**Spatio-temporal trends of illegal activities from ranger collected data in a Ugandan national park**

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**Abstract:** Biodiversity loss, even in protected areas, is often a consequence of illegal resource use. Understanding the patterns and extent of illegal activities is therefore essential for effective law enforcement and prevention of biodiversity declines. Here, we utilize extensive data, commonly collected by ranger patrols in many protected areas, and used Bayesian hierarchical models to identify drivers, trends and distribution of multiple illegal activities within the Queen Elizabeth Conservation Area (QECA), Uganda. Encroachment (e.g. by pastoralists with cattle) and non-commercial animal poaching (e.g. snaring for bushmeat) were the most prevalent illegal activities within the QECA. Our analyses showed that illegal activities occur in different areas of the QECA, with non-commercial animal poaching most widely distributed within the national park. Overall, ecological covariates, although significant, were not useful predictors for occurrence of illegal activities. Instead, the location of illegal activities in previous years was more important. There have been significant increases in encroachment and non-commercial plant harvesting (non-timber products) during the study period (1999-2012). We also show significant spatio-temporal variation in the occurrence of all activities. Our results show the need to explicitly model ranger patrol effort to reduce biases from existing uncorrected or catch per unit effort analyses. Prioritisation of ranger patrol strategies is needed to target illegal activities; these strategies are determined by protected area managers, and therefore changes at a site-level can be implemented quickly. These strategies should also be informed by the location of past occurrences of illegal activity: the most useful predictors of future events. However, since spatio-temporal analyses can reveal changes in illegal behaviour, regular patrols in areas of low occurrence are also required.**Introduction**

Despite the conservation of biodiversity being a key target for the United Nations’ Millennium Development Goals (Sachs et al. 2009), global biodiversity is in decline and drivers of these declines, such as climate change and illegal resource extraction, are increasing (Butchart et al. 2010; Craigie et al. 2010; Laurance et al. 2012). With current extinction rates 1000 times higher than background extinction rates (Pimm et al. 2014), estimates suggest that between 21-35% of tropical species will be threatened by extinction by 2030 (Wright & Muller-Landau 2006), prompting discussion of a biodiversity crisis (Brook et al. 2008) and a sixth mass extinction (Barnosky et al. 2011). There has been significant loss of habitat throughout the tropics (Achard et al. 2002) where biodiversity is highest (Hillebrand 2004; Adams & Hadly 2012) and human pressures are growing fastest (Cincotta et al. 2000; Laurance et al. 2012). The decline of tropical biodiversity, even in protected areas (Craigie et al. 2010; Laurance et al. 2012), is often linked to increased illegal trade of plant and animal products (Butchart et al. 2010; Burn et al. 2011; Maisels et al. 2013). However, the drivers and spatio-temporal variation of illegal activities within protected areas are poorly understood (Becker et al. 2013; Lindsey et al. 2013). Determining the drivers and patterns of illegal activities would enable more effective law enforcement and potentially reduce the decline of biodiversity within protected areas.

Whilst it is the rapid rise in poaching of high value wildlife products such as ivory and rhino horn for international markets that has recently made headline news (Cressey 2013), illegal activities within protected areas include a number of different activities from encroachment of neighbouring people for grazing and cultivation; through illegal plant harvesting (including timber extraction as well as collection of medicinal herbs, thatching grass, etc.) to animal snaring for bushmeat products (Schulte-Herbrüggen et al. 2013; Mackenzie & Hartter 2013). Pressures from illegal activities can be extraordinarily high: estimates suggest that nearly 10% of the Serengeti wildebeest population is poached each year (Mduma et al. 1999), with earlier poaching in Serengeti reducing large ungulate populations by 90% (Dublin et al. 1990; Hilborn et al. 2006). Similarly, the area of land illegally logged in protected areas of Kalimantan has been estimated at almost 10% per year between 1999 and 2002 (Curran et al. 2004). The ecosystem consequences of illegal activities within protected areas can be profound (see Beale et al. (2013b) for a brief review, from ecological cascades due to loss of keystone species to total habitat loss due to illegal land conversion). Furthermore, as natural resources are increasingly and unsustainably exploited in regions neighbouring unprotected areas, pressures are rising within (Wittemyer et al. 2008; Newmark 2008).

