Monitoring Conservation Threats, Interventions and Impacts on Wildlife in a Cambodian Tropical Forest.

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Declaration

This thesis is the result of my own work. The work of all others is appropriately acknowledged and referenced in the text.

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Abstract

While there are many scientifically rigorous methods for monitoring wildlife populations and the threats that they face, they are often difficult to implement in tropical forest environments. In some cases traditional gold standard methodologies can be employed despite the inherent practical and theoretical challenges, but in other situations more novel approaches must be developed. In this thesis we investigate these issues within the context of a large protected area in Eastern Cambodia.

The aims of this study were to; 1. Evaluate the status and trends of wild ungulate populations using distance sampling derived density estimates. 2. Develop and implement an approach to reliably estimate the detectability and abundance of wire snares, which currently represent the greatest threat to mammal populations within the area. 3. Quantify the association between snare abundance and a number of natural and anthropogenic factors hypothesised to influence snare placement. 4. Assess the utility of law enforcement records, and specifically catch-per-unit-effort (CPUE) indices derived from patrol data, as a tool for monitoring threats.

I present rigorous density estimates for several key ungulate species, representing the first such data from the entire lower Mekong region. Whilst smaller ungulate populations appear to be stable, larger species are likely undergoing a decline. A sampling protocol was developed for surveying snares which balanced the requirements of statistical rigour against feasibility and efficiency of implementation in the field. The results of this survey were analysed using N-mixture models to produce detectability-corrected spatially explicit estimates of snare abundance. As predicted, forest type, proximity to settlements, and distance to the Vietnamese border were shown to be important determinants of snare abundance whereas the relationship between snaring levels and both patrol effort and wildlife densities was less clear. This study also demonstrated that while CPUE indices derived from patrol data can adequately reflect true levels of threat, their utility depends greatly on the quality of the patrol data, and on identifying the appropriate spatio-temporal scale at which to undertake the analysis.

Acknowledgements

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Thanks also to all the crew at Silwood and the Zoo, a great bunch of people altogether.

Finally, thank you to my parents, for Annamoe at the beginning of this road and Glenealy at the end of this section of it.

And to Maggie. You started out with me in the first chapter and we parted ways at the last. A girl's best friend in the jungle.

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Chapter 1. Introduction

1.1 Background

1.1.1 Conservation Monitoring for Management

Conservation monitoring is crucially important for forewarning of impending species declines and extinctions, for creating triggers for management interventions, for assessing the effectiveness of management actions designed to preserve biodiversity, and for accumulating the data necessary to produce metrics representing the status of biodiversity (Lindenmayer et al. 2012).

Approaches to conservation monitoring can be conceptualised as continuum with "passive" or "surveillance" monitoring at one end and "targeted" or "question-driven" monitoring at the other. Passive monitoring is typically concerned with documenting change over some (usually long) time period in a given component of biodiversity. While this type of monitoring can yield useful information, for example, by detecting unanticipated changes (e.g. in habitat use by birds from British Breeding Bird Survey data; Newson et al. 2009), it has been criticised for not being hypothesis-driven and or having an obvious management focus (Nichols & Williams 2006; Lindenmayer & Likens 2010). In contrast, targeted monitoring focus on acquiring the information needed to discern among competing *a priori* hypotheses regarding the effectiveness of specific management actions (Nichols & Williams 2006). At the far end of this spectrum is adaptive monitoring (Lindenmayer & Likens 2009), which is directly related to adaptive management (Holling 1978; Walters 1986). In these approaches efficient learning is an explicit objective and the knowledge gained through monitoring creates a feedback loop through which management strategies are modified iteratively, ultimately leading to improved management outcomes (McDonald-Madden et al. 2010; Keith et al. 2011). Adaptive approaches are particularly appealing because they represent a way of dealing with the uncertainty that characterises the "crisis discipline" of conservation biology but although they are much lauded within the literature they are not often fully applied in practise (Lindenmayer & Likens 2009; Keith et al. 2011).

Nevertheless, successful conservation management and some form of targeted monitoring are increasingly recognised as being fundamentally interdependent (Stem et al. 2005; Gardner 2012). The effectiveness of conservation management can only be assessed through rigorous monitoring and reporting on trends in species populations, ecosystems and threats (Lindenmayer et al. 2012) and one of the primary objectives of conservation monitoring is to guide, inform and drive management decisions (McDonald-Madden et al. 2010; Jones 2011). In order to be able to evaluate the relative effectiveness of various management strategies targeted monitoring programmes must be underpinned by clearly-defined objectives, well-articulated conceptual models and rigorous study designs (Lindenmayer & Likens 2010).

The development of a robust conceptual model of the conservation problem forces both assumptions and objectives to be made explicit, even when information is sparse and the model is consequently simple (Green et al. 2005; Pullin et al. 2013). The use of logical framework or results chain approaches can further help to elucidate causal linkages between between interventions and conservation objectives and to identify key components of success and their associated monitoring requirements (Pullin et al. 2013).

In a conservation context a results chain is a tool which aims to clarify assumptions about how conservation action will influence indirect threats, opportunities, and direct threats to have a positive impact on conservation targets (Margoluis et al. 2013). An example of this type of approach is the framework and associated scorecard developed by the Cambridge Conservation Forum (Kapos et al. 2008), which draws on existing categorisations of conservation action (i.e. Salafsky et al. 2001; 2002; 2008), and emphasises the link between intermediate steps (such as activities, outputs and outcomes) and the ultimate success, in terms of meeting conservation targets, of a project (Kapos et al. 2009). Implicit in this approach is the requirement for monitoring on multiple levels; from input and output monitoring (i.e. documenting resources invested and activities implemented respectively) to outcome monitoring (i.e. quantifying changes in threats as a result) to impact monitoring (i.e. measuring the changing status of conservation targets) (Salzer & Salafsky 2006; Kapos et al. 2008; Margoluis et al. 2013).

Monitoring at each of these levels involves different sets of both methodological and practical challenges, all of which have implications for cost and feasibility of available approaches. These issues are an important consideration for managers as they decide not only on what proportion of available resources should be allocated to monitoring as opposed to taking action, but how monitoring resources should be subdivided across each of these levels (Salzer & Salafsky 2006).

1.1.2 Monitoring at Multiple Levels in Tropical Forests

Conservation targets may be ecosystems, communities, populations, or species (Kapos et al. 2008; Salafsky et al. 2008) and conservation initiatives in the tropics are often concerned with populations of rare and endangered species. Measuring change in the status of these populations requires data on species distribution, abundance or other relevant biological parameters and such data can be extremely difficult to acquire for the rare and elusive species that tend to be the focus of conservation concern in the tropics (Thompson 2004; Datta et al. 2008).

The estimation of abundance and related parameters requires investigators to address two critical sources of variation; spatial sampling and imperfect detection (Yoccoz et al. 2001; Williams et al. 2002). As areas of interest are frequently too large to be surveyed in their entirety, a sample of smaller areas must be selected in which to focus survey effort. Selection of sample locations must be conducted in a manner that permits inference about the entire area of interest (i.e. through the use of a probabilistic sampling scheme) (Thompson et al.

1998). The issue of detectability relates to the fact most survey methods exclude the possibility that investigators will observe every animal (or sign etc.) within a given sample location and therefore the counts obtained represent an unknown fraction of the animals present in the sampled area (Yoccoz et al. 2001). An array of approaches have been developed to deal with imperfect detectability, such as distance sampling, capture-recapture and occupancy based methods (Buckland et al. 2001; Williams et al. 2002; Mackenzie 2006). However, the extent to which these approaches can be applied in settings that they were not necessarily designed for, and the validity of underlying model assumptions in these contexts, remains unclear and in many cases untested (Singh & Milner-Gulland 2011).

The difficulties associated with both spatial sampling and detectability in the estimation of abundance and related parameters are exacerbated where the target species are rare (MacKenzie et al. 2005). Rarity is generally defined as a species occuring at a low density across a large range, but in a statistical sense (i.e. being present at low frequency within a sample) it can also be induced by a clustered distribution (Gaston 1994). Rarity is also often allied with a low probability of detection even the target species is present, and this can result in small sample sizes which tend to preclude the use of the traditional estimation techniques such as distance sampling and capture-recapture (MacKenzie et al. 2005) .

A range of practical impediments also apply to attempts to monitor changing population statuses in the tropics. The need to monitor at a landscape scale, in order to capture relevant larger scale dynamics, has been increasingly recognised (Sanderson et al. 2002; Jones 2011), but this can greatly increase the cost and logistical challenges involved in undertaking wildlife surveys, particularly in remote and inaccessible areas. Conservation initiatives in the tropics are often chronically underfunded (Balmford & Whitten 2003) and the level of investment required to conduct large-scale surveys based on rigorous sampling schemes may be beyond the budget of many conservation projects (Gaidet-Drapier et al. 2006). In addition, scientifically rigorous monitoring methods can be technically and analytically complex, which further hinders their application in contexts where human capacity may be limited (Danielsen et al. 2000; Rist et al. 2010).

Even in situations where all of the above obstacles can be negotiated and reliable population estimates for target species can be obtained, the inevitable time-lag between the implementation of a conservation action and any apparent population response means that impacts are unlikely to be measurable within a short or even medium-term timeframe (Kapos et al. 2008; Caro et al. 2009). Furthermore, linking population responses to conservation interventions is greatly complicated by the presence of multiple potentially confounding variables and complex interactions which can ultimately obscure the impacts of management efforts (Ferraro & Pattanayak 2006; Kapos et al. 2008). Thus, even where possible, measuring solely the status of biodiversity targets is usually insufficient to gauge the efficacy of the interventions an organization is implementing or how well it is implementing them (Salzer & Salafsky 2006).

Monitoring intermediate outcomes, such as threat prevalence, can facilitate an assessment of management effectiveness over shorter time scales and provide an opportunity for interventions to be managed more adaptively (Salafsky et al. 2002; Kapos et al. 2008). Not only does threat monitoring allow for more rapid response from managers but it also help to generate a better understanding of the underlying mechanisms and potentially complex ecological and anthropogenic interactions which are driving changes in target populations (Liu et al. 2007; DeFries et al. 2009).

The major proximate threats faced by protected areas in the tropics are habitat disruption and the overexploitation of wildlife and other forest-resources (Laurance et al. 2012). In most protected areas these detrimental activities are prohibited and collecting monitoring data on illegal resource use involves some unique methodological challenges (Gavin et al. 2010). This is primarily because illegal activities are characterised by being covert and sensitive in nature, and resource users often have significant incentives to conceal their actions and provide false information to investigators (Gavin et al. 2010).

Information gathered from resources users themselves is unlikely to be reliable due to fear of retribution and although there are recently developed techniques which minimise the perceived risk in answering sensitive questions truthfully (e.g. Solomon et al. 2007; St John et al. 2011; Nuno et al. 2013) these methods typically require large sample sizes and may not be applicable where informants are highly risk averse. An alternative approach is to use independent observations of illegal resource use which can be direct, for example through accompanied hunts (Rowcliffe et al., 2004) or indirect, for example through surveys for traps and snares (Wato et al. 2006a). In addition to the potential for bias caused by the presence of the observer with some of these methods, all approaches are also susceptible to the same sources of variation described above in relation to population estimation; i.e. imperfect detection and sampling error (Yoccoz et al. 2001; Nichols & Williams 2006).

Law enforcement records, for example those collected during routine patrols within protected areas, have also been used to assess threat (Hilborn et al. 2006; Holmern et al. 2007). However, the collection of law enforcement records is primarily a means of monitoring the implementation of interventions (i.e. at the level of inputs and outputs), which is important for promoting accountability and efficiency, and for tracking the investment of resources (Margoluis et al. 2013). The use of law enforcement data to additionally monitor threats (i.e. outcomes) is an appealing prospect because such data are cheap and readily available (Gavin et al. 2010; Keane et al. 2011). However, the extent to which law enforcement data can be used effectively in this way remains unclear (Keane et al. 2011). This is because law enforcement data is prone to severe inherent biases as a result of the non-linear relationship between patrol effort and encounter rates of infractions, the non-constant levels of patrol efficiency, and the potential for behavioural interactions between enforcement agents and perpetrators of illegal activity (Gavin et al. 2010; Keane et al. 2011).

1.2 Study Site

The Seima Protection Forest (SPF) covers 292,690 ha in eastern Cambodia, including a core area of 187,983 ha and two buffer areas to the east and west. The site is unusual in Indochina as it contains large areas both of evergreen/semi-evergreen forest and deciduous forest, together with a rich transition zone between them. Biodiversity values are high as a result of having large areas of relatively intact habitat with a relatively intact faunal assemblage. Of 41 Globally Threatened vertebrate species recorded in the SPF (4 Critically Endangered and 14 Endangered), many are thought to occur in globally or regionally important populations, including elephants, primates, wild cattle, several carnivores and a range of large birds.

Key direct threats in the SPF are unsustainable resource extraction (hunting, logging, fishing, other plant harvests), and forest clearance. Drivers include population growth, improving road access, the actions of large mining and agri-business companies, weak law enforcement and governance frameworks, limited recognition of the value of biodiversity and environmental services, and rising regional and global demand for both wild products and agricultural produce. Demographic surveys in 2008 estimated that there were 38 administrative villages in or on the border of SPF, with a population of about 19,200.

Since 2002 the SPF has been the site of an ambitious conservation project that is being implemented by the Forestry Administration (FA) in collaboration with the Wildlife Conservation Society, together with a range of other stakeholders. The conservation project centres around four direct interventions: maintaining political support, law enforcement, strengthening community natural resource management and developing alternative livelihoods, all supported by monitoring and fund-raising. To date project activities, most importantly law enforcement efforts, have been successful in moderating but not stopping major threats across much of the core area. Nonetheless, threats are rapidly increasing in scale and diversity, and the long-term future of the site is not yet assured.

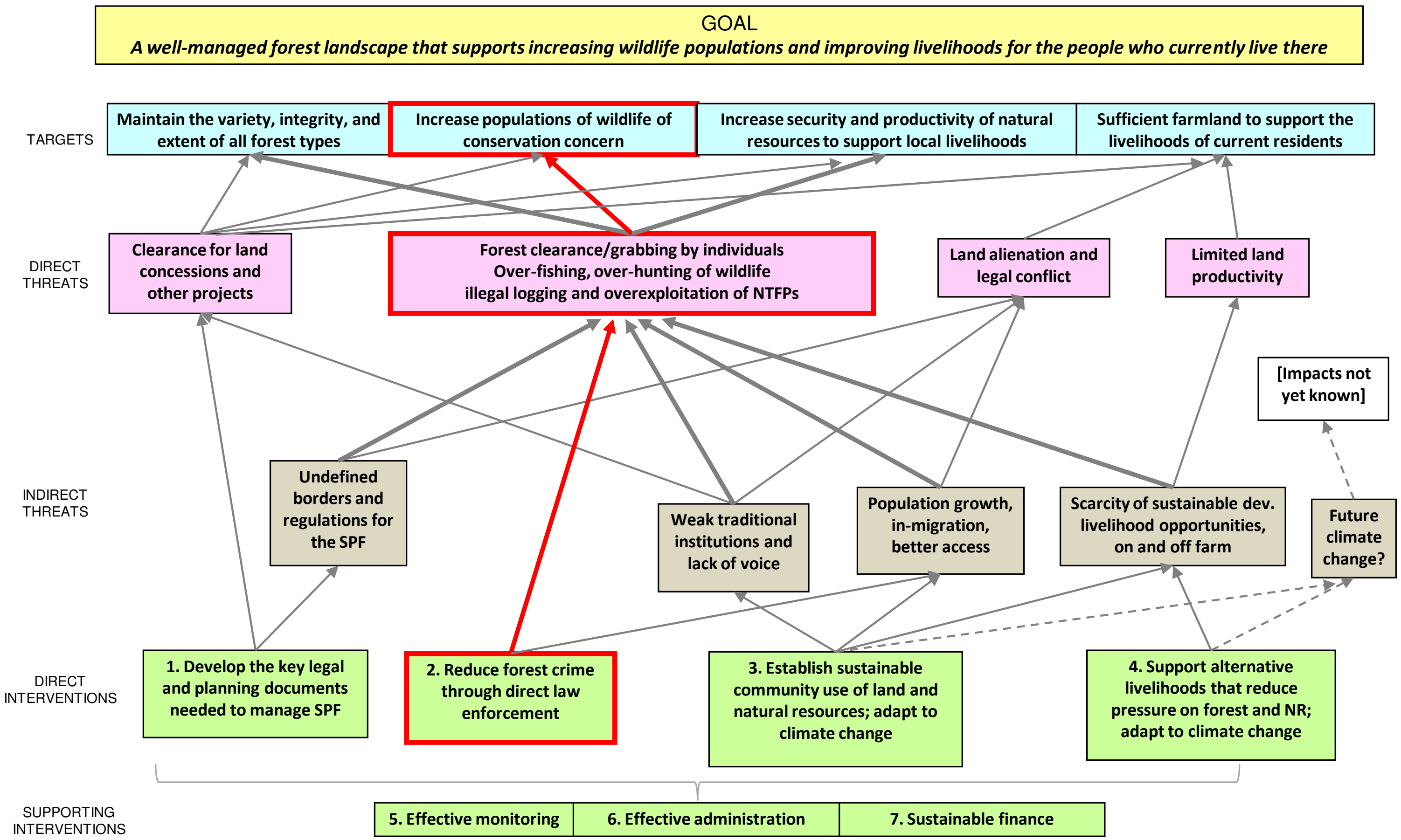

Figure 1 Schematic diagram representing a conceptual model of the conservation project being implemented in the Seima Protection Forest. The causal chain to be addressed by thesis is highlighted in red. Adapted from Evans et al. (2012).

