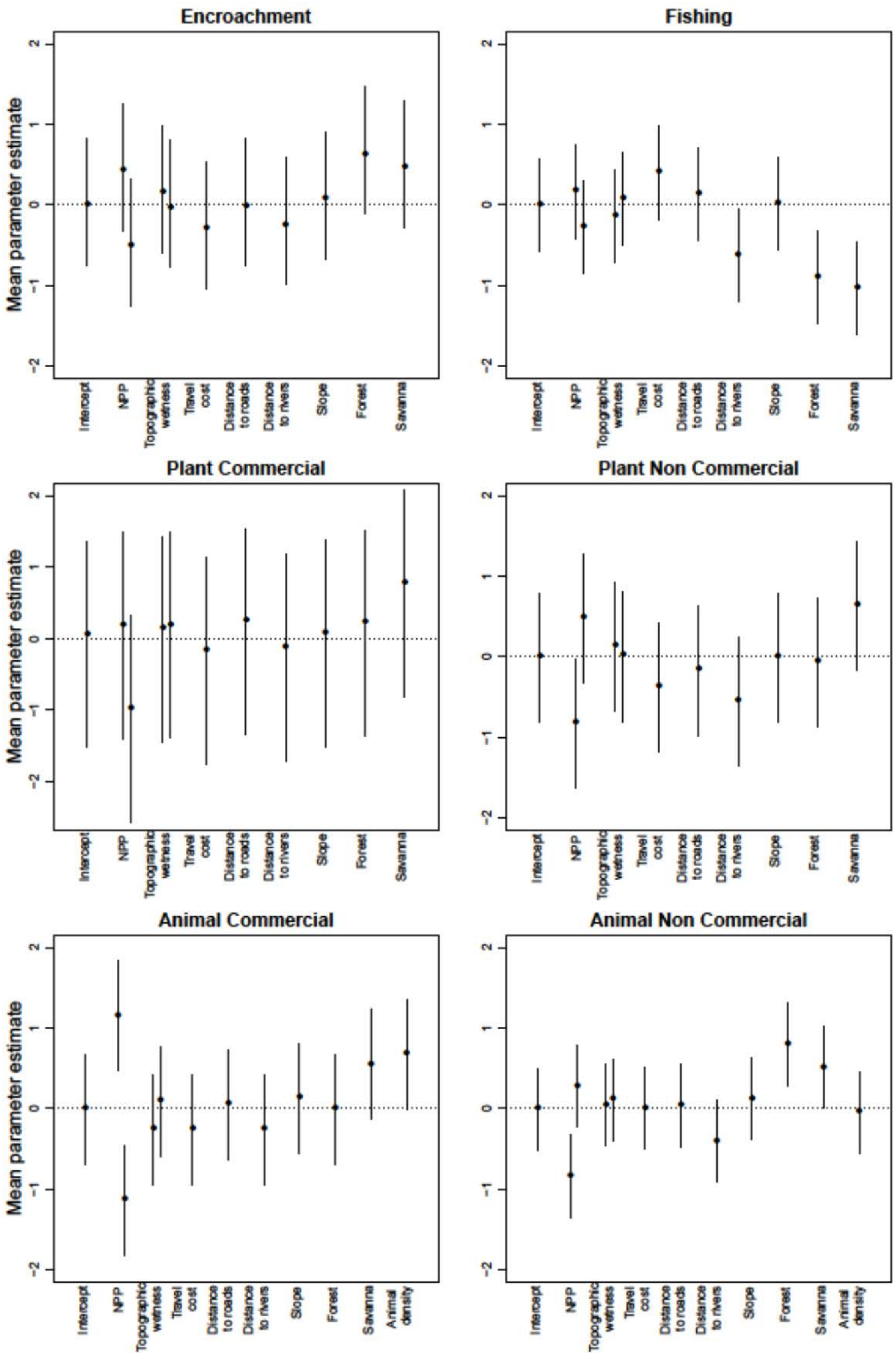

Figure 16. Mean parameter estimates for each covariate across illegal activity classifications. Where the 95% confidence interval bars do not overlap the zero (dashed) line, that covariate has a significant influence on the illegal activity.