Previous research on illegal resource use mainly focusses on single activities such as hunting for bushmeat (Nuno et al. 2013; Watson et al. 2013) illegal logging (Mackenzie & Hartter 2013; Green et al. 2013) or harvesting of rare or medicinal plants (Young et al. 2011). These studies are useful, providing information about the magnitudes and primary spatial trends in a number of activities. For example, encroachment for grazing appears to be a major threat to protected areas in Kenya (Kiringe et al. 2007), whilst demonstration that buffalo populations were lower in locations close to certain villages enabled more effective targeting of ranger patrols (Metzger et al. 2010). However, most analyses do not consider the full range of illegal activities that occur within a protected area and assess either temporal or spatial variation alone (see Mackenzie et al. (2011) and Plumptre et al. (2014) for exceptions). Single activity assessments ignore the potential for different processes to underlie different activities, yet managers need to know the temporal and spatial dynamics of all classes of illegal activity if they are to make informed decisions on resource use.

Existing methods to assess patterns of illegal activities from ranger based monitoring include analysis of raw patterns uncorrected for ranger effort, or use of encounter rates per unit effort (Hill et al. 2003; Hilborn et al. 2006; Jachmann 2008a; Mackenzie et al. 2011). However, these simple methods can give highly biased results as the analyses assume random or uniform survey effort across a protected area, yet ranger-based monitoring focusses on areas where illegal activities are expected to be highest (and are likely to have direct impacts on future events too). Consequently, encounter rates will not reflect the underlying trends of illegal resource use if the efficiency of ranger patrols improves over time. Depending on the particular assumptions made, the consequences of these biases may lead to systematic over- or under-estimates of illegal activities with little information on the scale of the bias, and will always lead to uncertain trends (Keane et al. 2011). Recently, methods have been developed that can account for spatial and temporal variation in surveillance effort by estimating the probability of detecting an event independently from the processes that drive the distribution of the events (Beale et al. 2013b, 2014), but these hierarchical models have not yet been applied to ranger-based monitoring data.

We used Bayesian, spatially explicit occupancy models to assess the spatial and temporal patterns of six classes of illegal activities, from commercial hunting of high value mammals to encroachment by pastoralists with cattle and subsistence harvesting of plants, within the Queen Elizabeth Conservation Area (QECA), Uganda, between 1999 and 2012. This dataset, derived from ranger patrol data collated using the Management Information System (MIST) database (Stokes 2010), is similar to the data gathered by rangers across many tropical protected areas. Since an understanding of poacher behaviour could be very useful for management of protected areas, we aimed to identify areas at greatest risk for each class of illegal activity, identify the ecological and anthropogenic drivers of spatial and temporal variation in illegal activities, and assess the spatial and temporal changes of each activity.

**Methods**

Our dataset consisted of 84,308 position records from 5,867 ranger patrols conducted between September 1999 and October 2012 in QECA, a mixed forest and savannah grassland protected area in south-western Uganda (Fig. 1). During all surveillance patrols (foot and vehicle), rangers record their location with handheld GPS units when sighting animals or evidence of illegal activities, or at 30 minute intervals after the last sighting or recorded position. Additional details on the dataset are provided in the Supporting Information (Appendix S1). Each illegal activity was then assigned to one of six classifications (Table 1 and Table S1 in Supporting Information) and aggregated annually to a 500 m presence / pseudo-absence grid. We fitted separate models to each class of activity across the entire time period as well as for annual subsets.

**Estimating ranger effort**

Because locations are recorded by rangers up to 30 minutes apart, we do not know the exact route of all patrols. Consequently, we estimated the patrol effort between known points using biased random bridges (Papworth et al. 2012). We used R packages adehabitatLT and adehabitatHR (Calenge 2006) to estimate probable routes between fixed points as a utilisation distribution (UD) of each patrol on a 500 m grid. Individual UD surfaces were summed by year to generate annual estimates of observer effort. Fully documented code is available as supplementary material (Appendix S2 in Supporting Information).