1.3 Aims and Objectives

This thesis uses the project underway in the Seima Protection Forest as a case study in order to explore how conservation monitoring might best be undertaken at multiple levels (Figure 2). The thesis has both methodological novelty in terms of trialling innovative approaches to monitoring and comparing the power to detect spatial trends in threats under different monitoring approaches, and conceptual novelty in developing new approaches to monitoring threats and population status. The overall research aim is to develop a robust framework for monitoring the status and trends of rare and threatened species, and their threats in tropical forests. This aim is addressed through the following objectives:

1. To assess the status of tiger and wild ungulate populations within the study site, using distance sampling for ungulates and camera-trapping and scat dog surveys for tiger.

2. To develop and implement an approach to reliably estimate the detectability and abundance of wire snares, which currently represent the greatest threat to mammal populations within the area.

3. To quantify the association between snare abundance and a number of natural and anthropogenic factors hypothesised to influence snare prevalence.

4. To assess the utility of law enforcement records, and specifically catch-per-unit-effort indices derived from patrol data, as a tool for monitoring threats.

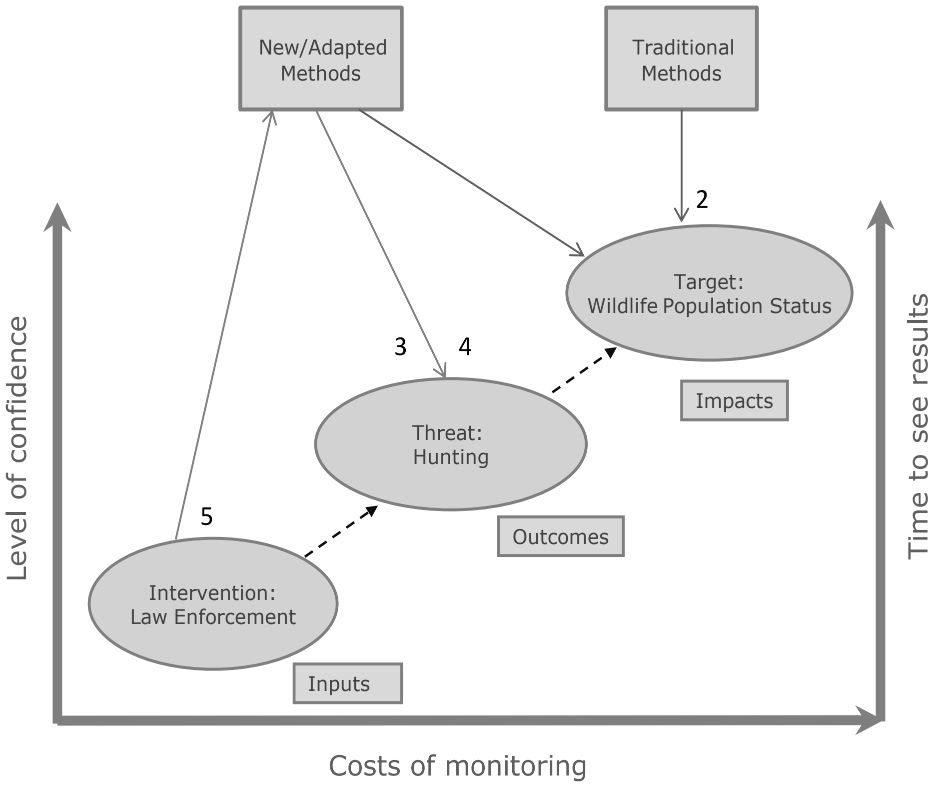

Figure 2 Schematic diagram representing the methodological framework for this research. Dashed arrows indicate assumed causal linkage. Numbers refer to relevant chapter numbers.

1.4 Thesis Outline

Subsequent to this introductory chapter, the thesis has the following structure:

Chapter 2: In this chapter I present the result of the first six years of a biological monitoring programme for ungulates and tigers in the Seima Protection Forest (SPF). Distance sampling was used to estimate population densities and, where possible, to generate population trend data for ungulate species. Camera-trapping and scat dog surveys were employed to assess the status of tigers. These results represent the first of their kind from the lower Mekong region for all of the species concerned.

This chapter is published as: O'Kelly HJ, Evans TD, Stokes EJ, Clements TJ, Dara A, et al. (2012) *Identifying Conservation Successes, Failures and Future Opportunities; Assessing Recovery Potential of Wild Ungulates and Tigers in Eastern Cambodia*. PLoS ONE 7(10): e40482. doi:10.1371/journal.pone.0040482. As first author I designed and carried out the surveys, and carried out the analyses.

Chapter 3: This chapter describes an innovative field experiment which was designed to provide a preliminary estimate of the potential detection probability of snares in a tropical forest setting, and to investigate how a range of factors might affect this detection probability. This experiment was also used to test the efficiency of snare survey sampling protocols and to evaluate the appropriateness of associated modelling approaches.

Chapter 4: The chapter describes a large-scale snare survey which was carried out across the entire study site. The results generated by this survey were analysed within a hierarchical modelling framework to produce a detectability-corrected spatially explicit index of snare abundance for the site. This framework was also used to determine the relationship between snare abundance and detectability and a range of potentially influential covariates.

Chapter 5: In this chapter I develop a framework for deriving threat measures from law enforcement monitoring data, and for comparing these measures with independent datasets. I then apply this framework to the SPF as a case study, using standard patrol records and the independent index of snare abundance from Chaper 3. Through this case study I assess the utility of patrol-derived catch per unit effort measures as a tool for monitoring threats.

Chapter 6: This chapter highlights key themes within the research, provides a synthesis of my major findings, and suggests directions for future research.

Chapter 2. Identifying Conservation Successes, Failures and Future Opportunities; Assessing Recovery Potential of Wild Ungulates and Tigers in Eastern Cambodia.

2.1 Introduction

Within living memory the dry forests of Indochina (Cambodia, Viet Nam and Lao PDR) were among the "great gamelands of the world" as they supported aggregations of ungulates, including Asian elephant (*Elephas maximus*), wild cattle (gaur *Bos gaurus*, banteng *Bos javanucis*, kouprey *Bos sauveli*, wild water buffalo *Bubalus arnee*) and deer (e.g. sambar *Rusa unicolor* and Eld's deer *Rucervus eldii*) impressive enough to rival those found on African savannas (Wharton 1966). These forests also purportedly supported high densities of large carnivores, including tiger (*Panthera tigris*), leopard (*Panthera pardus*) and dhole (*Cuon alpinus*) (Delacour 1940; Guérin 2010).

Conflict and economic development have wrought profound changes in recent decades and, although extensive areas of intact habitat remain (especially in Cambodia), ungulates and carnivore densities are typically perceived as being severely depressed, with many local extinctions apparently occurring even within designated protected areas (Duckworth & Hedges 1998; Timmins & Ou Rattanak 2001; Steinmetz et al. 2006). All Indochinese large ungulates other than wild pig (*Sus scrofa*) and red muntjac (*Munticaus muntjak*) are now globally threatened (IUCN 2011) and the kouprey (*Bos sauveli*) is considered most likely extinct (R. J. Timmins et al. 2008). Of the large carnivores, tigers are thought to have now disappeared from most of their former range across Asia (Sanderson et al. 2006; Walston, Robinson, et al. 2010) and the Indochinese tiger (*P. tigris corbetti*) is predicted to be the next sub-species to be extirpated (Lynam 2010). The "empty forest syndrome" (Redford 1992) is becoming an increasingly pervasive reality for the region (Corlett 2007; Wilkie et al. 2011).

Wild cattle, wild pig and deer comprise the primary prey base for top predators such as tiger, leopard and dhole (Sunquist et al. 1999; Karanth et al. 2004) and high ungulate densities have been found to be a critical determinant of viable tiger populations (Karanth & Stith 1999; Karanth et al. 2004). Retaining ungulate and carnivore communities also has important ecological implications beyond the intrinsic value of each species. For example, ungulates are instrumental in processes such as seed dispersal, nutrient cycling and succession, and they fulfill a key role in the maintenance of habitat structure, composition and dynamics (Danell et al. 2006).

The impoverished status of Indochina's forests today is generally attributed principally to high levels of illegal hunting, predominantly to supply local, regional and global markets with meat, trophies and other body parts (Desai & Vuthy 1996; Duckworth & Hedges 1998; Corlett 2007). Large-bodied mammals such as carnivores and ungulates are known to be especially vulnerable to extinction due to their intrinsically lower rates of population increase and the fact that they are disproportionately targeted by humans (Cardillo et al. 2005; Wilkie et al. 2011).

As part of its post-war reconstruction since 1992 Cambodia has demonstrated considerable commitment to biodiversity conservation with approximately 24% of the country now designated as protected areas (Kapos et al. 2010). With suitable investment the opportunity exists to recover large, diverse and robust mammal populations across extensive conservation landscapes. There is growing recognition that conservation efforts should be guided by wildlife monitoring programs that yield rigorous information on population abundance, distribution and responses to specific conservation interventions (Milner-Gulland & Bennett 2003; Nichols & Williams 2006; Jones 2011). Such information is a prerequisite for determining whether conservation initiatives are achieving their stated objectives and prioritizing investment accordingly (Sutherland et al. 2004; Nichols & Williams 2006; Ferraro & Pattanayak 2006). Across most of Indochina such programs are lacking. This is largely a consequence of the inherent financial, logistical and practical challenges associated with the estimation and monitoring of mammal populations in tropical forests (Datta et al. 2008), further compounded by the apparent low population densities now prevalent for most Indochinese species of conservation significance.

In this paper I present the results of the first six years of a pioneering program to monitor ungulates and tigers in the Seima Protection Forest (SPF) in eastern Cambodia. SPF forms part of a Global Priority Tiger Conservation Landscape (Sanderson 2010) and one of the largest remaining tracts of tiger habitat in Indochina (Lynam 2010). The paper has four principal components. Firstly, I present the current status and recent population trends of wild ungulates in SPF, obtained using distance-based sampling methods. To my knowledge these represent the most rigorous peer-reviewed estimates for these species in Indochina to date. Secondly, I assess the status of tigers through the application of a suite of intensive field survey methods. Thirdly, I assess the potential of the ungulate population to support recovery of wild tigers. Finally, I consider the implications of our results in the wider context of both ungulate and tiger conservation in Indochina.

2.2 Methods

2.2.1 Study Site

SPF (2927 km2 70-750m asl) has a tropical monsoonal climate with 2200-2800 mm/year of rainfall and up to 5 dry months per year from December-April (Evans et al. 2012). It represents a convergence of the Eastern Plains of Cambodia and the Southern Annamite mountain range and is characterized by a complex mosaic of forest types varying from fully deciduous to almost fully evergreen. The additional presence of areas of open grassland, numerous permanent water sources and mineral licks has resulted in a highly productive landscape (Figure 3). In 2000, surveys in SPF identified it as a site of high regional conservation priority for biodiversity in general, and for carnivore and ungulate species in particular (Walston et al. 2001; Evans et al. 2012). These surveys yielded the first ever photographs of wild tigers in Cambodia, and evidence of a largely intact assemblage of tropical forest ungulates (Walston et al. 2001). Qualitative assessments strongly suggested tiger and prey populations had recently undergone sharp declines and that densities were depressed compared to natural levels (Duckworth & Hedges 1998; Nowell et al. 1999; Timmins & Ou Rattanak 2001). However, although no empirical data were available, it was believed that these populations had been less severely affected than those at most other sites in Indochina, and populations were deemed to have high recovery potential (Duckworth & Hedges 1998; Nowell et al. 1999; Timmins & Ou Rattanak 2001).

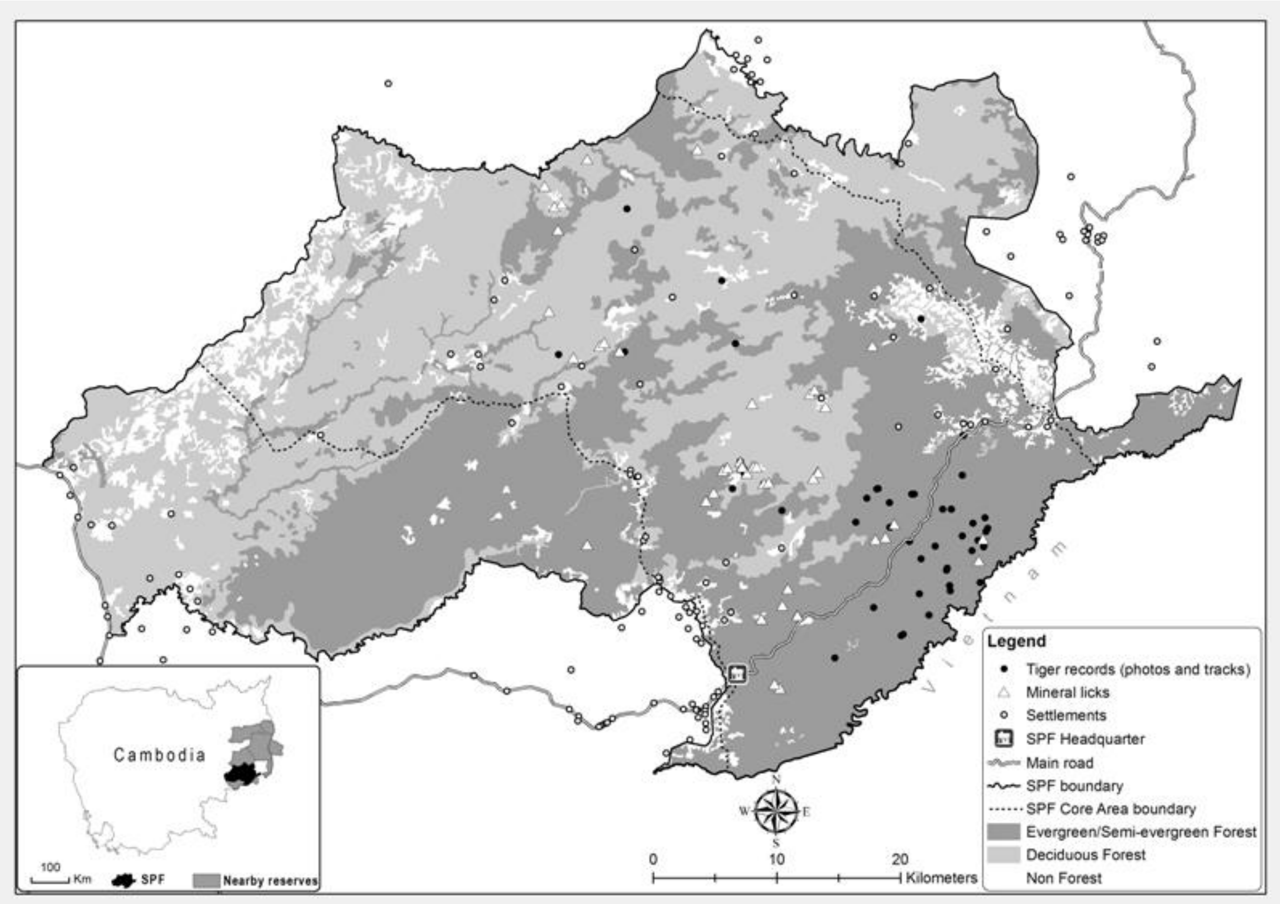

Figure 3 Tiger records in the Seima Protection Forest.

Since 2001, the site has been managed by the Forestry Administration (FA) supported by the Wildlife Conservation Society (WCS). The principal threat to large mammals in SPF is hypothesized to be direct hunting, and, in the case of large carnivores, the hunting of prey species (Lynam & Men Soriyun 2004; Evans et al. 2012). Habitat loss, degradation and disturbance are also likely to be increasingly significant (Evans et al. 2012). The primary strategy to address these threats is through direct law enforcement (Lynam & Men Soriyun 2004; Evans et al. 2012). Thus, management interventions in SPF have included a strong direct protection component aimed at relieving illegal hunting pressure on targeted species by means of anti-poaching patrols. Additional interventions implemented include policy support, community natural resource management and the development of alternative livelihoods (Evans et al. 2012).

From the earliest stages of this work a monitoring program was developed to quantify the response of wildlife to management interventions and to measure progress towards conservation objectives (Clements 2002; Nichols & Williams 2006). It covers tiger, seven ungulate species, six primates and one bird (green peafowl *Pavo muticus*). Here we report the results for tiger and for those ungulate species that form part of their regular prey base (i.e. all except elephant).

2.2.2 Ungulate surveys

2.2.2.1 Survey design

Line transect-based distance sampling methods were used to estimate ungulate density in SPF (Buckland et al. 2001). Distance sampling addresses two of the most problematic aspects of animal abundance estimation; spatial sampling and variation in detection probability. This allows for the generation of unbiased density estimates which can be compared across time and space. Survey design in SPF proceeded in two phases: Phase 1 (2005-2007) when designs were tested with low survey effort and Phase 2 (2008-2010) with an improved design, employing higher effort by more skilled field teams.

During 2005-2007 14 transects, each 3-5 km in length, were monitored within a 1086 km2 survey area encompassing the most important habitat for large-bodied mammals within the site (Clements 2002). Transects were placed randomly, with stratification by broad forest type (Figure 4). In 2005 and 2006 each of the 14 transects were surveyed twice per season (133 km total) and in 2007 they were surveyed three times (170 km total). As a consequence of the low survey effort during this period encounter rates for ungulate species were extremely low and variable.