4.4 Temporal trends in illegal activities

Across the activity classifications, only encroachment and non-commercial plant harvesting showed a significant trend over the full time period (1999 to 2012), with both continuing to increase (Table 4, Figure 17). Until 2011, encroachment and non-commercial plant harvesting showed a continuous increase since 2002 and 2004 respectively. For most classifications the mean probability decreased in 2012, with the exceptions being commercial plant harvesting and non-commercial animal poaching (Figure 17). In addition, non-commercial animal poaching was greatest in the period 2009-2012 in comparison to the previous six years (2003-2008).

Table 4. Median probability trends across each illegal activity class, across all years of data collection (1999-2012). Where the confidence intervals do not overlap zero, there is a significant trend (*).

Illegal activity	Probability trend	Confidence intervals (2.5%, 97.5%)
Encroachment	0.01*	0.05, 0.14
Fishing	0.06	-0.04, 0.14
Plant Commercial	-0.02	-0.23, 0.10
Plant Non Commercial	0.12*	0.06, 0.17
Animal Commercial	-0.02	-0.13, 0.06
Animal Non Commercial	-0.02	-0.06, 0.03

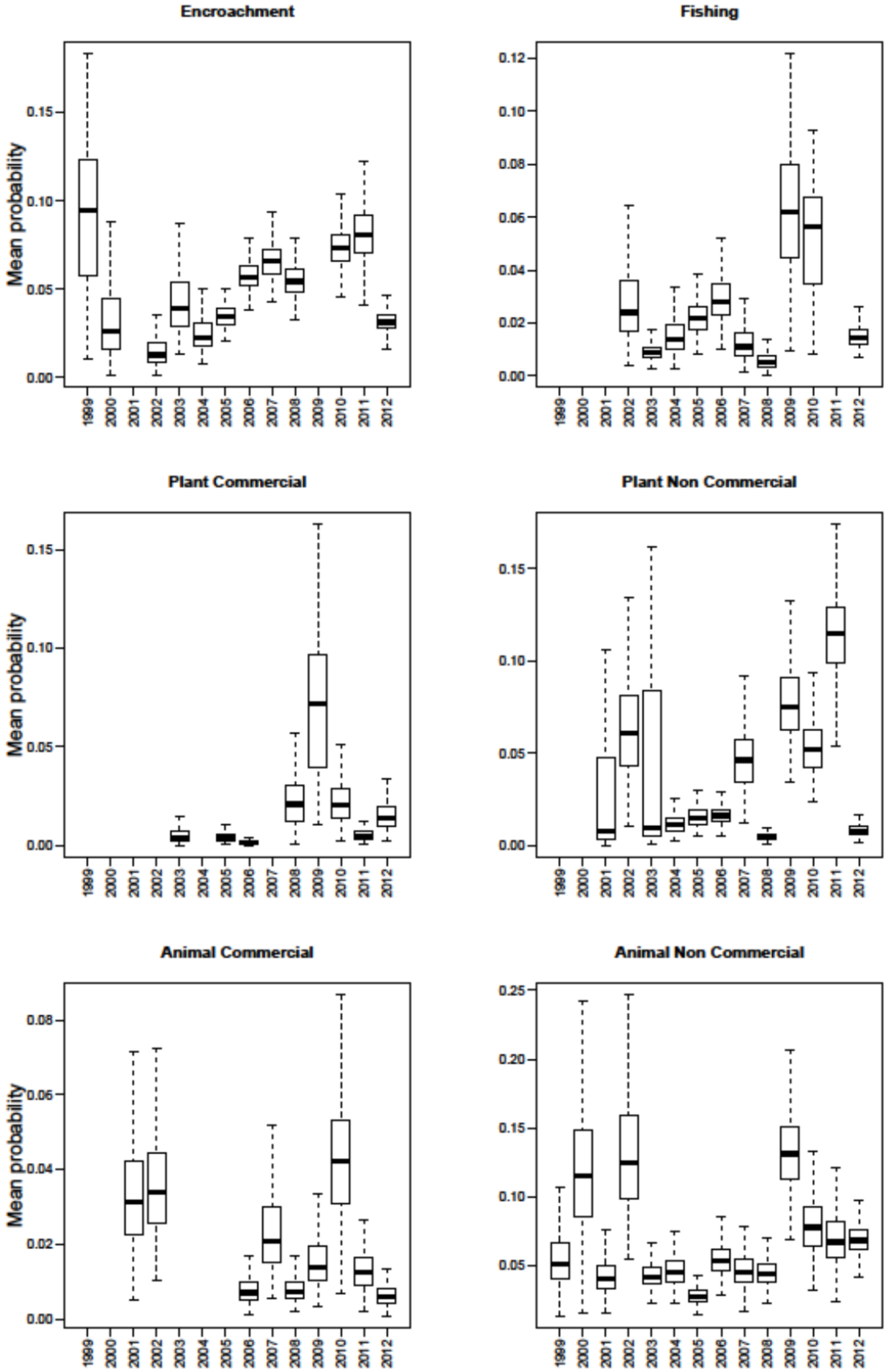

Figure 17. Annual trends in illegal activity in the QENP between 1999 and 2012. Missing annual data is due to models not converging which is likely to be caused by a low number of observations (<10) in that year.

4.5 Spatio-temporal trends

Figure 18 shows the temporal trend per 500m grid cell during the full time period (1999-2012) for each illegal activity, highlighting where there have been significant changes of the illegal activity during the full study period. With the exception of the South-Eastern forest habitat, encroachment has increased throughout the QENP. Trends of commercial plant activity appear to be driven by the location roads and forest habitat; there has been a decrease in activity close to roads, but an increase in densely forest areas.

Commercial animal poaching has increased in most areas with the exception of central savannah areas and around Lake George in the Northern area of the national park. Increases in non-commercial animal poaching between 1999 and 2012 have mostly occurred at boundary edges, for many areas in the QENP, this activity appears to have decreased over time.

There is also variation in the probability of illegal activities per grid cell in consecutive years (Figures 19- 21). These figures indicate that the observed annual trends (Figure 17) are sometimes driven by changes in small areas. For example, the increases in commercial animal poaching in 2007 and 2010 (Figure 17) are caused by an increase in probability in a small number of cells near Lake George and in the south-west of the QENP (Figure 18).