**Covariates of illegal activity occurrence**

We expected the spatial pattern of illegal activities to be influenced by a number of environmental covariates: Net Primary Productivity (NPP), Topographic wetness, distances to roads and rivers, terrain slope, wildlife density (species targeted by either commercial or non-commercial poachers respectively) and habitat (Table S2). Additional details on covariate data are provided in the Supporting Information (Appendix S1). Using the digital sources identified in Table S2, each of these variables was extracted at 500 m resolution grid using R (R Core Team 2012), with finer-scale data aggregated using the mean value. NPP was included as a proxy for the distribution of wildlife (Loarie et al. 2009; Duffy & Pettorelli 2012) and suitability for illegal grazing (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), and we assumed these trends were static over the year. 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 et al. 2006; Watson et al. 2013). In addition, habitat variation will influence animal 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).

**Statistical analysis**

We used a Bayesian hierarchical modelling approach to analyse the spatio-temporal distribution of each illegal activity separately. 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 variation in the detection of illegal activities by ranger patrols. Full details are provided in Beale et al. (2014) and briefly in the Supporting Information (Appendix S1) along with R and WinBUGS codes are (Appendix S3).

Statistical analysis was performed using R (R Core Team 2012) calling WinBUGS (Lunn et al. 2000) through the R2WinBUGS package (Sturtz et al. 2005). We took 1000 samples from 10000 Markov Chain Monte Carlo (MCMC) iterations after a burn-in of 1000 iterations.

The temporal trends of probabilities of each illegal activity were determined by calculating the mean values across all cells for each year for each of the 1000 MCMC iterations. Spatio-temporal trends for each activity and each cell were calculated using generalized linear models for each of the 1000 MCMC iterations with a quasi-binomial error structure, where the probability of detection per cell was the dependent variable and year the independent variable. Each spatial and temporal model therefore provides 1000 MCMC estimates of each parameter, fully propagating model-based uncertainty.

To compare the temporal trends identified by our models with those resulting from traditional analyses, using no correction for effort or captures per unit effort (CPUE), we used generalized linear models, with a Poisson error structure, for each activity classification. For the models of raw counts, ranger effort was the dependent variable and year the independent variable. For CPUE we used raw counts/effort as the dependent variable and year as the independent variable.

**Results**

We successfully fitted 71 occupancy models out of a possible 84 (Table S3). Models that failed to converge tended to have fewer than 10 recorded events in any year.

**Overall Patterns**

The spatial distribution of illegal resource use differed among the six categories (Fig. 2). Encroachment (mostly illegal cattle herding in QECA) was most common at the boundary of the QECA, especially in the North-west where there is a high population density of cattle in neighbouring land. Commercial plant activity (timber and charcoal) was most likely to occur in a restricted area in the South-east of the QECA within the Maramagambo Forest. 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. In addition, in the South of QECA in the Ishasha sector there are areas with a high probability of non-commercial and commercial animal poaching. In comparison to the other classifications, non-commercial animal poaching was widely distributed across the QECA with few obvious hotspots.

**Drivers of illegal activities**

Parameter values (summarised in Fig. 3, and corresponding effect plots in Figs S2 - S7) showed no consistent covariate influencing the probability of all classes of illegal activity, though significant effects were found for most activities individually, with the exception of encroachment and commercial plant harvesting. Target animal density strongly influenced occurrence of commercial animal poaching, but not non-commercial poaching. Habitat also influenced patterns of animal poaching; the probability of all animal poaching was greater in savannah habitats, and non-commercial poaching was highest in forest habitats. Travel cost from villages did not strongly affect any class of illegal activity, whereas fishing, non-commercial plant harvesting and non-commercial animal poaching were all higher closer to rivers. Increased travel cost led to lower probabilities of non-commercial plant harvesting and commercial animal poaching.

For NPP and topographic wetness there are two parameter estimates, representing the knots used in the smooth splines. Topographic wetness was never significant, commercial animal poaching was associated with lower levels of NPP, whilst non-commercial plant and animal poaching were both associated with a higher NPP.

**Temporal trends**

Across the activities, only encroachment and non-commercial plant harvesting showed significant overall trends (both increasing) between 1999 and 2012 (Table 1), although most classifications showed a decrease in 2012 and there was often considerable inter-annual variation (Fig. 4).