In 2008 sampling effort was increased eight-fold as each of the 14 transects was surveyed between 32 and 34 times, twice daily over a three-four day period (1359 km total). In 2010 this level of effort was maintained while the number of spatial replicates was increased and the survey area was expanded. The new design consisted of 40 x 4 km closed circuit transects, which were established across an enlarged 1807 km2 survey area corresponding to the SPF core zone (Figure 4). Transect placement was systematic, with a random starting point, which ensured representative spatial sampling of the entire SPF core zone. With the revised sampling design each of the 40 new transects was walked a total of ten times, twice daily over five consecutive days (1600 km total). No surveys were conducted in 2009.

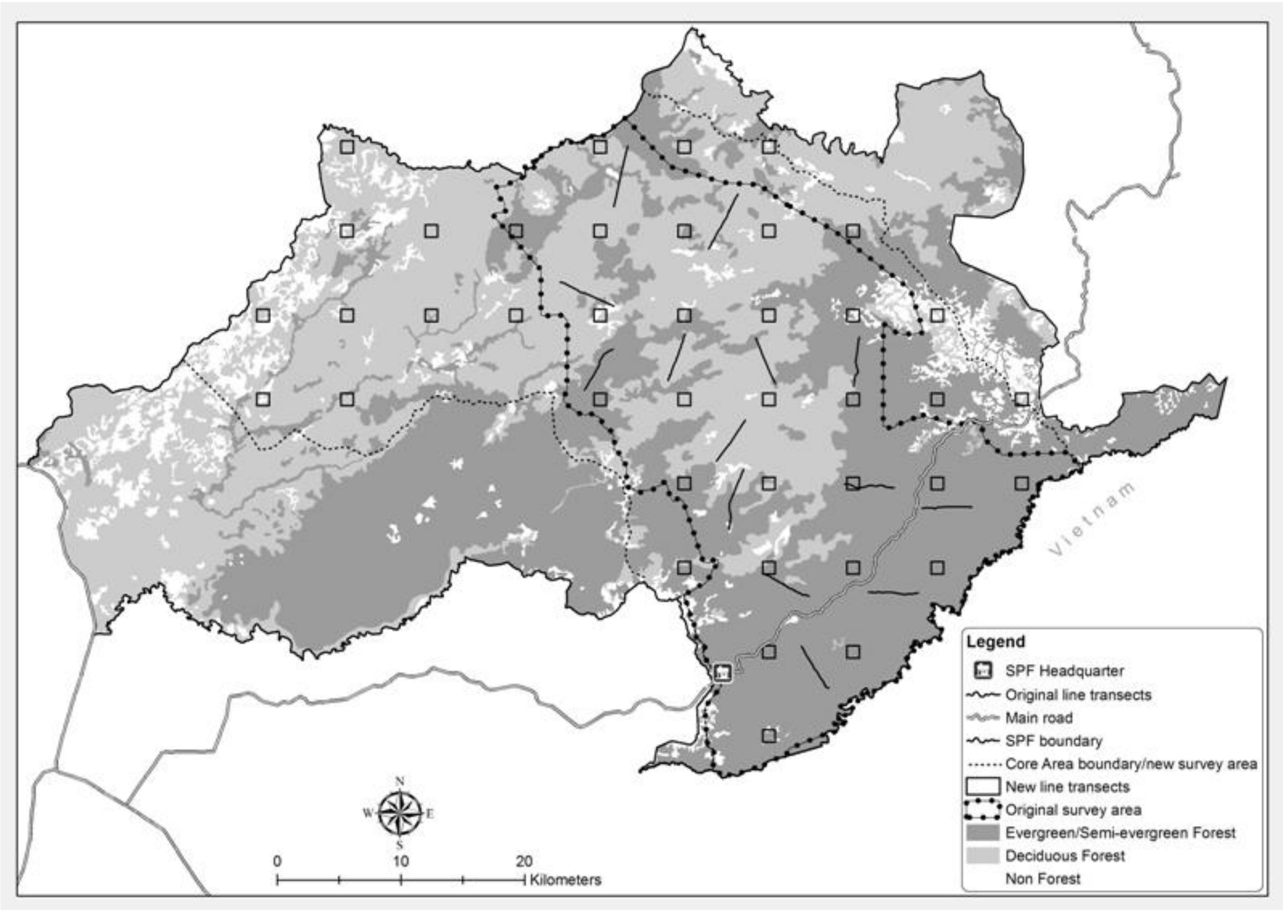

Figure 4 Line transect layout in the Seima Protection Forest.

2.2.2.2 Data collection

Field protocols were consistent across all years and based on standard line transect methodology for large herbivores (Buckland et al. 2001; Karanth et al. 2002). Transects were walked in the hours just after sunrise and those just preceding sunset by survey teams consisting of two trained observers only. Walking speed was between 1 and 2 km/hr. For each group of target species encountered the following information was recorded: location (UTM co-ordinates), species, size of cluster (i.e. group number), observer to cluster sighting distance, compass bearing to cluster centre, and compass bearing of the transect line. The latter three pieces of information were used to calculate the perpendicular distance of the centre of the observed cluster from the line. Garmin GPS units were used to record UTM coordinates, laser rangefinders to measure distances and sighting compasses to take bearings.

2.2.2.3 Data Analysis

Distance software version 6.0 (Thomas et al. 2010) was used to estimate encounter rates, detection probability, cluster density and abundance, and animal density and abundance of all target species. Prior to analysis, field data were checked for evidence of evasive movement before detection, and potential "rounding" and "heaping" errors (Buckland et al. 2001). Data were truncated to remove outliers and improve model-fitting. The model which best described the detection process was selected on the basis of Akaike's Information Criterion (AIC), although the goodness-of-fit tests were also considered, and the fit of proposed models to the observed data was examined visually. The methods used to estimate model parameters and to calculate the standard error, coefficient of variation and 95% confidence intervals for each parameter are described in detail in (Buckland et al. 2001). Analyses were carried out separately for each species, with the exception of wild cattle, where both species were combined due to small sample sizes. As all of the target ungulate species occur in groups, cluster density was estimated first and subsequently multiplied by estimated cluster size to provide an estimate of animal density. In cases where there was evidence of size bias in the detection process (at specified α of 0.15) cluster size was corrected by regression against probability of detection. Density estimates were multiplied by the surface area of the study site to obtain corresponding abundance estimates.

During Phase 1 (2005-2007), low sample sizes (less than the 60-80 observations recommended by (Buckland et al. 2001) prevented the estimation of annual detection probability and necessitated data pooling across all years (2005-2010). Global detection functions were derived separately for sambar, wild pig, red muntjac and a category combining both wild cattle species. These were then used retrospectively to generate annual population estimates for each species. Such an approach is imperfect in that it assumes a constant detection probability over time but with such low encounter rates this was considered the optimal approach. In Phase 2 (2008-2010), use of the global detection function to estimate annual densities was still required for sambar and wild cattle. For the more abundant species such as red muntjac and wild pig it was possible to estimate both species- and year-specific detection functions in 2008 and 2010. These estimates showed detection probability to be reasonably consistent across time for both species, partially validating the pooling approach for rarer species.

Two separate analyses were conducted for the 2010 data. Firstly, 2010 data were truncated to include only the area sampled between 2005-2008, enabling meaningful comparisons over time. Analysis of the full 2010 dataset was also carried out, to obtain an estimate for the entire core zone where surveys will be replicated in future years.

2.2.3 Tiger Surveys

2.2.3.1 Survey design

During 2005-2010 several field methods for surveying tigers were applied in sequence. As more information became available the objective changed from determining distribution to estimating population densities to reliably establishing presence of any remaining individuals.

2.2.3.2 Camera Trapping

Ad-hoc camera-trapping in SPF has been conducted on an on-going basis since 2000 and effort has been highly variable in terms of intensity of effort and camera-placement. Camera-trapping was initially carried out to investigate the presence or possible absence of various cryptic species during the first surveys of wildlife in the area. All camera-trapping to date has focused on the southern and central sections of the site, which is where earlier tiger records were concentrated.

During 2005 -2007 opportunistic camera trapping was concentrated on focal mineral licks and water sources, which are important sites for key tiger prey species. During 2008 - 2010, opportunistic camera trapping focused more on trails and dry stream beds, which tiger are known to use preferentially (Karanth & Nichols 1998; Karanth & Nichols 2002).

In 2007, a systematic camera-trap survey was conducted based on the capture-recapture sampling approach developed by (Karanth & Nichols 1998). The survey area encompassed 750km2 in the southern part of the site and was sampled in three consecutive blocks. Paired DeerCam units were placed in a total of 40 locations, for a period of 20 days per location (Figure 5). Prior to the installation, topographic maps were consulted and suitable trap locations were selected based on the presence of roads, trails, dry river-beds and other natural funnels in the topography, as well as on the existence of prior tiger records. It was ensured that each camera was a maximum of 5 km from another so that there were no "holes" in trapping effort (sensu Karanth & Nichols 1998). Camera-trapping took place over a 72 day period, resulting in a total effort of 820 trap-nights.

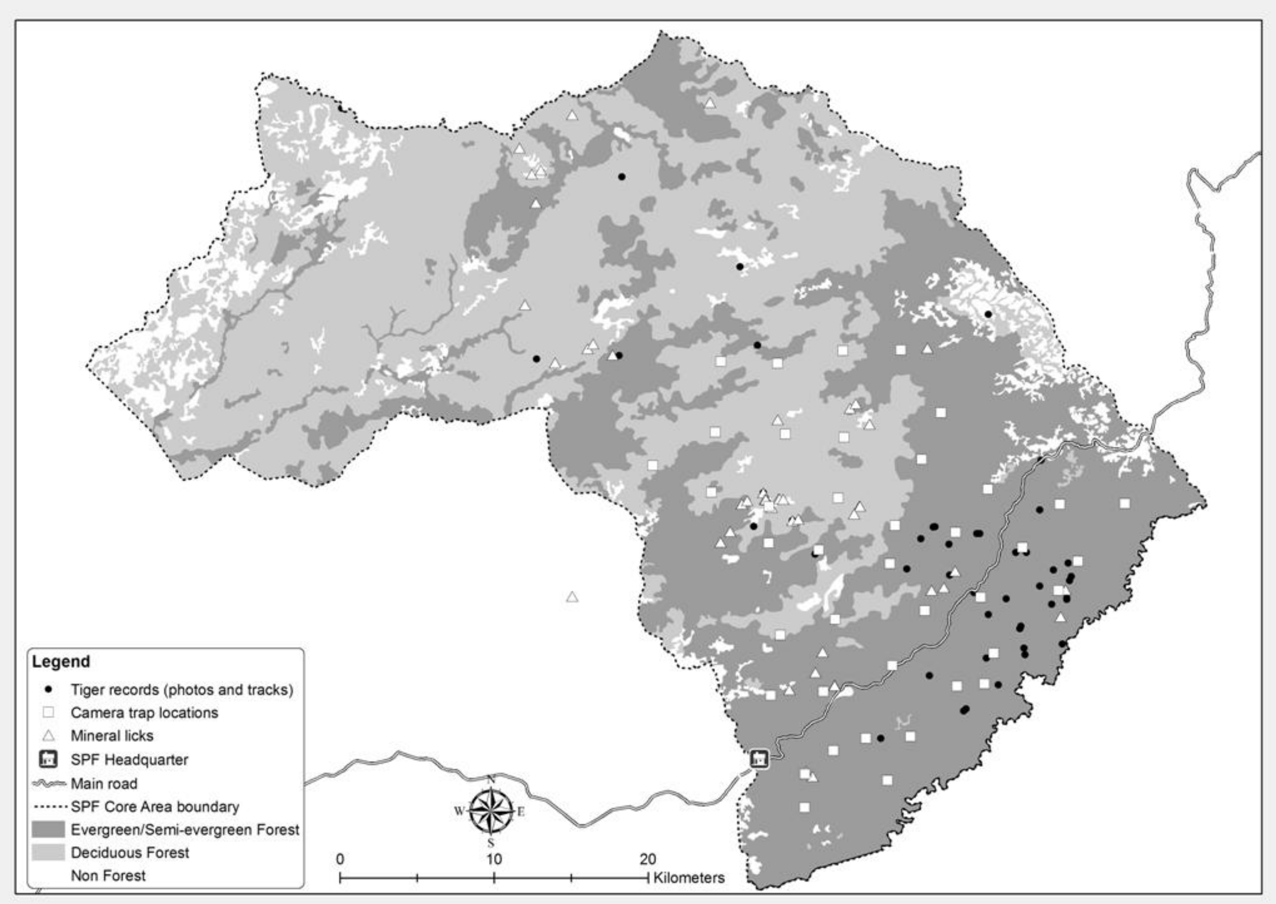

Figure 5 Camera-trap locations in the Seima Protection Forest.

2.2.3.3 Sign Surveys

In 2007, a permanent tiger team was established to identify and search potential tiger "hotspots" for all tiger sign including track, scrapes and scent marks. Members of the tiger team were trained at a site in Thailand where tiger sign could be reliably detected and identified. Tiger hotspots included those areas which are typically used by tigers (mineral licks, dry stream beds and forest trails), and where prey densities were thought to be high and levels of human disturbance low. The sign survey continued throughout the 2007/2008 field season and the team also followed up on any reports of tiger received from community members, law enforcement staff and other sources. The team also enlisted the help of one local former tiger hunter to assist with the survey.

2.2.3.4 Detection Dog Surveys

Following the negative results in 2007-2008 surveys there was increasing concern regarding the ability of survey teams to detect animals if they remained only at extremely low densities across a large area, so a specially trained scat detection dog was deployed. Detection dogs search by scent rather than sight which allows them to cover survey areas more efficiently and they can greatly increase the detection rate of survey targets in comparison with human search teams (Kerley 2010; Reed et al. 2011). They are particularly suitable for use in collecting monitoring data on elusive, low density species such as carnivores (Kerley 2010; Reed et al. 2011). In early 2009, a 5 year-old German Wire-haired Pointer arrived in SPF from the Russian Far East where she has been trained and worked as a tiger scat detection dog. From March - June 2009 and January - May 2010, field surveys were conducted by the dog and handler team. The team employed protocols analogous to that used by camera-trap and sign survey teams in that they systematically identified likely tiger hotspots within a pre-defined area and subsequently searched them exhaustively (Figure 6). The dog and handler team were also on hand to follow up on any local information received on tiger sightings or reports of tiger sign.

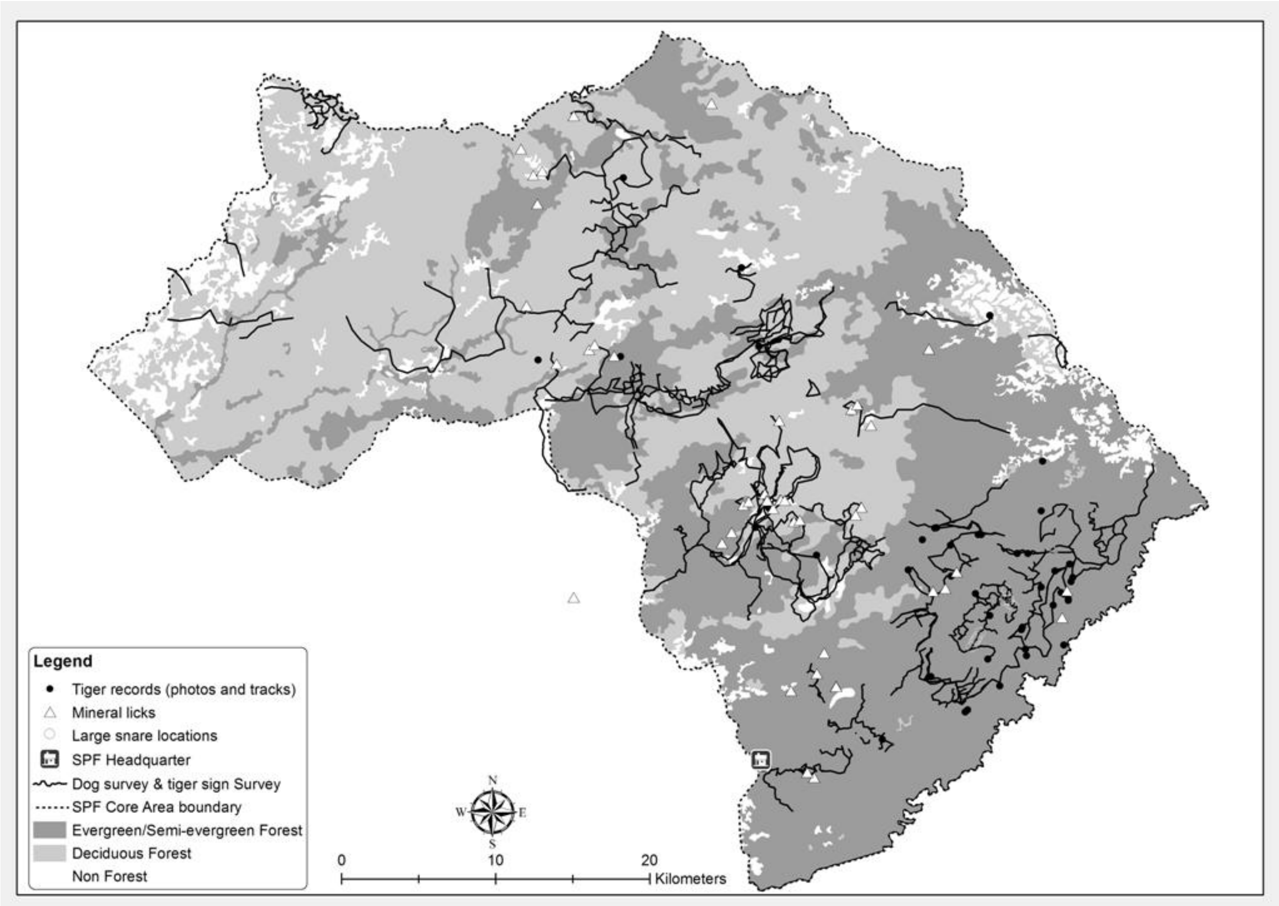

Figure 6 Scat-dog survey routes in the Seima Protection Forest.