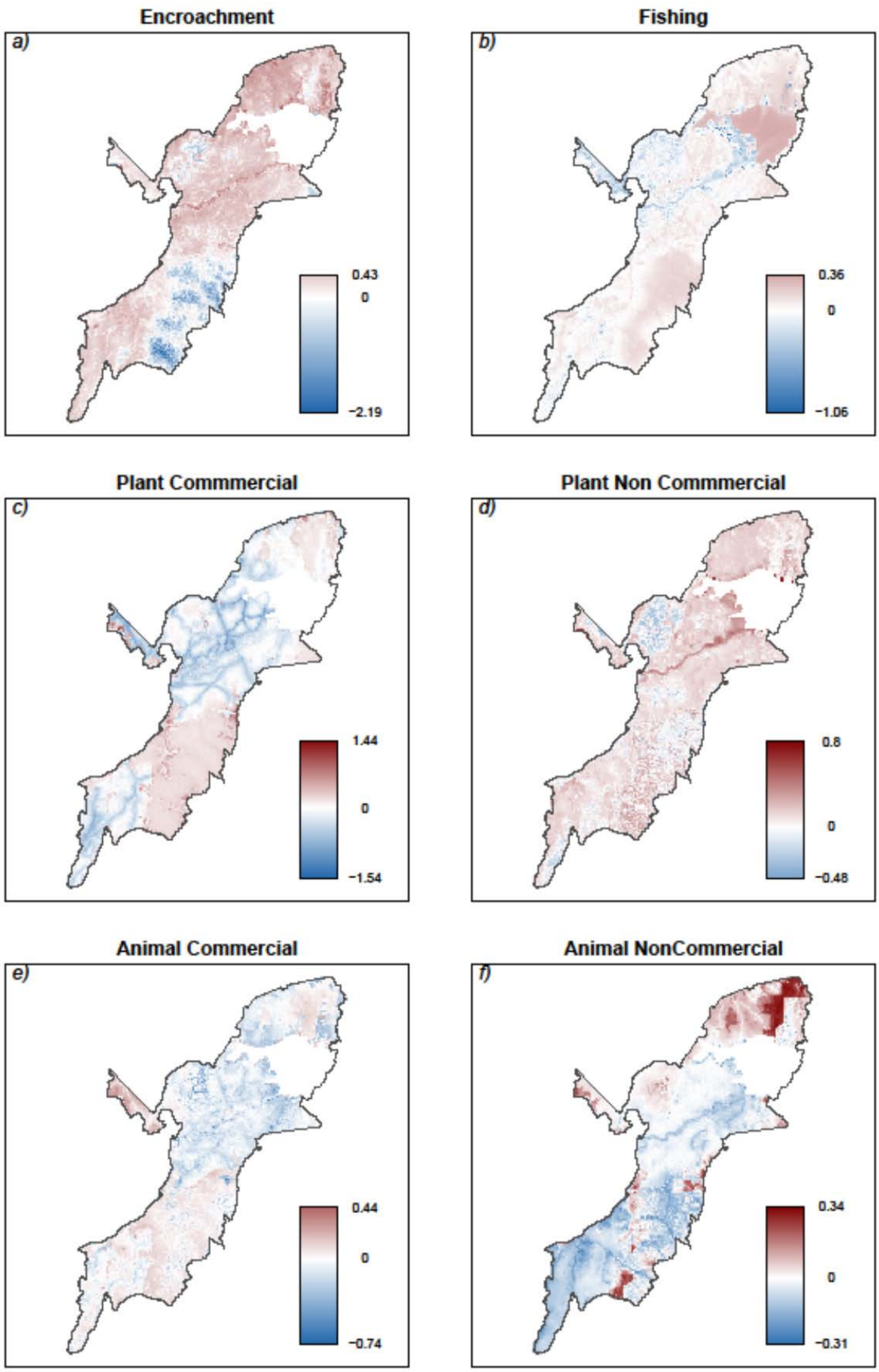

Figure 18. Temporal trends of illegal activities per grid cell (500m) between 1999 and 2012 in the Queen Elizabeth National Park. White indicates no significant change and darker colours indicate more significant trends during the full period