Using raw numbers of each class of illegal activity and no correction for effort, we detected a significant increase in each class (coefficients = 2.06-16.61, P <0.01; Table S4). The analysis of captures per unit effort identified significant increases in commercial plant harvesting and a significant decrease in non-commercial animal poaching (Table S4).

**Spatio-temporal trends**

Although only two activities showed overall temporal trends, we found significant spatio-temporal variation in occurrence of illegal activity for most activity classes (Fig. 5). With the exception of South-eastern forest habitat, encroachment has increased throughout the QECA (Fig. 5a). Spatio-temporal trends of commercial plant activity appear to be driven by roads, rivers and forest; there has been a decrease in activity close to roads and rivers, 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 in a few scattered locations with little apparent pattern.

**Discussion**

We succeeded in fitting 71 spatially explicit occupancy models to ranger-derived monitoring data, providing valuable insights into poacher behaviour in QECA. We found that the six different activities occur in different areas and correlate with different covariates. Some of these relationships have been identified previously (e.g. commercial animal poaching occurs where animal densities are greatest (Jachmann 2008b; Maingi et al. 2012)) or are otherwise obvious (e.g. illegal fishing is associated with water), but others are newly identified here (e.g. non-commercial animal poaching is associated with high wetness areas and near rivers, possibly because there is a need for a certain amount of woody vegetation to conceal snares and create funnels for wildlife to move into the snare). In contrast to analyses based on the total number of illegal activities and the simple capture per unit effort analyses often used in equivalent studies, we found evidence for significant temporal trends in only two activities, namely increases in encroachment and non-commercial plant harvesting. Uncorrected analyses suggested increases in all activities, whereas capture per unit effort analyses identified spurious trends in animal non-commercial and plant commercial, one positive, one negative (Table S4). These differences demonstrate the importance of our independent estimate of the observation process and highlight the unpredictability of the biases in simpler analyses. In the relatively few examples where we failed to fit a model (13 of 84), there were usually very few detections of the activity in question (<10 per year). This suggests our methods will be widely applicable to similar data sets, provided effort is known and detections are reasonably frequent. Although few activities showed significant overall temporal trends, we found evidence that the spatial occurrence of several activities has changed over time (Fig. 5). This information is important to ranger deployment, and demonstrates the value of a fully spatio-temporal analysis.

Of the two classes of illegal activity that show significant increases, encroachment represents perhaps the most immediate threat to the ecological integrity of the QECA, (the increase in non-commercial plant harvesting is caused by increased unlicensed harvesting of grass for thatch). The increased incidence of encroachment (Fig. 4) is likely due to the settlement within the QECA of refugees and their 10000-20000 cattle from the Democratic Republic of Congo in 2006, their subsequent eviction in 2007 and continuing encroachment since then (Moghari 2009).

Animal poaching is the primary concern of rangers on the ground, yet despite investment in anti-poaching, we found no temporal trend in either commercial or non-commercial animal poaching. This lack of change needs placing within the context of continent-wide increases in demand for bushmeat (Schulte-Herbrüggen et al. 2013; Lindsey et al. 2013) and recent rises in poaching for ivory (Burn et al. 2011; Maisels et al. 2013) suggesting that current patrol effort is successfully buffering QECA from external drivers. This result is encouraging, demonstrating that traditional law enforcement activities continue to be effective at protecting local sites and preventing increases in poaching, despite global trends, an observation consistent with data from South Luangwa National Park (Becker et al. 2013) that showed no change in snaring during 2006-2010 and results from southern Africa where despite rises in rhino poaching, other illegal activities remain rare within highly patrolled environments (Beale et al. 2013a). Spatially, we found that commercial poaching was primarily associated with a higher density of target animals, but no equivalent relationship for non-commercial poaching, which was instead more generally dispersed across QECA than other activities. The association of high-value commercial poaching with high density of target animals is unsurprising and confirms earlier results from Maingi et al. (2012). The difference perhaps reflects the differences in absolute abundance of the animal targets of commercial and non-commercial poachers: commercial poachers must hunt relatively few target animals in the areas where they are most abundant, whereas non-commercial poachers may trap sufficient animals in the most convenient areas with little regard to overall density by being able to leave their snares for several days or weeks.