2.3 Results

2.3.1 Ungulate Surveys

Estimated densities of ungulates in the SPF core zone in 2010 are shown in Table 1 and density trends during 2005-2010 in the smaller initial survey area are shown in Table 2. No Eld's deer were recorded on the transects.

Table 1 Density of ungulates in the expanded survey area 2010. These estimates are derived from the full 2010 dataset and are representative of the entire core zone. CV = % co-efficient of variation; CI = upper and lower 95% confidence intervals.

Species	No. Observations (n) [1]	Density (individs /km2)	95% CI lower	95% CI higher	CV%	Approximate no. individuals
Red Muntjac	169	1.75	1.22	2.51	18.14	3200 (2200-4500)
Wild Pig	52	2.04	1.19	3.49	27.69	3700 (2200-6300)
Wild Cattle[2]	19	0.29	0.11	0.77	50.8	500 (200-1400)
Sambar[3]	6	0.09	0.04	0.23	48.32	200 (100-400)

Table 2 Density of ungulates in the original survey area, 2005-2010. For this analysis the 2010 data were truncated to include only the original survey area in order to make meaningful comparisons over time. L = total transect length walked; n = number of observations of animal clusters, CV% = percentage co-efficient of variation, 95% CI = upper and lower 95% confidence intervals.

Species	Year	L (km)	n	Encounter rate (n/L)	Cluster size	Density (individs/km2)	CV%	95% CI lower	95% CI upper
Red Muntjac[4]	2005	113	9	0.08	1	1.11	40.5	0.48	2.58
	2006	113	15	0.133	1.1	2.39	25.21	1.4	4.07
	2007	170	25	0.147	1.1	2.55	20.81	1.64	3.95
	2008	1359	134	0.099	1.1	1.75	22.12	1.1	2.79
	2010	920	71	0.077	1.1	1.34	21.45	0.87	2.06
Wild pig	2005	113	3	0.027	2	1.44	54.47	0.48	4.28
	2006	113	5	0.044	1.2	2.4	49.47	0.88	6.51
	2007	170	9	0.053	3.1	2.87	40.55	1.25	6.58
	2008	1359	61	0.045	2.4	1.71	22.91	1.08	2.7
	2010	920	35	0.038	2.8	3.23	33.54	1.68	6.21
Wild cattle	2008	1359	28	0.021	3.1	0.61	36.59	0.29	1.27
	2010	960	15	0.016	1.5[5]	0.4	54.82	0.14	1.13
Sambar	2008	1359	22	0.016	1.3	0.41	70.1	0.11	1.57
	2010	960	6	0.006	1.2	0.16	46.2	0.06	0.38

1 Observations are of clusters of animals.

2 Data are pooled for the two wild cattle species; comparison of raw encounter suggests approximately equal densities of gaur and banteng but sample sizes are too low to estimate detection probability and density of each species.

3 Estimates for wild cattle and sambar are calculated using a detection function derived from data pooled across years 2010 & 2008.

4 Estimates for 2008 and 2010 are based on time-specific detection functions, whereas estimates for 2005 – 2007 are based on a global detection function derived from pooled data over this period.

5 When observations from entire extended survey area in 2010 are included the average cluster sizes is 3.1.

Table 3 Published ungulate density estimates (km^2) for sites ecologically comparable to SPF but with varying levels of protection.

Species	Nagarahole Tiger Reserve, India	Bhadra Tiger Reserve, India	Huai Kha Khaeng Wildlife Sanctuary, Thailand	Taman Negara, Malaysia	Seima Protection Forest, Cambodia	Source for other sites
All ungulates	56.1				*4.17*	Karanth et al. 2004
All ungulates		16.8			*4.17*	Karanth et al. 2004
Red muntjac	4.2			3.2	*1.75*	Karanth & Sunquist 1992, Kawanishi & Sunquist 2004
Wild pig	4.2			4.17	*2.04*	Karanth & Sunquist 1992, Kawanishi & Sunquist 2004
Wild cattle			1.8		*0.29*	Srikosamatara 1993
Sambar			4.2		*0.09*	Srikosamatara 1993

Wild pig and red muntjac densities can be estimated more precisely than other target species. Populations of both appear to have undergone fluctuations over the past five years (Table 2), but the data provide no evidence of sustained declines or increases. Red muntjac in particular appears to have increased and then decreased quite markedly. The difference between the 2010 estimate and that of 2007 is statistically significant ($z = -2.008$ $p < .05$) but there are no statistically significant differences between 2010 and any other year (2005 $z = 0.416$ $p > .05$, 2006 $z = -1.576$ $p > .05$, 2008 $z = 0.861$ $p > .05$), suggesting that the 2007 estimate was exceptionally high.

Density estimates for wild cattle exist only for 2008 and 2010 (due to low sample sizes for previous years) and it is not yet possible to examine trends over time. These estimates were obtained using a detection function derived from data pooled across time and species (banteng and gaur) and the precision is low. As data accumulate in future years for both species, the accuracy and precision of the detection function will improve, and can also be applied retrospectively.

The number of sambar observations was low and until sufficient data are available to generate a reliable detection function the figures presented remain provisional for this species. There is also some evidence of evasive movement by sambar before detection, which would violate the assumptions of distance sampling and may result in under-estimates of density and abundance.

Observations of gaur, banteng and sambar were concentrated within the central and southern parts of the site, mainly in areas remote from human influence. Gaur and sambar observations were most frequent in evergreen and semi-evergreen habitat while banteng were typically observed in semi-evergreen and deciduous forest. Wild pig and red muntjac were recorded relatively uniformly on transects across all habitats, and observations were moderately common even in areas subject to high levels of human disturbance. This suggests that these species are more tolerant of anthropogenic pressures than sambar, gaur or banteng.

2.3.2 Tiger Surveys

During 2000-2002 eight camera trap images of at least three individual tigers were captured, with none since. During 2000-2007 over 50 tiger sign records were obtained in SPF, mostly tracks (Figure 3). The last confirmed record was a print found in early 2007. Intensive sign surveys during 2007-2008 failed to yield any tiger records. The former tiger hunter who assisted the survey team during 2008 was unable to locate any tiger sign but did lead the team to over a dozen large cable snares, believed to have been targeting tiger (Figure 6). The detection dog surveys also failed to locate any tiger scat. We conclude that there are currently no resident tigers remaining in SPF, although it remains plausible that transient animals sometimes visit the site.

2.4 Discussion

2.4.1 The status of ungulates in SPF

The core zone of SPF supports approximately 500 wild cattle (gaur and banteng combined), 200 sambar, 3200 wild pig and 3700 red muntjac. Most of these species are also present, albeit in likely smaller populations, outside the core zone. Eld's deer, southern serow and Asian elephant are also present (Walston et al. 2001), making this one of the most intact assemblages of large ungulates surviving in Indochina. However, kouprey, wild water buffalo and rhinoceros, all presumably once present (Walston et al. 2001; Weiler et al. 2006), must have been extirpated before the period of recent surveys.

Despite the fact that estimates for some species are lacking in precision, these data show that the surviving populations of large ungulates at the SPF retain high regional conservation significance. This is particularly true for banteng, currently believed to have a highly fragmented global population of approximately 5000-8000 (Robert J. Timmins, Duckworth, et al. 2008). In the context of the broader ungulate assemblage it is notable that the SPF elephant population was estimated at 101 -139 individuals in 2006 based on dung DNA surveys, and hence is also of at least regional significance (Pollard et al. 2008).

The biodiversity significance of SPF is further enhanced by its position within an unfragmented transboundary conservation landscape of over 15 000 km2, encompassing nine reserves (see inset Figure 3), at least two of which (Phnom Prich Wildlife Sanctuary and Mondulkiri Protected Forest) still also support highly significant populations of large ungulates, including several thousand banteng (Gray et al. 2011), which is of global significance.

The combined density of large ungulates, excluding elephant, in the SPF core zone is 4.17 km-2 (Table 1). Natural densities in Indochinese forests are unknown since we have not traced any published, statistically robust density estimates for these ungulates in Indochina. However, given the historical accounts of ungulate abundance (e.g. (Wharton 1966) and video footage of large herds of wild cattle, no longer seen anywhere in Cambodia) and the apparent suitability of habitat as assessed by experts (Duckworth & Hedges 1998; Walston et al. 2001), SPF ungulates densities are likely to be far below the potential carrying capacity of the site. In ecologically similar areas elsewhere in tropical monsoonal Asia, where threats are comparably lower, densities of these species are notably higher than in SPF (Karanth & Sunquist 1992; Srikosamatara 1993; Karanth et al. 2004; Kawanishi & Sunquist 2004) (Table 3).

Although site specific factors may affect the transferability of estimates in the literature, borrowed estimates from other sites can be taken as a broad indicative range of what these habitats could support. The supposition that the current depressed densities in SPF are largely a consequence of past hunting is substantiated by local reports of previously higher densities of ungulates and extremely high levels of hunting during the 1990s (Desai & Vuthy 1996; Walston et al. 2001).

Based on the quantitative and qualitative evidence available it seems likely that ungulates underwent steep declines prior to the implementation of conservation activities, but that these declines were halted or slowed during the period under study. Importantly however, the populations of large ungulates in SPF are threatened with a resumption of declines. Law enforcement and wildlife survey teams have recorded high levels of hunting of ungulates in recent years, particularly as access has improved and human migration into the landscape has increased. Guns and snares are the main techniques used and there have been several confirmed incidents of hunting of wild cattle and sambar (Evans et al. 2012). While hunting with wire snares persists, the level of gun hunting is undoubtedly lower in the core zone than was observed prior to 2002 (e.g. Desai & Vuthy 1996; Walston et al. 2001) when no conservation action was in place and before national gun confiscation campaigns reduced the availability of firearms (Evans et al. 2012). However, recent observations suggest that gun hunting is gradually increasing again and the level of hunting pressure is high in relation to the small numbers of large ungulates remaining.

The coarse distribution patterns of gaur, banteng and sambar are broadly consistent with recorded habitat preferences elsewhere in the range of these species (Wharton 1966; Duckworth & Hedges 1998; Robert J. Timmins, Steinmetz, et al. 2008). However, not all areas of apparently suitable habitat in SPF are occupied. The evidence suggests that large ungulates have generally persisted in areas characterized by good quality habitat together with some level of protection from hunting, either by virtue of their inaccessibility, or as a result of anti-poaching efforts, or both. This has implications both for the future of these populations within SPF and also for populations in other areas where levels of law enforcement are lower and hunting pressure may be higher.

Estimates for wild pig and red muntjac suggest that populations of both species within SPF are relatively stable and remain moderately abundant despite high hunting pressure. Nevertheless, densities are somewhat lower than would be expected in unhunted sites (Table 3) and while SPF harbours relatively healthy populations of both species, there is potential for further recovery. Further analyses are needed to investigate full the impact of hunting on both large and small ungulate populations, and also to assess the effectiveness of law enforcement at curbing hunting activities.

2.4.2 Implications for tigers

Tigers were reportedly quite common in eastern Cambodia as recently as the 1990s (Desai & Vuthy 1996; Nowell et al. 1999) but surveys over the last four years have found no surviving resident population in SPF. This appears to be true for the whole Eastern Plains landscape (Lynam 2010). Whilst it is conceivable that a few individuals may persist in neighboring protected areas, dedicated surveys, also involving camera-trapping and scat-detection dog surveys, have produced no confirmed evidence of tiger presence since November 2007 (WWF, unpublished data).

Multiple interacting factors are implicated in the rapid loss of the SPF tiger population. Intensive targeted tiger hunting took place in and around SPF during the 1990's (Walston et al. 2001). It is also conceivable that the ungulate prey base was depleted to the extent that tiger reproduction and survival rates were lowered (Karanth & Stith 1999), thereby further accelerating declines. In the early 1990's it was estimated that 100 to 200 tigers a year were being exported from Cambodia through wildlife markets in Phnom Penh and on the Thai border, with most of the animals reportedly brought in by soldiers posted to the more remote areas of the country (MOE 2006). However, the Forestry Administration's Wildlife Protection Office documented a pronounced decrease in poaching records from sites across the country; from 85 poached animals in 1998, to one in 2001, to zero in 2004 (Weiler et al. 2006). The apparent sharp decline in poaching levels may have been indicative of a final crash in tiger numbers after 15 years of exceptionally high hunting pressure countrywide (Weiler et al. 2006; Lynam 2010). By the time conservation interventions were first implemented in SPF in 2002 it was known that the tiger population there was small, but it was believed to hold the greatest potential for recovery of any site in Cambodia. In retrospect, the individuals photographed in SPF may have represented a remnant population with little hope of recovery given the conservation resources available, the escalating threats they were to face over the coming years and the level of investment now known to be required to secure tiger populations (Walston, Robinson, et al. 2010; Walston, Karanth, et al. 2010).

Given the absence of a resident tiger population, we contend this landscape does not constitute a 'source site' (Walston, Robinson, et al. 2010) and no longer meets the criteria for designation as a Global Priority Tiger Landscape (Karanth & Stith 1999). The SPF no longer receives any tiger-specific funding for conservation activities, and tigers are not currently a management priority. Nevertheless, as the only large (>10,000km2) block of dry forest habitat available for tigers anywhere in Southeast Asia, the landscape retains exceptional national and regional importance and remains a potential recovery site for the Indochinese tiger in the future, provided adequate prey and protection for tigers is assured (Walston, Robinson, et al. 2010). To restore prey populations, poaching must be eradicated over large areas and other human activities in the vicinity of potential tiger and prey recovery areas must be strictly regulated (Lynam 2010). Promising initial steps have been taken in SPF but significantly increased long-term investments will be needed to achieve success (Evans et al. 2012). An inviolate core area will also be essential if tiger re-introduction is to be considered (Walston, Karanth, et al. 2010). We believe that re-introduction is the only feasible option to restore wild tigers to Cambodia.

Our results enable us to estimate the number of tigers that current and potential future ungulate populations in SPF could support. The current prey base is c.7500 animals. Using Karanth et al.'s 2004 model (Karanth et al. 2004), which assumes an average kill rate of 50 ungulates/tiger per year requiring a base population of 500 ungulates/tiger, the core area currently harbours sufficient prey to support about 15 tigers (i.e. about 5 breeding females). This is well below the recommended minimum of 75 tigers (c. 25 breeding females) in a healthy source site (Kenney et al. 1995; Walston, Karanth, et al. 2010), but if prey densities in SPF were recovered to an ecologically feasible carrying capacity of 20 ungulates per km^2 then the 1800 km^2 core zone of SPF alone could potentially support over 70 tigers.

If similar prey densities prevail across the core areas of the other two key reserves for large ungulates within the proposed tiger conservation landscape the current prey base would be c.23 500 which is insufficient to sustain the recommended minimum of 50 breeding females (c. 150 tigers) required for long-term viability (Walston, Karanth, et al. 2010). These calculations show that the recovery of prey populations will be a necessary precondition for successful tiger recovery. Given the regional significance of the ungulate populations themselves, their importance to other predators such as dhole and leopard and the likely benefits to many other, co-occurring threatened species (Evans et al. 2012), this would be a valuable conservation outcome in its own right.

Continued rigorous monitoring of prey is a crucial part of such an effort, otherwise managers are 'flying blind'. Repeating surveys on an annual or biennial basis and progressively improving the precision of estimates will identify population trends and allow the testing of hypotheses about the driving factors. The long history of monitoring in SPF also makes this a key regional demonstration and training site, and, along with the recently established program in adjacent sites (Gray et al. 2011), the only quantitative benchmark that exists regarding the numerical status of ungulate populations anywhere in Indochina.

2.4.3 Broader implications for the conservation of tigers and ungulates in Indochina

SPF is one of the better protected reserves for large ungulates in Indochina, with active law enforcement in place since 2002. Thus, the low densities evident here may imply even lower numbers at many other sites in the region and should heighten concerns regarding the vulnerability of Indochina’s remaining large mammal populations. Furthermore, whilst it has long been established that not all suitable forest tracts remaining across Asia are occupied by tigers (Karanth & Stith 1999; Rabinowitz 1999; Walston, Robinson, et al. 2010) more rigorous scrutiny of areas where viable tiger populations are currently assumed to persist may reveal extremely low densities and even absences, as is reported in this paper, and was found by (Johnson et al. 2006; Jenks et al. 2011). It is often assumed that large forest blocks 'must' have a few wily tigers hanging on but defying detection; we suggest that this is true less often than conservationists might wish.

Empirical data must be made available to distinguish conservation successes from failures and prioritize conservation investment accordingly (Sutherland et al. 2004; Ferraro & Pattanayak 2006). Without scientifically defensible data on which to base a reliable assessment, the wider status of tiger and prey populations in Indochina remains little more than speculation (Rabinowitz 1999). Our findings underline the acute need for improved population estimates and trend data for large mammals from key sites in Indochina, and re-emphasize the need for urgent remedial conservation measures in this region. Our results also demonstrate that not only can statistically and biologically robust monitoring methods be applied when challenging conditions prevail, but that they can also provide a solid scientific foundation for pragmatic conservation strategies.