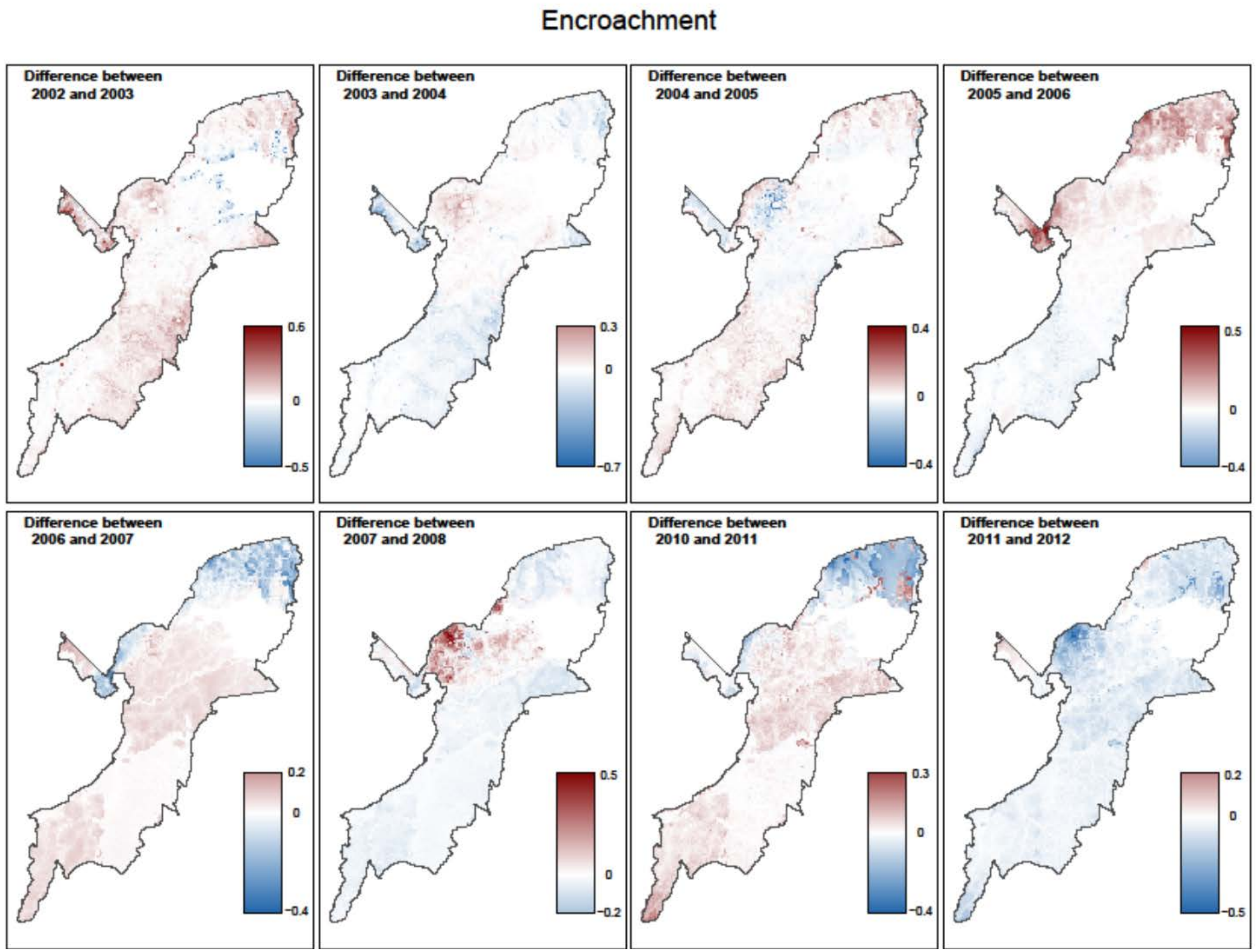

Figure 19. Changes in the probability of encroachment per grid cell (500m) between consecutive years. White indicates no change, and darker colours indicate greater changes between years.