Human density outside the QECA is high close to areas where both commercial and non-commercial plant harvesting are most likely (Uganda Bureau of Statistics 2006). Similar results have been reported in other tropical protected areas, where forest disturbance was more likely closer to higher human density (Allnutt et al. 2013; Mackenzie & Hartter 2013), suggesting that these patterns are primarily driven by the need for fuel and construction (Naughton-Treves et al. 2007; Mackenzie et al. 2011). Additional ranger patrols in and around the Maramagambo forest are important for monitoring future changes in illegal resource use because of the high biodiversity value and pressures from high human densities in harvesting endangered species such as *Prunus africana* for medicine and fuel (Plumptre 2002; Sheila 2009). Currently, there is some legal (licensed) harvesting of non-timber forest products within QECA, providing a valuable resource to local communities as noted elsewhere (Abbot & Mace 1999; Mackenzie et al. 2011). When not licenced such activities are illegal, and in setting legal harvest quotas it is important to assess the sustainability of both legal and illegal plant harvesting.

Although we identified significant correlates for most illegal activity classes, the correlations were generally weak and had wide confidence intervals and we identified none at all for encroachment and non-commercial plant harvesting (Fig. 3, Figs S2 - S7). Several expected patterns were not found: e.g. in contrast to studies in Kenya (Wato et al. 2006; Kimanzi et al. 2014) we found no association between non-commercial animal poaching and travel cost or distance to roads, presumably reflecting differences in poacher behaviour between the two areas. Instead, much of the spatial pattern was explained by the spatially explicit random effect rather than covariates. There are several possible explanations for this: (a) we are missing important covariates, (b) the covariate surfaces we used are not sufficiently accurate, (c) there are strong unmodelled interactions between covariates, or (d) illegal activities are genuinely not strongly correlated with covariates. Whilst both (a) and (b) are possible explanations, we consider them relatively unlikely: we used a suite of covariates common to similar analyses (e.g. Wato, Wahungu & Okello 2006; Watson et al. 2013), we did find evidence of significant effects with most covariates, and we have considerable first-hand experience of QECA that confirms the reliability of the surfaces used. There are perhaps good reasons to expect complex interactions between covariates. Travel cost may be weighed up against animal density, or individuals may be seeking to optimise their success at multiple activities at once: an illegal pastoralist with cattle may well seek to set snares whilst in the protected area, but is perhaps unlikely to do so in the immediate vicinity of his own cattle. Such interactions may be real, but are too complex to estimate given the noisy data available, meaning that for practical purposes this explanation and the final one are equivalent: illegal activities in QECA are not strongly correlated with simple environmental covariates. Perhaps we should not be surprised: predicting human behaviour is notoriously difficult (Gavin et al. 2010), individual poachers have areas of operation that are highly personal (C.M. Beale pers. obs.) and ranger activities may disrupt optimal poaching conditions such that few correlations with covariates remain. Although this does mean it is difficult to predict patterns of illegal activity based on covariates alone, and despite significant spatio-temporal variation over the long term, our annual models showed broadly similar patterns for each activity year on year: encroachment tended to occur in the north west, illegal logging in the Maramagambo forest, commercial animal poaching along the Kazinga channel, etc. Consequently, the best empirical prediction of future poaching activity will come from the current distribution, and intelligence-driven ranger patrols based on the detailed knowledge generated through these analyses will likely improve detections of illegal activities.

Although the past does seem to be the best predictor of the future for the illegal activities analysed here, our spatio-temporal analyses provide evidence that longer-term changes in illegal activities also occur. These changes presumably reflect changes in poacher behaviour either in response to changing ranger effort (e.g. the decrease in commercial animal poaching in the south may be associated with the large increase in ranger effort in this region over the study period), or as a consequence of changing demand for different natural products (e.g. the decline in plant harvesting along rivers (Fig. 5c) probably reflects declines in demand for fishing floats from *Aeschynomene elaphroxylon* (Ambatch) trees as a consequence of legal supply being made available elsewhere (A.J. Plumptre pers. obs.)). Such temporal change in poacher behaviour is often suggested (Keane et al. 2008) and forms the justification of a deterrence -based approach to ranger activities, but this is the first empirical evidence for such temporal behavioural shifts. A consequence of this is that whilst optimising ranger effort in high occurrence areas is generally wise, it remains important to maintain sufficient patrol effort in areas where detections are expected to be lower to monitor spatial change in patterns over time, a similar recommendation to that of Watson et al. (2013). Determining the deterrence effects of patrols and identifying the threshold at which patrol effort prevents the occurrence of illegal activities are important future requirements, and will aid patrol strategy decisions and improve patrol efficiency in resource-limited settings.