Chapter 3. Experimentally Estimating the Detectability of Wire Snares in Seima Protection Forest

3.1 Introduction

The use of snares is one of the simplest but most effective hunting techniques practised in the tropics (Fa & Brown 2009). Despite the threat posed by this form of hunting to mammals in Southeast Asia (Corlett 2007) reliable assessments of snaring prevalence within protected areas are non-existent. One of the primary reasons for this is that rigorous methods for estimating the extent of snaring have not yet been developed. Studies have addressed snaring levels within some African protected areas, (Wato et al. 2006a; Becker et al. 2013) but these studies are susceptible to bias arising from unaccounted for spatial variation (i.e. small plots in relation to size of area and non-random sampling) and imperfect detection. This is because snares share many of the characteristics of the species they target; they are habitat specific, extremely difficult to detect, and occur in large, inaccessible areas. And just as for rare species in the tropics, traditional methods for population estimation which address the problems of imperfect detection and representative spatial sampling are extremely difficult to implement in these conditions.

Although snares are widely used within protected areas, they are concealed by the hunters who set them, and because of the large size of many of these areas, they are likely to occur at a relatively low density overall. This means that efforts to estimate snare abundance are fraught with both statistical and practical difficulties, and also that snare detectability is likely to be low. Simple plot sampling methods could be used for snares (as are commonly used for plant populations), with plots chosen according to some probability-based sampling design, but in the context of a large protected area employing this method at a scale large enough to obtain useful data would simply be unfeasible (see Table 4). Unless an assumption is made that all snares are detected with certainty (for example within a very small plot) a method for counting snares must provide estimates of abundance that are adjusted for incomplete detectability. Although this can be achieved through the use of distance sampling or capture re-capture techniques, these methods are time-consuming and expensive, and it is difficult to determine how such approaches might best be adapted to incorporate within snare surveys in a cost-effective manner (Table 4).

The use of hierarchical models within ecological studies has become an increasingly popular means of dealing with the issue of imperfect detection by simultaneously modelling both the spatial variation in abundance and the observation process itself (Royle & Dorazio 2006; Royle & Dorazio 2008). These models are particularly appealing because they can incorporate a wide range of sampling protocols, including distance sampling, removal sampling, double-observer sampling and capture-recapture sampling, simply by specifying different stochastic descriptions of the observation process (Royle 2004a; Kéry & J. A. Royle 2010). The binomial mixture (N-mixture) and multinomial mixture models of (Royle 2004a; Royle 2004b; Royle et al. 2007) are one sub-class of hierarchical models that offer a flexible approach to estimating both abundance and detection probability using count data.

In order to parameterise N-mixture and multinomial mixture models, sampling protocols are needed which allow detectability to be separated from abundance, and this is achieved through replication (Kéry & J. A. Royle 2010). The binomial mixture model requires a repeated-measures type of sampling protocol where replicate counts are obtained at a number of spatial locations (Royle 2004a). The replicate counts can be made through repeat visits to each location or through multiple observers. The multinomial mixture model has the additional requirement of replicate observations of individually recognizable units (Kéry & J. A. Royle 2010). This final requirement may not be practically feasible in some circumstances and where it is it, it may increase sampling costs in terms of time or effort. This has implications for the design of any monitoring programme for snares based on these methods, as managers will place a high priority on logistical feasibility and cost-effectiveness (Jones 2011).

Table 4 Potential methods for estimating snare abundance associated strengths and weaknesses.

		Advantages		Limitations	
Method	**Product**	**For Estimation**	**Feasibility**	**For Estimation**	**Feasibility**
CPUE indices from patrol records	Index of abundance (assuming that CPUE is proportional to underlying abundance which may not always be the case).	Large quantities of data available.	Data are inexpensive to collect. Extensive temporal and spatial coverage.	No estimate of detection probability (which will be highly variable). Often extreme temporal and spatial bias in patrol data. Non-linear relationship between patrol effort and snare encounters.	Primary function of patrols teams is not data recording so competency in this area may be variable. Recording and managing data may divert effort away from actual protection activities, i.e. patrols.
Random or systematic plots/quadrats/strip transects.	Abundance per sample unit which can be extrapolated across entire survey area or used as an index of relative abundance (for comparisons across space or time).	May be no need to estimate detection probability if area of sample unit is small and 100% detectability is assumed.	Simple field protocols.	To ensure 100% detectability plot or transect area would need to be extremely small. If only a tiny proportion of a site is sampled, extrapolation of results across entire area may not be appropriate. To sample larger, more representative proportion is likely to be prohibitively expensive.	Observers cannot search purposefully. In large sites where snares occur at relatively low densities, random or systematic placement of small plots/transects may result in zero detections of snares in many or even all sample units.
Recce transects	Index of relative abundance (for comparisons across space or time).	High number of encounters (relative to systematic/random samples).	Observers can search purposefully. Less effort required than fixed transects (path of least resistance). Intuitive field protocols.	No estimate of detection probability. Due to spatial bias in sampling results are not representative and cannot be extrapolated across entire area. Observer bias may be severe if survey teams differ in levels of ability or training.	Difficult to plan for logistically as survey routes are not pre-determined in time or space. Difficult to train survey teams as a balance is required between standardised protocols (i.e. approximately equal survey effort) and use of teams own initiative (to identify most likely snare locations).

Distance-sampling (i.e. systematic line transects)	Absolute density; estimates are reliable, comparable (temporal and spatial) and unbiased (provided model assumption are met).	Detection probability explicitly estimated. Generally acknowledged as a “gold standard” method in terms of population estimation.	Although field protocols are technically demanding, once teams have been trained in these techniques they can readily be applied in other contexts (i.e. surveying for other targets/species)	High numbers of encounters (minimum 60-80) required to produce reliable estimates.	Systematic or random transects may result in zero encounters. Complexity of field protocols makes training teams and implementing surveys difficult, effort intensive and expensive. For snares in particular; difficult to define moment of detection for standardising measurements.
Capture-recapture 1: Repeated sampling occasions at survey sites	Absolute abundance (modelled potentially as a function of covariates).	Detection probability explicitly estimated. A large number of models and model extensions developed for application in a wide array of contexts.	Purposefully searching possible if variable routes used on each sampling occasions. Multiple capture methods could be used i.e. patrol teams and survey teams.	Difficult to assess if and how violations of model assumptions might occur. For example, what does the concept of population closure mean when applied to snares and can closure be assumed? Or, does it seem likely that all snares in a “population” have an equal probability of capture?	Multiple visits to sampling locations is extremely inefficient in this environment. Re-captures would depend on snares remaining in circulation (so that they can be encountered on subsequent occasions). This is not feasible ethically as snares must be destroyed or disabled when encountered.
Capture-recapture 2: Multiple observers visit survey sites simultaneously	Absolute abundance (modelled potentially as a function of covariates).	See above	Improved efficiency (compared to consecutive sampling occasions) Purposefully searching possible if variable routes used.	See above	Leaving snares in place for subsequent observers to encounter is unethical unless they are disabled, which could affect detection process. If observers use fixed routes all snares likely to be captured by all observers (cueing, tracking etc). If observers use variable routes this may result in few or no re-captures.

The field experiment presented in this study was designed to provide some baseline information on the potential detection probability of snares in a tropical forest setting, on how certain factors might affect this detection probability, and how best to estimate detection parameters within this context. As a precursor to this experiment two sets of sampling protocols, developed to estimate the abundance and detectability of avian populations using point counts and also suitable for analysis using N-mixture and multinomial mixture models respectively, were identified as having potential to adapt for use with snares. The first of these is a simple repeated counts approach, where multiple visits to spatially replicated sites are made (Kéry et al. 2005). The second is a double-observer approach (Nichols et al. 2000; Alldredge et al. 2008) where counts are made by two observers simultaneously, again at spatially replicated sites, and counts are compared to identify individuals (in this case snares) encountered by both observers. This independent double-observer approach is exactly analogous to a capture-recapture model with two sampling occasions, with each observer being equivalent to an occasion.

The first objective of this study is to determine the detection probability for snares in an experimental context, such that the true abundance of snares is known. Within a controlled environment it is possible to observe directly whether and to what extent the detection probability of snares varies between snare type, habitat type and observer. It is hypothesised that detectability will be lower in more closed habitats (evergreen forest) than in open habitats (mixed forest) and that groups of snares (drift lines) will have a higher detection probability than single snares. As teams participating in this experiment have similar levels of skill, and are all highly motivated, it is expected that detection probability should be relatively consistent across teams.

The second objective of this study is to assess the suitability of the selected sampling protocols and associated modelling techniques for reliably and efficiently estimating the detectability and abundance of snares. In particular the study examines which of the two potential modelling approaches best estimates the actual abundance of snares and the detectability observed in the experiment. The advantage of a repeated count approach using N-mixture models is that it is very simple and can be employed even when data are sparse (i.e. if there are few detections) (Royle 2004b). For the double-observer approach to be successful a certain proportion of snares needs to be detected by both observers, and it was not known to what extent this could be achieved in this field context. If it is feasible to obtain repeated detections of the same snares, the benefit of being able to apply the multinomial mixture model is that it is expected to provide a more precise estimates due the extra information it incorporates (Kéry & J. A. Royle 2010).

3.2 Methods

3.2.1 Experimental Strategy

To directly observe the detection probability of snares it was necessary to create an artificial closed "population" of snares and then deploy teams to search for these snares. As snares are so difficult to detect, search teams must have a certain leeway to follow apparent hunter trails or investigate likely features they encounter as they survey, such as streams and hillsides (both favoured by hunters for setting snares). During this experiment multiple large plots or "sites" were surveyed by multiple teams, with each team searching freely (i.e. not on fixed survey routes) and independently of one another within a given site. Each team corresponded to an "observer" and the snare incidents encountered by teams constituted the count data. The experiment was designed in such a way that all of the following could be clearly determined from data; (1) The position of all available snares, (2) The routes taken and snares found by each team, and (3) The instances where multiple teams encountered the same snare.

3.2.2 Sampling Locations

This experiment was conducted over a week long period in October 2011, in the core area of the SPF. Two sampling locations were selected, representing the dominant habitat types within the reserve. The first location was in an area of mixed forest in the central sector of the core area and the second was in an area of evergreen forest in the southern sector of the core area. At each location a number of sites were delineated, firstly by marking them out on a topographical map and subsequently by inputting the relevant UTM coordinates into handheld Garmin GPS units. All sites measured 1km by 1km and 12 sites were marked out in the mixed forest area while 10 sites were marked out in the evergreen forest area. The mixed forest sites were all situated adjacent to one another while the evergreen forest sites were divided into two groups of six and four sites, with several kilometres between the two groups but with sites adjacent to one another within each group.

3.2.3 Survey Teams

A total of seven teams participated in the experiment, each consisting of one experienced team leader from the permanent biological monitoring team stationed within the SPF headquarters, together with two local assistants from villages within and around the core area. When recruiting local assistants, team leaders attempted to seek out individuals who had experience of hunting, and in particular hunting with wire snares, within the core area. However, although relatively widely practised, hunting with snares is a prohibited activity within the SPF and local people are disinclined to openly admit their involvement. Thus team leaders had to rely to a large extent on their own judgment and experience when selecting appropriate individuals.

3.2.4 Field Protocols

Snares are typically constructed using a looped brake cable or similar type of wire which is buried under leaf litter or suspended just above the ground (Figure 7). The loop is attached via another length of wire to an anchor pole, usually a strong flexible sapling which is firmly fixed in the ground. A simple trigger mechanism is sometimes incorporated, constructed using small twigs and activated by an animal stepping through the loop. In this experiment it was necessary to ensure that no animals were inadvertently captured or injured and so it was not possible to use real snares. Instead, plastic string was used rather than wire, and this was loosely attached to an anchor pole, with no trigger mechanism. These replica snares were divided into two types, reflecting the types of snare commonly used for hunting in the SPF. Single large snares were set individually within dense undergrowth whilst groups of smaller snares were set at intervals along a low brushwood drift fence, designed to guide prey into the snares. The intention was that replica snares looked similar enough to the genuine article to mimic the detection process for search teams, but to present no danger to wildlife in the area.

Sampling took place over a two day period at the mixed forest location and over a three day period at the evergreen forest location, due to the more difficult terrain which characterised the latter. On the first day at each location each team was allocated a number of sites together with the equipment to construct "snares". The teams were instructed to set a randomly assigned number of snares, between 1 and 20 (as a best-guess approximation of what actual snare densities might be). Each team decided on the distribution of snares across their sites and were encouraged to choose the best position and the most appropriate type of snare (i.e. single snare or drift line) according to their own previous experience of encountering (or using) snares within the SPF. Although they did not necessarily have to set snares at all sites, all teams chose to do so. Each team was supplied with detailed topographical maps and used Garmin GPS units to navigate within their assigned sites, to record the locations of the snares they had set and to track their exact routes. Finally, all team members were also instructed not to disclose or discuss the locations of their set snares with other teams.

On the subsequent days (day two for the mixed forest sites and days two and three for the evergreen forest sites) teams were again assigned a number of sites, chosen randomly with the exception that no team would search a site that it had set snares in on day one. Each site was surveyed by two separate teams independently (both teams on the same day in the mixed forest sites and on consecutive days in the evergreen sites), and each team was required to aim for approximately two kilometres of walk-effort within each site, following a route of their own choosing. They used the topographical maps and their knowledge of where snares are likely to be set to search each site to the best of their ability. Team leaders were primarily concerned with navigation and data recording while local assistants searched for snares. Teams recorded the UTM coordinates of all snare incidents encountered (snare incidents refers to both single snares and groups of snares within drift fences) and the type and number of snares. Their precise route was recorded by the GPS tracklog function.

Figure 7 Single snare with covering layer of leaf litter removed.

3.2.5 Analysis

All of the GPS data, relating to all snares set and snares found by both search teams, together with the routes taken by teams, were downloaded and examined in ArcMap software. Firstly, the number of snare incidents actually detected was compared to the number of snare incidents available to detect, in order to determine the "true" detection probability in this experimental context. Snare incidents which were detected by both survey teams were also identified at this stage. The data were subdivided by snare type, team and by habitat to explore potential differences in detection probability. For this part of the analysis individual snare incidents were aggregated across all sites (by type, habitat and team) so that no distinction was made between sites. However, GPS tracklog routes were also examined visually within each site to compare how each of the two survey teams searched.

Secondly, aggregated counts of snare incidents within each individual site were tabulated for the first and second survey teams. These data were analysed in package "unmarked" (Fiske & Chandler 2011) in R version 2.14.0 (R Core Team 2012). Due to the limited quantity of data available no distinction was made between habitat, teams or snare type for this analysis, although this would be possible with a larger dataset. Two separate fitting functions "pcount" and "multinomPois" were explored. The first of these functions fits the N-mixture model originally developed for spatially and temporally replicated avian point count data (Royle 2004b; Kéry et al. 2005) whereas the second fits the more general multinomial-Poisson mixture model developed for data collected using survey methods such as removal sampling or double observer sampling. Although the multinomial model was expected to prove a better estimator it was of interest to see how the N-mixture model performed, as repeat encounters of the same snare may not occur in other situations (or may not be easy to indentify). For both of these approaches a latent Poisson distribution was assumed for abundance at each site, although alternative distributions can be specified for N-mixture models (Royle 2004b; Kéry et al. 2005). The detection process was modelled as binomial in the first approach whereas a multinomial distribution was taken for the detection process in the second approach (Royle 2004a; Royle & Dorazio 2006).

The use of N-mixture models does not require the unique identification of individual snare incidents across visits (although within visits individuals must be identifiable to avoid double-counting), and each visit to a given site by a survey team is analogous to a separately repeated point count. For the purposes of this model, where two teams both encountered a given snare incident the detections were assigned to both visits but were not associated with each other. With the multinomial-Poisson mixture model, each visit is treated as an independent count but one where individuals can be uniquely identified and matched if counted by another team. In general, the use of multinomial observation models would be expected to improve inference with respect to detectability, as a result of the more detailed information they utilise.

3.3 Results

Over the entire 22 sites a total of 115 snare incidents were set (Table 5), 35 of which were detected by at least one team and 11 of which were detected by both teams (Table 6). A greater proportion of snare incidents was detected in evergreen forest sites compared to mixed forest sites, and a greater proportion of drift lines was detected than single snares, in both mixed forest sites and evergreen forest sites (Table 6). The proportion of snare incidents detected in the first and second visits was similar, although it was slightly higher for the second visit, in both habitat types (Table 6).

Table 5 Distribution of snare types set across sites in different habitat types.

Mixed forest site	Drift Lines	Single snares
1	3	2
2	0	3
3	2	0
4	3	4
5	3	0
6	1	10
7	1	6
8	1	4
9	2	2
10	1	4
11	1	1
12	2	2
Total	20	38

Evergreen forest site	Drift Lines	Single snares
1	2	5
2	3	5
3	3	3
4	0	8
5	4	3
6	2	0
7	2	4
8	1	2
9	2	5
10	2	1
Total	21	36

Table 6 Number and type of snares set (i.e. available for detection) in evergreen (EVG) and mixed (MF) forest, number of snares found by all teams over first and second visits, and associated detection probabilities for each.

Snare/Habitat Type	No. Set	Found Pass 1	Found Pass 2	Found at least once	Found both times	Detection Pass 1	Detection Pass 2	Overall Detection
MF drift line	20	3	4	5	2	0.15	0.20	0.25
MF single snare	38	4	6	8	2	0.11	0.16	0.21
MF ALL	58	7	10	13	4	0.12	0.17	0.22
EVG drift line	22	5	8	10	3	0.23	0.36	0.45
EVG single snare	35	9	7	12	4	0.26	0.20	0.34
EVG ALL	57	14	15	22	7	0.25	0.26	0.39
ALL	115	21	25	35	11	0.18	0.22	0.30

Due to the high number of teams and relatively small number of sites there is little information to definitively identify differences in detection probability between teams. This is further complicated by the non-equal allocation of sites between teams (for logistical reasons), as well as the variability in the number of snare incidents available for detection within these sites. While the limited data shows some variation in the proportion of snares detected by different teams, ranging from 11% to 30% (Table 7), this difference is not statistically significant ($chi^2 = 5.6$, df = 6, p = 0.47).