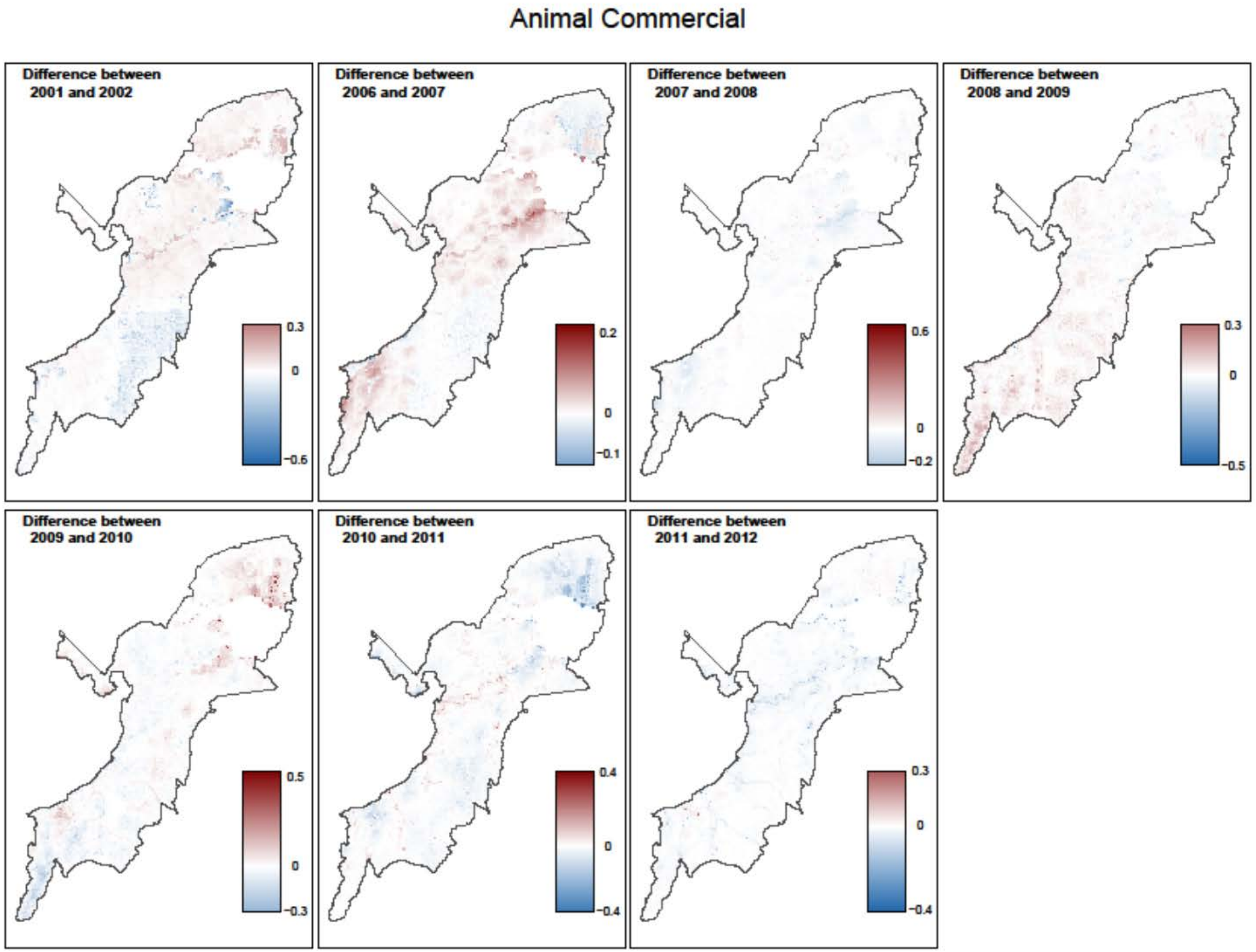

Figure 20. Changes in the probability of commercial animal poaching per grid cell (500m) between consecutive years. White indicates no change, and darker colours indicate greater changes between years.