In conclusion, explicit modelling of ranger search effort is important, as capture per unit effort and uncorrected analyses can lead to spurious correlations. Existing patrol strategies are unable to target illegal activities because these events occur in different areas, therefore some prioritisation is required, after which patrol routes need to be optimised. Although ecological covariates are significant, they are not particularly useful for prediction; the best way to predict illegal activities in the future is the immediate past, and these patterns should provide the primary information for developing patrol activities. Spatio-temporal analyses can reveal relatively subtle changes in illegal activities that may be missed by spatial or temporal analyses alone and reflect changes in poacher behaviour over time. Since changes occur, to reduce biodiversity loss we must ensure that rangers also regularly patrol areas where current illegal activity is low to ensure identification of new problem areas.

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**Supporting Information**

Additional details describing the database, obtaining covariate data and statistical analysis (Appendix S1), R code for the effort calculation and covariate manipulations (Appendix S2), WinBUGS code (Appendix S3), list of illegal activities as reported in the MIST database (Table S1), details on ecological covariates (Table S2), model completion success (Table S3), temporal trends of raw counts of illegal activities and CPUE (Table S4), correlation of covariates (Fig. S1), and marginal effects for all six illegal activities classifications (Figs S2-S7) are available online. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of material) should be directed to the corresponding author.

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Table 1. Classification of illegal activities within the Queen Elizabeth Conservation Area and associated median probability trends (occurrence) across all years that data have been collected.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Activity**  **Classification** | **Examples of values in MIST database** | **Number of records** | **Occurrence trend (coefficient)** | **Confidence intervals (2.5%, 97.5%)** |
| Encroachment | Livestock grazing, mining, trespassing | 1570 | 0.01*b* | 0.05, 0.14 |
| Fishing | Fishing | 443 | 0.06 | -0.04, 0.14 |
| Plant Commercial | Pitsawing, cultivation | 260 | -0.02 | -0.23, 0.10 |
| Plant Non Commercial | Medicinal plants, grass harvesting | 605 | 0.12*b* | 0.06, 0.17 |
| Animal Commercial*a* | Hippo, elephant, buffalo | 241 | -0.02 | -0.13, 0.06 |
| Animal Non Commercial*a* | Snares, other animal hunting, honey harvesting | 1589 | -0.02 | -0.06, 0.03 |

*a* Although we separate animal poaching into two classes, the primary distinction is in the value of the target: commercial animal poaching involved high value products from large herbivores, typically using active hunting methods where the product is likely to be transported regionally, whereas non-commercial poaching is focussed on lower value bushmeat for subsistence or local markets only, typically using snares.

*b* significant trend

**Figure legends**

Figure 1. Location of Queen Elizabeth Conservation Area and the broad habitat classifications derived from aerial photographs and high resolution satellite imagery (Plumptre et al. 2014)

Figure 2. Occurrence probabilities of illegal activities in the Queen Elizabeth Conservation Area. (a) encroachment, (b) fishing, (c) commercial plant harvesting, (d) non-commercial plant harvesting, (e) commercial animal poaching, (f) non-commercial plant harvesting

Figure 3. Mean parameter estimates for each covariate across illegal activity classifications: (a) encroachment, (b) fishing, (c) commercial plant harvesting, (d) non-commercial plant harvesting, (e) commercial animal poaching, (f) non-commercial plant harvesting

Figure 4. Annual trends in illegal activities in the Queen Elizabeth Conservation Area. 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

Figure 5. Spatio-temporal trends of illegal activity per grid cell (500m) between 1999 and 2012 in the Queen Elizabeth Conservation Area. White indicates no change and darker colours indicate more significant trends during the full period







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