The visual inspection of GPS tracklogs revealed that teams did overlap in their survey routes but not to any major extent (See Figure 8 for an example). The teams surveyed both on and off existing trails and survey routes tended to coincide on trails. The degree of overlap observed between teams also appeared to be greater within evergreen forest sites when compared to mixed forest sites.

Table 7 Variation between teams, aggregated across both habitat types and snare types.

Team	Total Available Snares	Total Snares Found	Detection
A	42	9	0.21
B	40	5	0.13
C	42	10	0.24
D	18	2	0.11
E	23	7	0.30
F	36	9	0.25
G	29	4	0.14

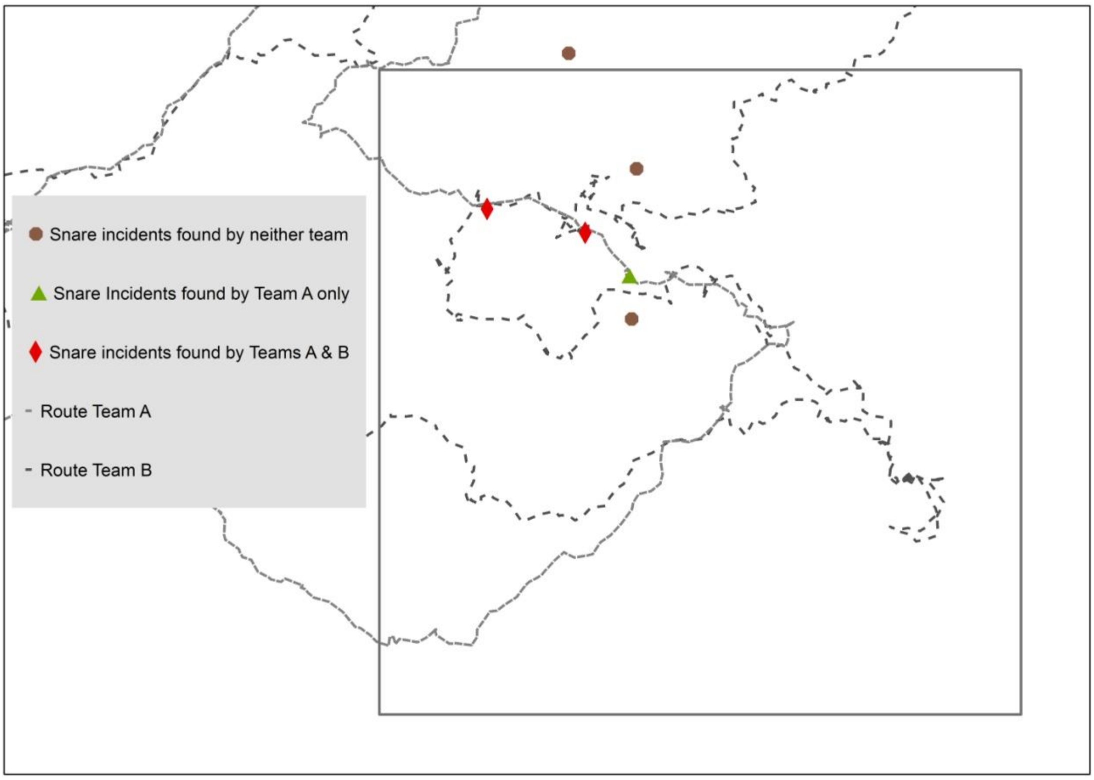

Figure 8 GPS tracklogs showing survey routes taken by independent teams within one mixed forest site. The locations of snare incidents available for detection, and snare incidents detected by one or both teams are also shown.

An additional point worth noting is that nine genuine snare incidents (i.e. snares which been placed independently by hunters not involved in this experiment) were detected by teams during the course of this experiment. One of these incidents, involving a drift line, was encountered by two teams, while the other eight were encountered by one team. These genuine snares were disabled by removing the wires, although the drift fence remained in place.

The results of the two analyses performed in the package unmarked, based only on the data concerning snare incidents found by search teams, are presented in Table 8. Estimates for both detection probability and the mean abundance of snare incidents per site are provided for both of the modelling approaches tested. The N-mixture models results, which are derived from the simple repeated counts, are closer to "true" detection probability and abundance, than the multinomial mixture model results, which are based on the double-observer method. The standard errors associated with the estimates were higher, however, for the N-mixture model than for the multinomial mixture model. The N-mixture model slightly underestimated detectability and also underestimated mean abundance per site whereas the multinomial mixture model greatly overestimated detectability and underestimated mean abundance per site.

Table 8 Models estimates from two approaches compared to true values. Average abundance per site calculated by dividing total number of snares set by total number of sites.

Model	Binomial Mixture	Multinomial mixture	True Value
Abundance Estimate	3.39	2.00	5.2
SE	1.72	0.43	
Detection Probability	0.28	0.48	0.30
SE	0.14	0.09	

3.4 Discussion

An overall detection probability of 0.3 in this experimental context supports the supposition that detection rates for snares are relatively low. In most ecological surveys only a small proportion of the total area will be sampled, and in the case of snares, realistic search effort may allow only a small proportion of the total number snares of present to be detected. However, had the teams not been allowed to search purposefully (for example if they searched along random transects) the detection probability would likely have been far lower.

As predicted drift lines containing multiple snares are more conspicuous than single snares and this is reflected in their higher detection probability in both habitat types, and particularly in dense evergreen forest where single snares are especially difficult to pick out. Surprisingly, however, overall detectability of snares was higher in evergreen forest sites than in mixed forest sites, which is contrary to expectations. Of possible relevance is that the mixed forest sites were surveyed first and these particular field protocols were initially unfamiliar to search teams. It may be that they gained confidence and experience as the experiment progressed and this caused their search efficiency to increase as they moved on to the evergreen forest sites, leading to higher numbers of detections. An alternative explanation is that within evergreen sites the difficult terrain means that teams are to some extent constrained in their choice of routes, whereas in more open mixed forest sites teams can traverse the site freely. Teams both setting and searching for snares in the evergreen forest may be forced to follow similar paths as they are the only ones available. The fact that a greater number of double detections occurred in the evergreen forest than the mixed forest sites (7 versus 4) may bear this out, but with such small numbers this equally could be down to chance.

This raises the issue of whether teams may be cueing each other, for example by tracking one another or noticing greater disturbance around the vicinity of a snare incident (because teams have stopped at these locations). However, although team members are experienced trackers and may even recognise the trails left by their fellow teams, they have no way of discerning whether the trail was made by a team setting the snares or a another team searching, and in the latter case they have no reason to believe another team will be any more effective than they are at locating snares. Furthermore, in any survey conducted to locate "real" snares, search teams will inevitably follow cues they believe to be related to the movement of hunters, i.e. trails and camps, and in fact this is the most efficient method to detect snares and so in reality is a technique search teams *should* be employing, even in this experiment. Regardless, the examination of tracklog routes did not appear to show an overwhelming degree of overlap between teams, and although the overlap does appear to be greater within evergreen sites, this is probably due to the more restricted movement in this habitat, as described above. Finally, although the proportion of snares detected on the second visit is slightly higher than on the first visit, to sites in both habitat types, the difference is marginal and unlikely to be attributable to teams tracking one another. The vast majority of ecological surveys are concerned with non-human species but in studies like this, where "signs" of illegal human activity are the target, it may be practical to capitalise on the fact that search teams may naturally tend to navigate in a similar manner to the perpetrators of such activities.

Although there was variation in the proportion of snare incidents detected by different teams, these differences were not statistically significant. Given the similar levels of skill and training amongst team leaders it was expected that search efficiency would be approximately equivalent. It seems likely therefore that the apparent variation is an artefact of the small sample sizes involved.

Typically in a double-observer approach both teams (i.e. observers) will search simultaneously while repeated visits are generally carried out consecutively. In this experiment some sites were searched on the same day and some on successive days. Given that snare incidents do not change (in terms of their availability for detection) over a two-day period, both approaches are exactly equivalent in terms of sampling protocols in this context. With regard to the analysis, however, the model used for the double-observer approach incorporates an extra layer of information, i.e. the double-detections, which is discarded for the repeated visit model. Despite this, the repeated visit model provided more accurate estimates of detectability and mean abundance per site. The over-estimate of detectability from the double-observer model may be a result of some degree of non-independence between teams, but this is difficult to explore further with such limited data. Indeed, the performance of both models was likely to be affected by the small sample sizes involved in this experiment.

In this experiment we attempted to mimic the field conditions in which a "real" snare survey might be undertaken to as great an extent as possible. However, the teams involved in this experiment were comprised of similar types of individuals, none of whom were actually hunters intent on catching prey and avoiding capture themselves. It may be that the movements of these teams probably had more in common with one another than with such hunters, and they most likely had similar ideas with regard to where to both set and search for snares. Furthermore, snares occurred at moderately high densities and were distributed relatively constantly across sites within this experimental scenario. In a "real" survey context there is likely to be greater spatial heterogeneity in terms of snare distribution and densities could be either far lower or, indeed, far higher locally. Where multiple hunters are operating within an area they may employ a range of strategies and preferences for snares placement, and for how they construct and conceal their snares.

It is possible therefore that the number of double-detections (i.e. repeated detections of the same snare by both teams) achieved in a real snare survey would be somewhat lower than observed in this experiment. Counts of real snares could also be considerably lower in areas of low hunting intensity. Thus, in some conditions a double-observer approach may simply not be feasible or appropriate means of monitoring snares. The repeated visit approach does not depend upon double-detections and could be implemented even in situations where low counts and large number of zeros are expected. When these considerations are combined with the apparently superior performance as an estimator of the N-mixture model, this approach seems to offer the greatest potential in terms of future large-scale surveys.

3.5 Conclusion

Prior to this study there was virtually no information available relating to the practise of snaring which could help inform the design of any large-scale assessment of snaring prevalence. Despite the wide array of methodologies available for population estimation and trend monitoring, the majority remain untested in tropical forest settings, both with regard to the validity of underlying model assumptions and also in terms of the practical feasibility in what tend to be challenging field conditions.

Although this experiment focused on an artificial scenario, it has provided a preliminary estimate of the detection probability of snares and yielded useful insights into what factors might affect snare detectability. It has also helped to distinguish between potential approaches to estimating snare abundance and detectability and demonstrated that a method using simple repeated counts at multiple sampling locations could be both feasible and effective.

Validation of field sampling techniques and associated modelling approaches is an important research concern within applied ecology (Alldredge et al. 2008). Field experiments have been used in the past to test the reliability of population estimation techniques (Mares et al. 1981) and more recently to investigate factors affecting detection probability (Alldredge et al. 2007; Simons et al. 2007) but they remain rare due to the inherent difficulty of finding suitable populations (i.e. for which independent parameter estimates exist) or re-creating field survey conditions. When (Carothers 1973) used taxicabs in Edinburgh to investigate the performance of closed population capture-recapture models his choice of a non-animal target was obviously a practical expedient but increasingly conservation scientists are recognising the need to focus their attentions on human activities as a mean of monitoring threats to wildlife. This study further confirms that just as conservation biology can borrow techniques originally developed in the social sciences (Nuno et al. 2013), ecological methods can be equally transferable to human contexts (Rowcliffe et al. 2004; Papworth et al. 2012).

Chapter 4. Estimating snare abundance and detectability in the Seima Protection Forest, Cambodia.

4.1 Introduction

Hunting, be it for local subsistence or to supply ever-expanding regional and global markets with meat, pets, trophies and other body parts, arguably constitutes the greatest current threat facing wild vertebrates in tropical Asia (Corlett 2007; Steinmetz et al. 2010). Unsustainable hunting can have dire consequences not just in terms of causing species extirpations and degrading the ecological integrity of forest systems, but also through its impact on the livelihoods of the rural, often marginalised, people who depend on these resources (Milner-Gulland & Bennett 2003; Robinson & Bennett 2004).

Traditional approaches to the monitoring of illegal resource use (i.e. interview-based techniques, self-reporting, direct observation) all have methodological challenges associated with them, primarily due to the fact that resource users typically have significant incentives to conceal their activities (Gavin et al. 2010). This can cause users to alter their behaviour in the presence of observers or provide misleading information to investigators, thus introducing potentially unquantifiable bias to studies (Keane et al. 2008; Gavin et al. 2010). A common alternative method of monitoring illegal resource use within protected areas involves the use of law enforcement records collected during routine patrols (e.g(Hilborn et al. 2006; Holmern et al. 2007; Jachmann 2008a). Such an approach is attractive in that patrol data are cheap and readily available, and utilising them as a monitoring tool can represent an efficient use of scarce conservation resources (Keane et al. 2011). However, these data are essentially a by-product of attempts to actively deter illegal activities and this can severely restrict their usefulness for secondary monitoring purposes (Gavin et al. 2010; Keane et al. 2011).

Monitoring of illegal activities, including using patrol data, are vulnerable to two major sources of bias; imperfect detection and sampling error, analogous to the issues affecting ecological monitoring of spatial and temporal patterns of wildlife abundance. The importance of considering imperfect detection and spatial sampling error when designing conservation monitoring programs has been repeatedly highlighted within the ecological literature (Yoccoz et al. 2001; Legg & Nagy 2006; Nichols & Williams 2006; Kéry & Schmidt 2008; Schmidt et al. 2013) and these issues are equally applicable to the monitoring of threats as to the monitoring of target populations. Poorly designed monitoring programs can preclude robust inference for the system of interest and limit the utility of monitoring data for management (Nichols and Williams, 2006).

The continued development of methods which can produce unbiased estimates of illegal resource use is crucial not just for reliable inference regarding the true state of threats but also as a means of validating more cost-effective approaches such patrol-derived indices. In developing these methods careful design can be used to ensure that the sampling approach employed is both sufficient in terms of effort and representative of the system of interest, while limiting the issues caused by sampling error (Brashares & Sam 2005), but accounting for imperfect detection can be more challenging. The issue of detection error is of particular relevance to illegal hunting, not only because it hinders reliable monitoring of this threat, but also because a key factor in successful poaching deterrence is a high rate of detection (Leader-Williams & Milner-Gulland 1993; Hilborn et al. 2006; Dobson & Lynes 2008). And yet, to our knowledge, there are no published studies which attempt to estimate the extent or impact of illegal hunting using methods which explicitly address the problem of imperfect detection.

An extensive body of theoretical and empirical ecological research is devoted to strategies for distinguishing between variation which is related to spatial or temporal variation in an underlying ecological process of interest (i.e. occurrence or abundance) and variation which is due to imperfect observation of this process (i.e. detectability; (Buckland et al. 2001; MacKenzie et al. 2002; Pollock et al. 2002; Royle et al. 2005; MacKenzie 2006). The development of flexible hierarchical models such as the multinomial and binomial N-mixture models of (Royle 2004a; Royle 2004b) has greatly improved researchers' ability to simultaneously account for spatial variation in abundance of target species and variation in detection probability. Variants of binomial mixture models have been widely adopted for analysing animal counts, both for the estimation of habitat-specific abundance and to evaluate species' responses to management practices (Kéry et al. 2005; Chandler et al. 2009; Schlossberg et al. 2010). By jointly modelling the ecological and the observation processes, these methods allow for more reliable inference about the true ecological state and the response of the system to management actions. To date these models have most frequently used in the analysis of avian point count data, although they have also been employed in the study of mammal and amphibian populations (Mazerolle et al. 2007; Zellweger-Fischer et al. 2011). A natural extension of the methods is to adapt them for the modelling of observations of signs of human activity, such as snares, rather than the wildlife signs used in more traditional ecological studies.

In this paper we present a case study applying this class of models to measuring snaring prevalence in a protected area in Eastern Cambodia. As elsewhere in the tropics, the use of wire snares is a common method of hunting in this region, as the equipment involved is affordable and easily accessible to locals, and the technique is effective over a wide range of species (Noss 1998; Fa & Brown 2009; Becker et al. 2013). This form of hunting is particularly detrimental because in practice it is often indiscriminate and wasteful (Noss 1998; Wato et al. 2006a; Lindsey et al. 2011), and the use of snares is illegal in Cambodia. However, the inconspicuous and covert nature of this activity means it is extremely difficult to detect perpetrators or snares, and consequently the enforcement of snaring prohibitions is challenging (Noss, 1998). These same traits greatly impede robust assessments of snaring prevalence, but without accurate measurement of such illegal activities, managers cannot easily evaluate the success of conservation actions designed to reduce snaring rates, or design more efficient interventions as a result (Hockings et al. 2000; Milner-Gulland & Bennett 2003; Gavin et al. 2010).

The aim of this study was to develop an approach which could reliably estimate the abundance and detectability of snares but that could be implemented within a typically challenging forest context. There results of this study will also be of direct use to management and so our objectives were both methodological and policy-relevant. The first of our objectives was associated with the field component of the study whereas the remainder were related to the subsequent modelling process. They were; *Objective 1.* Develop an appropriate sampling design for a snare survey to produce data suitable for assimilation within a hierarchical modelling framework. *Objective 2.* Analyse the resultant snare data using N-mixture models to generate a detectability-corrected spatially explicit index of snare abundance. *Objective 3.* Quantify *a prior* hypothesised relationships between "control" covariates and both detectability & abundance. *Objective 4.* Investigate potentially more complex relationships between snare abundance and additional covariates of interest, including wildlife densities and patrol effort.