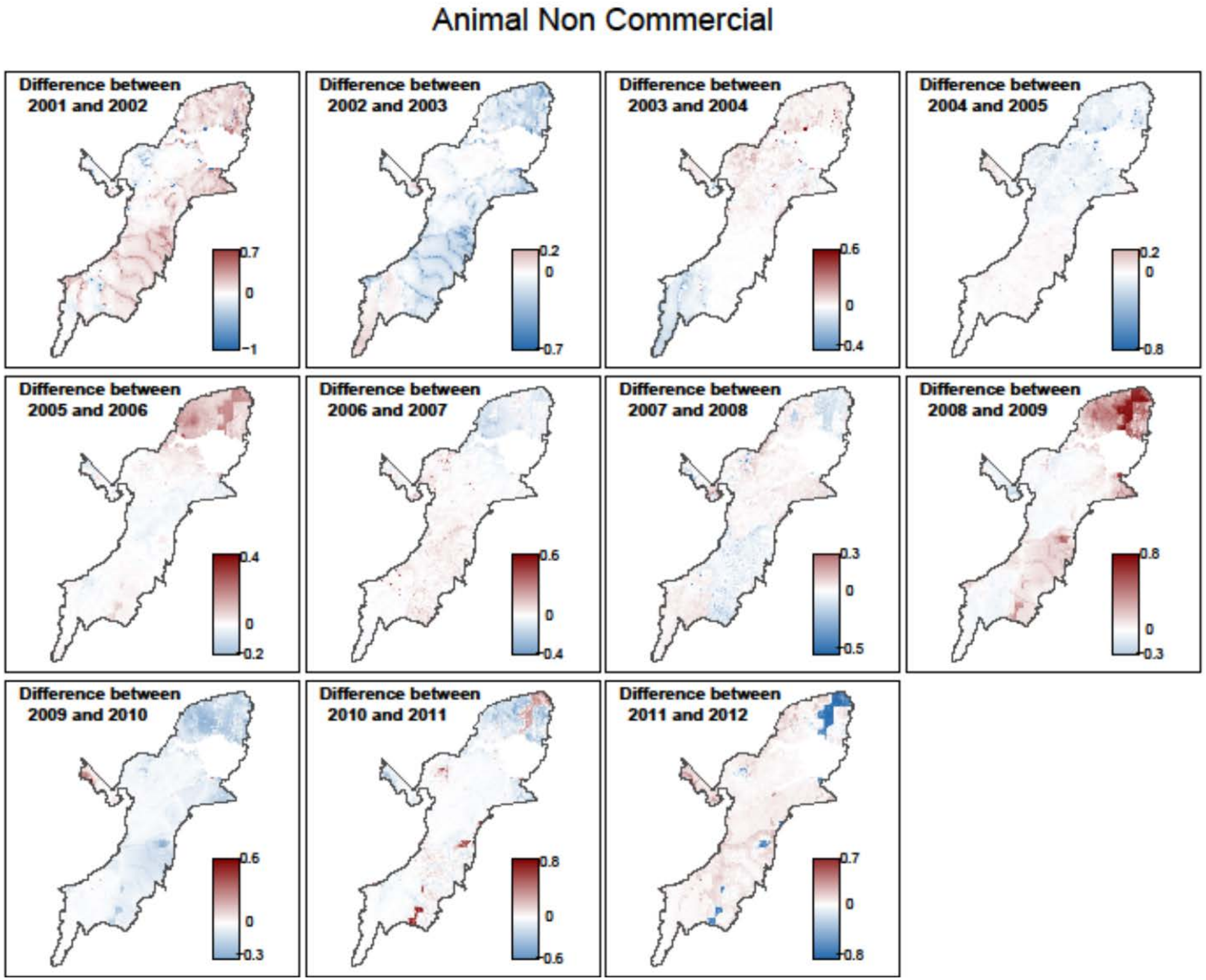

Figure 21. Changes in the probability of non-commercial animal poaching per grid cell (500m) between consecutive years (2002-2012). White indicates no change, and darker colours indicate greater changes between years.

5 Preliminary conclusions

We believe this is the first analysis assessing patterns and drivers across multiple types of illegal resource use, while robustly accounting for spatial and temporal changes in observation effort.

Our results highlight the differences in the spatial distribution and temporal trends among the six groups of illegal activities, and these differences have important implications for the design of ranger patrols. Because there are clear differences in the location and trends among the six classifications, a universal ranger patrol schedule is not appropriate for targeting or identifying particular illegal activities. For example, commercial animal poaching and commercial plant harvesting are unlikely to occur in the same areas (Figure 15); existing patrol routes could be improved by targeting particular activities.

During the first 4 years of the study period (1999-2002) the increase in number and coverage of patrols will be because of the greater use and availability of equipment and technology by ranger patrols. Despite a continuing increase in ranger activity within the QENP since 2003, there is also a continuing increase in some illegal resource use such as encroachment and non-commercial plant harvesting, and some evidence of an increase in non-commercial animal poaching between 2003 and 2012. Ideally ranger patrols should focus on high probability areas, but because trends have changed over time rangers should also attempt to patrol low probability areas less frequently in order to monitor spatio-temporal trends of illegal activities throughout the QENP.