4.2 Methods

4.2.1 Methodological Framework

This application of N-mixture models depends upon both spatial and temporal replication within the data (Royle 2004a; Royle 2004b; Kéry et al. 2005), and a sampling design was required which incorporated both multiple sites (i.e. spatial replicates for the abundance component of the models) and repeat visits to each site (i.e temporal replicates to allow for the estimation of detection probability). Given the severe logistical constraints associated with field surveys in this context, together with the specific challenges associated with finding snares (see Chapter 3), the resulting sampling design involved a balance between maximising the efficiency of data collection and adhering to best practise in terms of scientific rigour.

N-mixture models in this context can be viewed essentially as extensions of the Poisson generalized linear model (GLM) or generalized linear mixed model (GLMM), with an additional stochastic component that explicitly models the observation process (Kéry & J. Andrew Royle

2010). These models can produce reasonable measures of abundance, corrected for imperfect detection, without the need for individual detection and even in cases when data are relatively sparse (Royle 2004a; Royle 2004b; Royle & Dorazio 2006).

N-mixture models can also be particularly useful for investigating how both the abundance process and the detection process vary as a function of environmental covariates (Schlossberg et al. 2010; Chandler & King 2011; Sillett et al. 2012). In the case of snares, multiple potentially interacting factors are likely to influence both of these processes. Although the nature of some of the relationships involved can initially seem to be intuitive, for example, proximity to population centres might be expected to lead to higher snaring levels, greater complexity may be revealed through closer inspection. For example the confounding effects of forest type, prior wildlife depletion and law enforcement might lead to snaring levels having a non-linear relationship to proximity to population centres. The influence of other factors, such as the potential impact of law enforcement on deterrence of snaring at different spatial and temporal scales, remains largely undetermined.

In light of this our modelling approach incorporated two phases, the first of which examined covariates for which we had some clear *a priori* hypothesis with regard to their relationship to abundance and/or detectability. These variables can be viewed as "control" covariates which are primarily important for the purposes of spatial prediction. The second phase involved including additional covariates in order to explore the relationship between threats (i.e. snaring rates), interventions (i.e. patrol effort) and impacts (i.e. wildlife densities). Whilst the relationships and potential causal linkages between these aspects are of fundamental interest to conservation managers, they are also likely to be multifaceted and difficult to predict or interpret with any certainty.

4.2.2 Study Site

The Seima Protection Forest (SPF) covers 292,690 ha in eastern Cambodia, and is part of a trans-boundary complex of nine inter-connected reserves covering well over 1.5 million ha, one of the largest conservation complexes in South-East Asia (Evans et al. 2012). With over 90% high quality forest cover, the reserve is unusual in Indochina in that it contains large areas of both evergreen/semi-evergreen forest and deciduous forest, which together form a complex mosaic with many sub-types and transitional zones (Baltzer et al. 2001; Evans et al. 2012). Biodiversity values within SPF are very high in a south-east Asian context and of the 41 Globally Threatened vertebrate species recorded (4 Critically Endangered and 14 Endangered), many occur in globally or regionally outstanding populations, including elephants, primates, wild cattle, several carnivores and a range of large birds (Evans et al. 2012; O'Kelly et al. 2012). The SPF has been under the management of the Forestry Administration (FA) supported by the Wildlife Conservation Society (WCS) Cambodia Program since 2002. Four direct interventions have been implemented; maintaining political support, strengthening community natural resource management, developing alternative livelihoods, and law enforcement.

Almost 20,000 people are living on or within the boundaries of SPF and communities comprise both indigenous ethnic minorities for whom the reserve is their ancestral home, and ethnic Khmer, the majority of whom have arrived during a more recent wave of in-migration (Pollard & Evans 2010). Agriculture (primarily shifting cultivation but also the production of cash crops) is the dominant livelihood, but residents are also heavily forest dependent and, in addition to other forms of NTFP collection, a critical source of income for many families is tapping of liquid resin from *Dipterocarpus* trees, which takes place very widely throughout the reserve, with traditional tenure systems dictating individual ownership of the trees (Evans et al. 2003; Evans et al. 2012). A wide range of both direct and indirect threats to biodiversity and livelihoods have been identified. These include forest clearance (both by local families and, on a larger scale, as a result of economic land concessions), unsustainable resource extraction (over-fishing, over-hunting, illegal logging and over-harvest of NTFPs), population growth and in-migration, increased access and growth in market demand, weak law enforcement and governance structures, and insufficient technical capacity amongst conservation agencies and NGOs (Evans et al. 2012).

The most significant threat to key wildlife species in SPF is over-hunting. Cambodia's national animal the Kouprey *Bos sauvelii* would have once occurred here but is now believed to be globally extinct, and wild Water Buffalo *Bubalus arnee,* rhinoceroses (both Javan *Rhinoceros sondaicus* and Sumatran *Dicerorhinus sumatrensis* conceivably occurred) and more recently Tiger *Panthera tigris corbetti* have all been extirpated from the area - almost certainly as a consequence of hunting (O'Kelly et al. 2012). Populations of larger ungulates, pangolins, turtles and many other taxa have also been dramatically reduced through the use of guns, snares, traps, dogs, poison baits and many other methods of hunting (Lynam & Men Soriyun 2004; Drury 2005). The hunting of protected or rare species is prohibited by Forestry Law in Cambodia. Indigenous communities are permitted to hunt non-listed species for consumption using traditional methods but the use of guns and wire snares is prohibited. In recent decades gun hunting was widespread and intense, peaking during the 1990s but subsequently dropping as the 1998 national gun confiscation campaign greatly reduced the proliferation of weapons (McAndrew et al. 2003; Loucks et al. 2009). There are some indications that gun hunting may be increasing again (FA/WCS, unpublished information) but the use of snares persists as the predominant form of hunting and currently represents the most pressing threat to many wildlife species.

4.2.3 Sampling Design and Field Protocols

Although relatively numerous, snares are extremely difficult to detect, and while snare locations tend to be aggregated in space they are also dispersed across a very large survey area. In addition, undertaking any type of field survey in this context entails major logistical constraints, and in particular the costs of travel to survey locations are disproportionately higher than those of the survey activities themselves. Several methods were considered before an appropriate sampling protocol was developed (see Chapter 3 for details) and the final design was tailored to address the specific scientific goals of the study, the unique characteristics of snares, and feasibility in terms of logistics and economics. Key considerations included;

- The need for both spatial and temporal replication (multiple sites and repeat visits to sites) to enable the analysis of data using N-mixture models.
- The need to optimise the efficiency of sampling by minimising travel costs.
- The need to maximise the number of snare encounters by survey teams and to provide an opportunity for multiple teams to encounter the same snares (i.e. “re-captures").
- The need to include an existing set of permanent line transects (used annually for biological monitoring; see Chapter 2) so that snare abundance could be correlated with existing information on wildlife densities during the modelling process.

Sampling took place across the entire core area of SPF (187,983 ha) and involved 40 “clusters” of sites. Each cluster consisted of 12 x 1km^2 “sites” in square-shaped circuit formation, surrounding one of the permanent line transects (Figure 9). The original line transects, and hence the cluster of survey sites, were positioned according to a systematic design with a random starting point in order to ensure optimal spatial coverage (Thomas et al. 2010). The cluster design minimised travel time and the “wasted” effort that results from survey teams moving between sites. However, it is worth noting that there is a trade-off here between the efficiency of the design in practical terms and the reliability of statistical inference due to the potential non-independence of sites within a cluster .

The rationale for situating clusters around line transects was that previously collected distance sampling data could be used to estimate transect specific densities for ungulate species likely to be targeted by hunters. The estimates produced were then assigned to all of the sites in a cluster, to function as a covariate in the modelling process described below. The line transect itself, and its immediate vicinity, was not sampled directly, both to minimise disturbance and also because hunters might conceivably either avoid or purposely target these areas because the vegetation is cleared for ease of passage of the survey team.

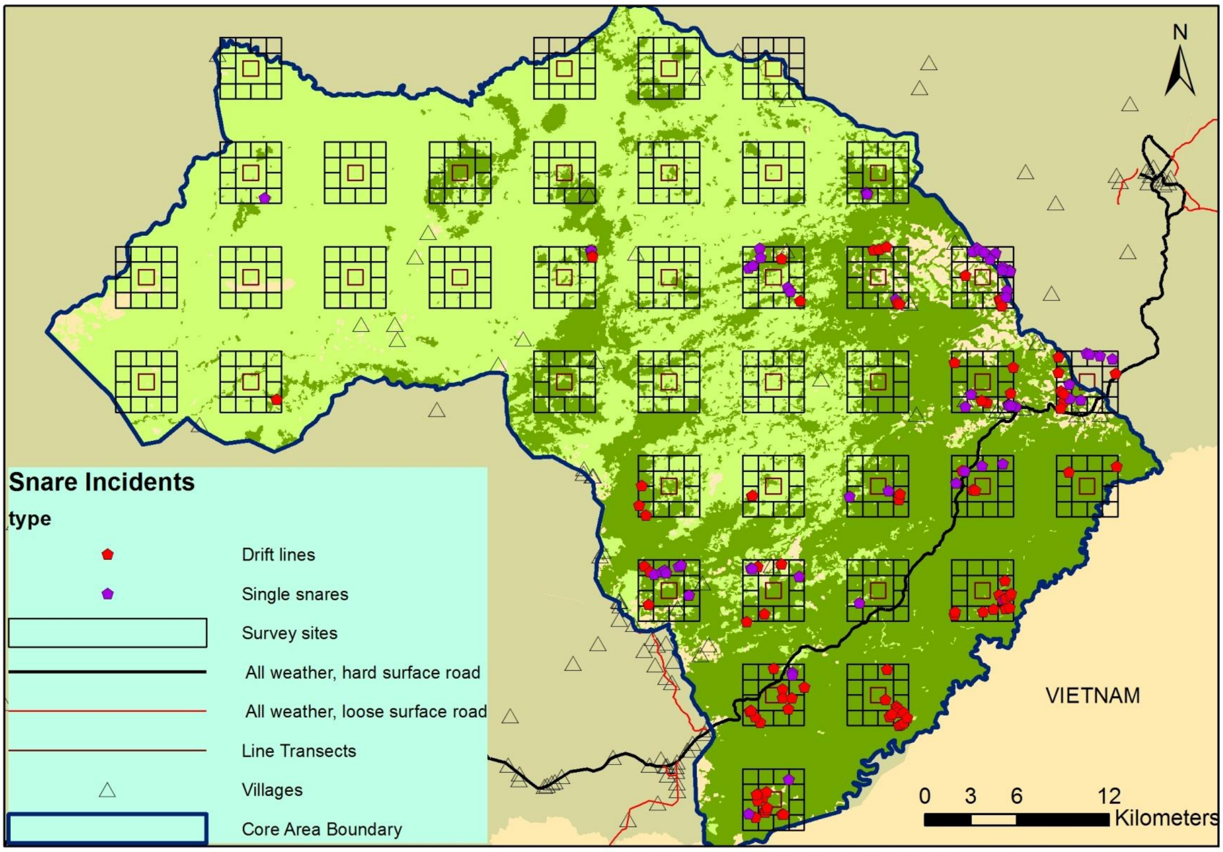

Figure 9 Sampling locations for the snare survey, consisting of 40 "clusters", each containing 12 "sites".

A total of 37 clusters were completed, out of a possible 40 (Figure 9), the final three being omitted due to time and manpower constraints. Of these 37 clusters, 28 were surveyed by two teams while nine were surveyed just once. Each cluster was surveyed over a two to four day period, depending on terrain, and if surveyed by two teams, this was done simultaneously. This approach was taken to maximise sampling efficiency as multiple temporal replicates involving repeat visits at different times, with associated travel and logistical costs, was prohibitively expensive in this context.

The snare survey was conducted between February 2011 and February 2012, but effort was concentrated in the dry season (Nov-Feb) when logistical constraints are lessened. A total of nine teams participated in the survey and between one and six teams were deployed at any one time. Teams consisted of two or three members, one team leader to record data and navigate, and one or two local guides to assist in spotting snares. Teams walked a minimum of 2km per 1km^2 site, choosing routes through the parts of the site that they thought most likely to contain snares, whilst also maximising spatial coverage of the site. When deciding their routes, teams preferentially targeted patches of evergreen forest, ridges and hills, water bodies, mineral licks and any visible wildlife or hunter trails. Teams generally completed between two and four sites each day and routes were recorded using a GPS tracklog function.

Two main types of snare are common within the study site; single wire snares, usually medium or large sized, and drift lines consisting of multiple smaller cable snares set at varying intervals along a continuous, low drift fence constructed from bamboo and brushwood. If snares are old and no longer in use or very new they may not be fitted with wires or cables. The actual number of snares, and whether they are set, is clearly relevant with respect to mortality risk but during this study an observation corresponded to a snare "incident" regardless of the age, type or number of snares concerned (although this was also recorded). In terms of detectability, only the first snare in a drift line is important, as all others in the line will have a detection probability of close to 1. It should be noted that due to their structural characteristics there may be differences in both detectability and abundance between single snares and drift lines but, as no evidence for this was found (Chapter 3), they were treated as equivalent in this context.

The locations of all snare incidents encountered was recorded, together with a number of key attributes including type and number of snare(s), estimated age of snare(s), habitat type and evidence of any captures (i.e. live animals, carcasses, bones etc.). Whilst surveying, teams also collected data on human activities encountered as well as animal signs and observations. Cables and wires were removed from all snares, and spring/anchor poles were cut, thus preventing future use of the structure. All encountered snares were marked with flagging tape after being disabled, and the presence of this marker was recorded if another team encountered the same snare incident (as this constituted a "re-capture"). The flagging tape was placed inconspicuously in order to avoid inadvertently cueing a second team, but teams knew where to look for the marker once they had encountered an incident.

4.2.4 Modelling Strategy

4.2.4.1 Binomial Mixture Models

The simplest of N-mixture models assumes that there are no changes in abundance over the survey period, in which case repeated counts (corresponding to visits by multiple survey teams in this case) within sample location i are treated as independent realizations of a binomial random variable with parameters N_i (local abundance) and p_i (detection probability). It is further assumed that N_i comes from some common distribution specified by parameters to be estimated from the data. The structure of these models is described in detail in (Royle 2004a; Royle 2004b) and Kéry et al. (2005).

All models in this analysis were fitted using the package “unmarked” (Fiske & Chandler 2011) in R version 2.14.0 (R Core Team 2012). The fitting function “pcount” within the unmarked package fits the N-mixture model of Royle (2004) with the latent abundance distribution specified by the user, while the detection process is modelled as binomial.

4.2.4.2 Covariate Selection

A wide range of natural and anthropogenic factors could theoretically influence the abundance, distribution and detectability of snares. A full list of the potential covariates considered is given in Table 9. Measures for each covariate were derived from existing GIS data sets (i.e. forest cover classifications, digital elevation maps, road and river layers etc.), from internal project databases (i.e. location of settlements and patrol stations, biological monitoring records and law enforcement records), and from the snare survey itself (i.e. survey walk effort, relative slope of survey route).

Table 9 ***A priori*** **predictions regarding selected covariates.**

Covariate	Hypothesised relationship with abundance	Hypothesised relationship with detectability	Rationale
Vector Ruggedness Measure	Positive (to a maximum level)	_	Field observations suggest that hunters preferentially set snares in moderately hilly areas (typically drift lines of snares are set running parallel to the gradient of a slope) but that extremely rugged areas are avoided.
Dense Forest Cover	Positive	Negative	Hunters rely on the presence of dense understory to construct and conceal their snares. Conversely, these same habitat characteristics make the detection of snares increasingly difficult as dense forest cover increases
Distance to Village	Non -linear	_	Snaring is expected to be concentrated close to settlements, due to villagers protecting their fields from crop-raiding wildlife and limitations in terms of access to the forest. However, areas of high prey abundances further from villages may attract hunters, and they may also hunt in parallel with resin collecting activities which are dispersed throughout the reserve.
Distance to Boundary	Negative	_	Levels of snaring are expected to decrease as proximity to the reserve boundary increases, due to lessening ease of access and the difficulty of transporting supplies in, and catches out.
Distance to Station	Positive	_	Levels of enforcement should be at their highest around the stations where patrol teams have a permanent presence and/or conduct regular patrols in the vicinity. This would be expected to create a strong deterrence effect.
Distance to Vietnam	Negative	_	Anecdotal reports and field observations suggest that large numbers of Vietnamese hunters cross the border into the SPF from more highly populated areas in order to engage in commercially-motivated intensive snaring activities. Thus, snaring levels would be expected to increase closer to this border.
Average Effort	_	_	In order to account for variation within effective sampled area due to unequal survey effort, this was specified as an offset for abundance within all models.

Season	Unknown	_	One supposition has been that hunting increases in the dry season as access to all areas of the reserve is easier and wildlife congregates around limited water and forage resources. Local informants have also contended that hunting increases during the wet season as the surreptitious movement of hunters is greatly facilitated by the wet ground and dense foliage.
Survey Climb	_	Negative	As the terrain becomes more difficult to traverse the detection probability for snares will likely decrease as search efficiency will be lowered.
Survey Effort	_	Negative	With increasing survey effort higher levels of fatigue may lead to lower search efficiency and a decrease in detection probability.
Muntjac Density	Unknown	_	Wildlife densities may be expected to decrease as snaring levels increase but this may be confounded by the fact that hunters target areas where wildlife densities are at their highest.
Pig Density	Unknown	_	" " "
Cow Density	Unknown	_	" " "
Foot & Motorbike Patrols	Unknown	_	Increasing patrol effort would be expected to cause a deterrence effect and lower snaring levels. However, this may be confounded by the fact that patrol teams target areas where snaring levels are at their highest.