In addition, the drivers influencing the occurrence of illegal resource use also differ among the six groups. However, overall the explanatory variables are relatively weak predictors, suggesting that the spatial effects are more useful for predicting illegal activities; the past does seem to be the best predictor of the future for the illegal activities analysed. An exception to the majority of weak predictors, is the density of commercial animals (Hippo, Buffalo and Elephant), which was positively associated with a greater probability of commercial animal activity. This suggests that poachers are actively targeting high density areas, a result that could also be used to inform ranger patrol effort.

6 Future work

The immediate plan is to complete this analysis as a manuscript for publication. This will either be directed towards ecology journals such as Ecology Letters or Journal of Applied Ecology, or towards conservation journals such as Conservation Biology or Biological Conservation.

There are three other protected areas within the Greater Virunga Landscape (GVL) to which the current analysis will be applied: Virunga National Park (VNP), Kibale National Park (KNP) and Murchison Falls National Park (MFNP). The explanatory variables and measure of patrol effort have already be complied for KNP, and we about to start running the statistical models for this protected area. Initial data checking of VNP and MFNP have also been completed.

Related to these next steps, there is also the opportunity to run additional analyses on the sites within the GVL including: (1) assessing species distributions that have been recorded as part of the ranger patrols, (2) use of the data from the year 2013 as an additional analysis that could potentially be used to validate and support the existing analysis, and (3) use of some more precise explanatory data, such as more detailed vegetation and habitat maps that have been generated.

In addition, whilst this analysis has focussed poacher behaviour, we will also make a more detailed assessment and analysis of ranger patrol effort to develop a spatial model of ranger patrols. This model can be used to assess how effective the existing patrols are at targeting areas where illegal resource use is high, whether ranger patrols effort can be efficiently maximised to target areas where the probability of illegal resource use is high, and assess the deterrence effects of existing patrol effort. Such analysis can be used to inform and improve existing ranger patrols, and will provide additional support to management of law enforcement (Plumptre *et al.* 2014). This analysis will also be written as a manuscript for publication, and only requires extracting extra information out of the current model outputs, rather than any substantial new modelling techniques.

References

Beale, C.M., Baker, N.E., Brewer, M.J. & Lennon, J.J. (2013) Protected area networks and savannah bird biodiversity in the face of climate change and land degradation. *Ecology letters*, **16**, 1061–8.

Beale, C.M., Brewer, M.J. & Lennon, J.J. (2014) A new statistical framework for the quantification of covariate associations with species distributions (ed D Kriticos). *Methods in Ecology and Evolution*, **5**, 421–432.

Kaltenborn, B.P., Nyahongo, J.W. & Tingstad, K.M. (2005) The nature of hunting around the Western Corridor of Serengeti National Park, Tanzania. *European Journal of Wildlife Research*, **51**, 213–222.

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**, 1164–1173.

Knapp, E.J. (2012) Why poaching pays: a summary of risks and benefits illegal hunters face in Western Serengeti, Tanzania. *Tropical Conservation Science*, **5**, 434–445.

Nuno, A., Bunnefeld, N., Naiman, L.C. & Milner-Gulland, E.J. (2013) A novel approach to assessing the prevalence and drivers of illegal bushmeat hunting in the serengeti. *Conservation biology: the journal of the Society for Conservation Biology*, **27**, 1355–65.

Papworth, S.K., Bunnefeld, N., Slocombe, K. & Milner-Gulland, E.J. (2012) Movement ecology of human resource users: using net squared displacement, biased random bridges and resource utilization functions to quantify hunter and gatherer behaviour. *Methods in Ecology and Evolution*, **3**, 584–594.

Plumptre, A.J., Fuller, R.A., Rwetsiba, A., Wanyama, F., Kujirakwinja, D., Driciru, M., Nangendo, G., Watson, J.E.M. & Possingham, H.P. (2014) Efficiently targeting resources to deter illegal activities in protected areas (ed EJ Milner-Gulland). *Journal of Applied Ecology*, **51**, 714–725.