Correlations between covariates were examined to avoid any potential redundancy within the finally selected set. To enhance convergence of the numerical optimization algorithm, all covariates were standardized: route length was log-transformed and the remainder were transformed into standard normal deviates by first subtracting the arithmetic mean and then dividing by the standard deviation.

4.2.4.3 Mixture Distribution and Goodness of Fit

Specifying the appropriate distribution for the latent process of snare abundance has important implications for the validity of the estimates obtained (Kéry et al. 2005). We tested a Poisson and a negative binomial mixture distribution for abundance. We expected that a negative binomial distribution would provide the best representation of the overdispersion within our data, and, indeed, these models did fit well. However, negative binomial models can be unstable when the dataset is relatively sparse or when extreme over-dispersion is indicated, and this distribution may therefore not always be an ideal choice (Kéry et al. 2005). In our analyses, negative binomial models proved highly sensitive to increasing values for the upper boundary of integration, resulting in instability in the maximum likelihood estimates. Thus we proceeded with a Poisson mixture distribution for snare abundance.

We used parametric bootstrapping to evaluate the goodness-of-fit of the final set of selected models. For this procedure, parameters were fixed at the maximum likelihood estimates obtained for the model in question, and 500 replicate data sets were generated. For each replicate data set, parameters were estimated and several fit statistics were computed. We then compared the value of the fit statistics for the observed data set to the reference distribution obtained from the simulated data sets.

4.2.4.4 Modelling Process

Given the number of potential covariates for both abundance and detectability and the complexity of the system being investigated, there are a vast number of combinations of factors which could conceivably affect the response variable of detection-corrected snare abundance. As well as being unfeasible in practical terms to examine all possible combinations, especially if including multiple interactions and polynomial terms, it could lead to overparameterization and the generation of spurious findings (Burnham & Anderson 2002). This prospect is of particular concern in this context, where our knowledge of the system is extremely limited. In developing a limited set of candidate models we therefore focused on the simplest of models, in order to avoid over-fitting and to prevent the inclusion of models with functional relationships amongst variables for which we had no reasonable interpretation (Johnson & Omland 2004).

We used a multi-step process to address *a priori* hypotheses on factors affecting abundance and detectability of snares and to find the best combination of covariates that we had reason to believe were influential. We compared models using Akaike's Information Criterion (AIC) and using ΔAIC, the distance in AIC units from the most parsimonious model. As a rule of thumb, we assumed models with ΔAIC <2 were broadly equivalent in terms of fit (Burnham & Anderson 2002).

We firstly modelled snare abundance by adding the site-level covariates of dense forest cover, terrain ruggedness, season, distance to village, distance to patrol station, distance to reserve boundary and distance to international border. We considered a linear and a quadratic effect for distance to village and terrain ruggedness, on the basis that snare abundance might be expected to peak at some median level for these covariates. Survey route length varied both within and between sites, and to account for this variation in sampling effort we specified an offset variable in the abundance component of the model using log-transformed effort (km walked) per site. Where sites were surveyed twice effort was averaged across both visits. All combinations of these site-level covariates were investigated, resulting in 194 models being fitted. The two best fitting models, with the lowest AIC score, were selected to take forward to the next step.

Secondly, we modelled covariates hypothesised to affect detection probabilities. These included the site-level covariates of dense forest cover, which remained constant across visits, and the observation-level covariates of relative climb and survey effort which were specific to a visit. Thus, for the modelling of detection probability, actual survey effort per site per visit was used rather than the average used for the abundance model component. The two models selected from step one were extended to include all possible combinations of these covariates for detectability. This resulted in a further 28 models being fitted. A final model containing covariates for both abundance and detectability was selected from this step, based on AIC, and this model can be considered the most robust of the models explored in this study.

In the final step, we examined models containing covariates which theoretically may affect abundance but for which the functional relationship between variables is likely to be of a more complex nature. The covariates considered during this phase included ungulate densities (wild pig, wild cattle and red muntjac, both individually and combined) and measures of patrol effort (foot patrols, motorbike patrols, vehicle patrols, and combinations of these patrol types). Each of these covariates was added to the model selected from step two and various combinations of important effects, as indicated by AIC, were tested. This final stage of the modelling process can be seen as exploratory in that the causal relationships between snare abundance and wildlife population densities, and between snare abundance and patrol effort, cannot be easily determined, and are potentially complicated by unidentified confounding variables and interactions between variables which we were unable to model.

4.3 Results

4.3.1 Snare Encounters

The total survey effort was 2,200km and 140 snaring incidents were encountered by survey teams. 64 of these observations involved single snares and 76 were drift lines comprised of multiple snares (Figure 9). The number of incidents per site ranged between 0 and 6, and at least one incident was encountered in 74 of 444 sites surveyed. The sites with one or more encounters were dispersed across 18 of the 37 clusters. Only three snare incidents were encountered by both teams within a site, thus precluding the use of "re-capture" data within the analysis. Not all snares encountered were set with wire cables, but over 1,300 wire cables were removed by teams from the 440 km^2 surveyed, and all snares were disabled.

4.3.2 Model and Covariate Selection

For the abundance component of the modelling, adding each of the site-level covariates improved model fit considerably when compared to the null model, as indicated by AIC (Table 10). When ranked according to AIC, the top four models had ΔAIC <2 and all included dense forest, distance to reserve boundary, distance to international border, distance to village (with a quadratic effect) and season. The models ranking first and second each excluded only one covariate, distance to patrol station and terrain ruggedness respectively, and these were the two models used in the next step. All seven of the covariates considered were included in the model ranked third while the model ranking fourth excluded both distance to patrol station and terrain ruggedness.

The inclusion of the three covariates for detection further improved model fit according to AIC (Table 10). When all combinations of these detection covariates were added to the two models selected above, AIC ranking again resulted in another four top models with ΔAIC <2. Two of these models contained all three covariates for detection, but dense forest was absent from the detection component of the other two models. Within the abundance component ruggedness was no longer included in any model, and distance to patrol station was absent from two of the four. The top-ranking model, which including all covariates except distance to patrol station and terrain ruggedness, was taken forward to the more exploratory stage of the analysis described below.

In the final phase of the modelling process the inclusion of covariates related to patrol effort tended to slightly improve model fit whereas the inclusion of covariates relating to animal density generally did not, with the exception of muntjac density. Models with a single added covariate relating to one of the various measures of patrol effort and also a model with muntjac density were the highest ranking according to AIC (Table 11). However, for all of these models ΔAIC was less than 2 when compared to the best model from step two described above. None of models containing combinations of patrol effort and wildlife densities provided a better fit than the best model from step two described above (Table 11).

Table 10 Model selection process incorporating three phases. Step one models include site level covariates for abundance only and step 2 models include site and observation level covariates for both abundance and detectability. Step 3 is the exploratory phase an and includes covariates related to wildlife densities and law enforcement effort. Models with delta AIC less than 2 are shown.

Step 1								Step 2			Step 3								
Dense forest cover	Distance to boundary	Distance to station	Distance to village	Distance to Vietnam	Distance to station	Season	Ruggedness	Relative climb	Dense forest cover	Survey effort	Foot patrols	Motopatrols	All patrols	Foot and moto patrols	Muntjac Density	Pig Density	Wild cattle density	AIC	delta
+	+	+	+	+	-	+	+	na	na	na	na	na	na	na	na	na	na	643.10	0.00
+	+	+	+	+	+	+	-	na	na	na	na	na	na	na	na	na	na	643.50	0.39
+	+	+	+	+	+	+	+	na	na	na	na	na	na	na	na	na	na	643.70	0.54
+	+	+	+	+	-	+	-	na	na	na	na	na	na	na	na	na	na	643.80	0.69
+	+	+	+	+	-	+	-	+	+	+	na	na	na	na	na	na	na	633.04	0.00
+	+	+	+	+	-	+	-	+	-	+	na	na	na	na	na	na	na	633.60	0.56
+	+	+	+	+	+	+	-	+	+	+	na	na	na	na	na	na	na	634.29	1.25
+	+	+	+	+	+	+	-	+	-	+	na	na	na	na	na	na	na	634.55	1.51
+	+	+	+	+	-	+	-	+	+	+	-	-	+	-	-	-	-	631.90	0.00
+	+	+	+	+	-	+	-	+	+	+	-	+	-	-	-	-	-	631.92	0.02
+	+	+	+	+	-	+	-	+	+	+	-	-	-	+	-	-	-	632.34	0.45
+	+	+	+	+	-	+	-	+	+	+	-	-	-	-	+	-	-	633.00	1.10

Table 11 Exploratory covariates with coefficients. Each model consisted of a base model from step 2 (in bold in table) and with various covariates added.

Model	Covariates								AIC	delta
	Foot patrols	Motopatrols	All patrols	Foot and moto patrols	Muntjac Density	Pig Density	Wild cattle density	Small ungulates combined		
Step3.1	-	-	-0.242	-	-	-	-	-	631.90	0.00
tep3.2	-	-0.233	-	-	-	-	-	-	631.92	0.02
Step3.3	-	-	-	-0.211	-	-	-	-	632.34	0.45
Step3.4	-	-	-	-	0.208	-	-	-	633.00	1.10
Step2.1	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**633.04**	**1.14**
Step3.5	-	-	-	-	0.220	-0.168	-	-	634.25	2.35
Step3.6	-	-	-	-	-	-	-0.095	-	634.33	2.43
Step3.7	-	-	-	-	-	-0.148	-	-	634.43	2.53
Step3.8	-	-	-	-	-	-	-	0.123	634.46	2.56
Step3.9	-	-	-	-	0.199	-	-0.084	-	634.47	2.57
Step3.10	0.019	-	-	-	-	-	-	-	634.96	3.06
Step3.11	-	-	-	-0.187	0.189	-0.135	-0.097	-	635.47	3.57
Step3.12	-	-	-	-	-	-0.162	-0.103	-	635.59	3.69
Step3.13	-	-	-	-	0.209	-0.176	-0.091	-	635.61	3.71

4.3.3 Estimates of Detectability and Abundance

When applied to avian point count data, for which they were originally developed, N-mixture models produce estimates of the average abundance of bird populations per sample location. In the analysis of the snare survey data, abundance can be interpreted as the expected number of snare incidents exposed to sampling along a 1km segment of a survey route. Since the width of the survey routes was not fixed, the effective area sampled is unknown and expected density of snares per site cannot be calculated. In the dense forest terrain, being present on the survey route does not necessarily mean that the snare is exposed to sampling, because it could still be impossible to detect with the best capabilities of the survey team. Furthermore, because counts corresponded to snare incidents rather than actual numbers of snares the resultant measure can be most appropriately viewed as an index of snare abundance. Detectability in this case is the probability that a snare incident will be detected, given that it is exposed to sampling.

Results from step two of the modelling process are considered the most informative this context. For each of the selected models back-transformed estimates of expected probability of detection and index of abundance when all the relevant covariates are fixed at their mean are given in Table 12. Abundance estimates for models containing covariates differ substantially from the null model, which treats abundance and detectability as constant. Estimates of detectability remain relatively consistent across models, at an average of 0.32 (standard error = 0.08) indicating that on average for any given kilometre walked only one snare incident is detected for every three that are present.

Table 12 Back-transformed estimates of abundance (snare incidents per km) and detectability from the four robust models identified at step 2, when all covariates are fixed at their mean. Estimates for abundance are presented for both seasons whilst detectability does not vary by season.

Model	Covariates										Index of abundance				Detection Probability			
	Season	Dense forest cover	Distance to boundary	Distance to station	Distance to village	Distance to Vietnam	Distance to station	Ruggeddness	Relative climb	Dense forest cover	Survey effort	Predicted	SE	lower	upper	Predicted	SE	lower	upper
Step2.1	dry	+	+	+	+	+	-	-	+	+	+	0.18	0.06	0.09	0.36	0.36	0.10	0.20	0.56
	wet	+	+	+	+	+	-	-	+	+	+	0.30	0.10	0.15	0.59				
Step2.2	dry	+	+	+	+	+	-	-	+	-	+	0.19	0.06	0.10	0.36	0.28	0.09	0.15	0.47
	wet	+	+	+	+	+	-	-	+	-	+	0.31	0.11	0.16	0.60				
Step2.3	dry	+	+	+	+	+	+	-	+	+	+	0.18	0.06	0.09	0.36	0.36	0.10	0.20	0.56
	wet	+	+	+	+	+	+	-	+	+	+	0.29	0.10	0.14	0.57				
Step2.4	dry	+	+	+	+	+	+	-	+	-	+	0.19	0.06	0.10	0.36	0.29	0.09	0.15	0.48
	wet	+	+	+	+	+	+	-	+	-	+	0.30	0.10	0.15	0.58				

4.3.4 Covariate Effects on Abundance and Detectability

The inclusion of covariates within models allows us to quantify associations between abundance and key environmental gradients. The models indicate that there is considerable spatial heterogeneity in local snare abundances and that seasonal variation is also present. Coefficients of the covariates from selected models from step two of the modelling are shown in Table 13.

A "typical" location can be characterised by specifying mean values for all spatial covariates within a model, and in so doing we see predicted estimates of abundance in the dry season that are approximately one third lower than equivalent estimates for the wet season. Similarly, we can examine predictions of abundance across a range of values for each of the spatial covariates individually, whilst all other covariates are fixed at their average values.

In terms of forest type a typical location has just under 50% dense forest cover, and snare abundance is extremely low in sites with dense forest cover below this average level. Above this level, predicted abundance increases rapidly as the proportion of dense forest cover increases, and predictions for sites with full cover are over six times higher than for an average site. With respect to proximity to villages, predictions of snare abundance initially decrease as distance to village increases, up to a distance of approximately seven kilometres, after which they begin to increase with greater distances from villages, up to a maximum distance of 13 kilometres. At 13 kilometres from a village snare abundance is predicted to be three times higher than the average, but on this gradient abundance is at its highest around the outskirts of villages, where it is predicted to be four times higher than the average. Snare abundance decreases both with distance to the reserve boundary and with distance to the international border. However, whereas predicted snare abundance within one kilometre of the reserve boundary is over just 25% higher than the average, predicted abundance within one kilometre of the international boundary is greater than the average by two orders of magnitude, indicating the stark difference between the strength of these effects. When the index of terrain ruggedness is included in models, predictions of snare abundance increase as terrain ruggedness increases, but at either end of the spectrum of terrain ruggedness predictions of abundance differ from the average by less than 10%. Surprisingly, snare abundance appears to decrease with distance to patrol station. However, this effect is relatively weak, with predicted abundance at one kilometre from a station just 20% higher than the average, whilst predictions at the maximum distance of 26 kilometres from a station are 35% lower than the average.

In the more exploratory models (Table 11) there appeared to be a negative relationship between all measures of patrol effort and snare abundance (i.e more effort is associated with fewer snares), with the exception of foot patrols. However, predicted snare abundance for a site with no patrol visits (all patrol types combined) is less than 5% higher than predicted abundance for a site with the average number of patrol visits (3.5). There was also a negative relationship between wild cattle and wild pig density and snare abundance, whereas the relationship between muntjac density and snare abundance was positive. Using a model containing red muntjac as a covariate, predicted snare abundance for sites with the highest muntjac densities are around 80% higher than the average.

The same approach can be used to explore how both site level and observation level (i.e. related to an individual visit) covariates affect detectability. Detectability decreased with increasingly dense forest cover, such that predicted detectability in sites with 10% forest cover is seven times higher than a site with 100% forest cover. A steeper relative slope on the route surveyed also reduced detectability and predictions of detectability on the flattest routes are up to 10 times higher than for the steepest routes surveyed. Finally, route length had a positive relationship with detectability; for example, predictions of detectability for routes of three kilometres were 20% higher than for routes of two kilometres.

Table 13 Coefficients of covariates from selected models from step 2.

Model	Intercept (*Abundance*)	Season	Distance Boundary	Distance Station	Distance Village	Distance Village (quadratic)	Distance Vietnam	Dense Forest	AIC	delta AIC
Step2.1	-2.53	0.48	-0.25	-	-0.58	0.26	-0.70	1.37	633.04	0.00
Step2.2	-2.51	0.49	-0.24	-	-0.61	0.27	-0.72	0.62	633.60	0.56
Step2.3	-2.53	0.45	-0.24	-0.15	-0.58	0.27	-0.59	1.32	634.29	1.25
Step2.4	-2.50	0.45	-0.23	-0.18	-0.61	0.28	-0.60	0.61	634.55	1.51

Model	Intercept (*Detection Probability*)	Relative Climb	Dense Forest	Route Length	Number Parameters	AIC	delta AIC
Step2.1	-0.57	-0.47	-1.19	0.20	11.00	633.04	0.00
Step2.2	-0.93	-0.52	-	0.24	10.00	633.60	0.56
Step2.3	-0.57	-0.47	-1.13	0.19	12.00	634.29	1.25
Step2.4	-0.92	-0.51	-	0.23	11.00	634.55	1.51

4.3.5 Snare Distribution Maps

The final model selected in step two was used to create spatially explicit predictions of detectability-corrected snare abundance across the entire core area. The resulting map (Figure 10) shows clearly how snaring is concentrated in the southern sector of the site, close to the Vietnamese boundary and around villages and patrol stations. The southern sector of the site is also the area with the highest proportion of dense evergreen forest.

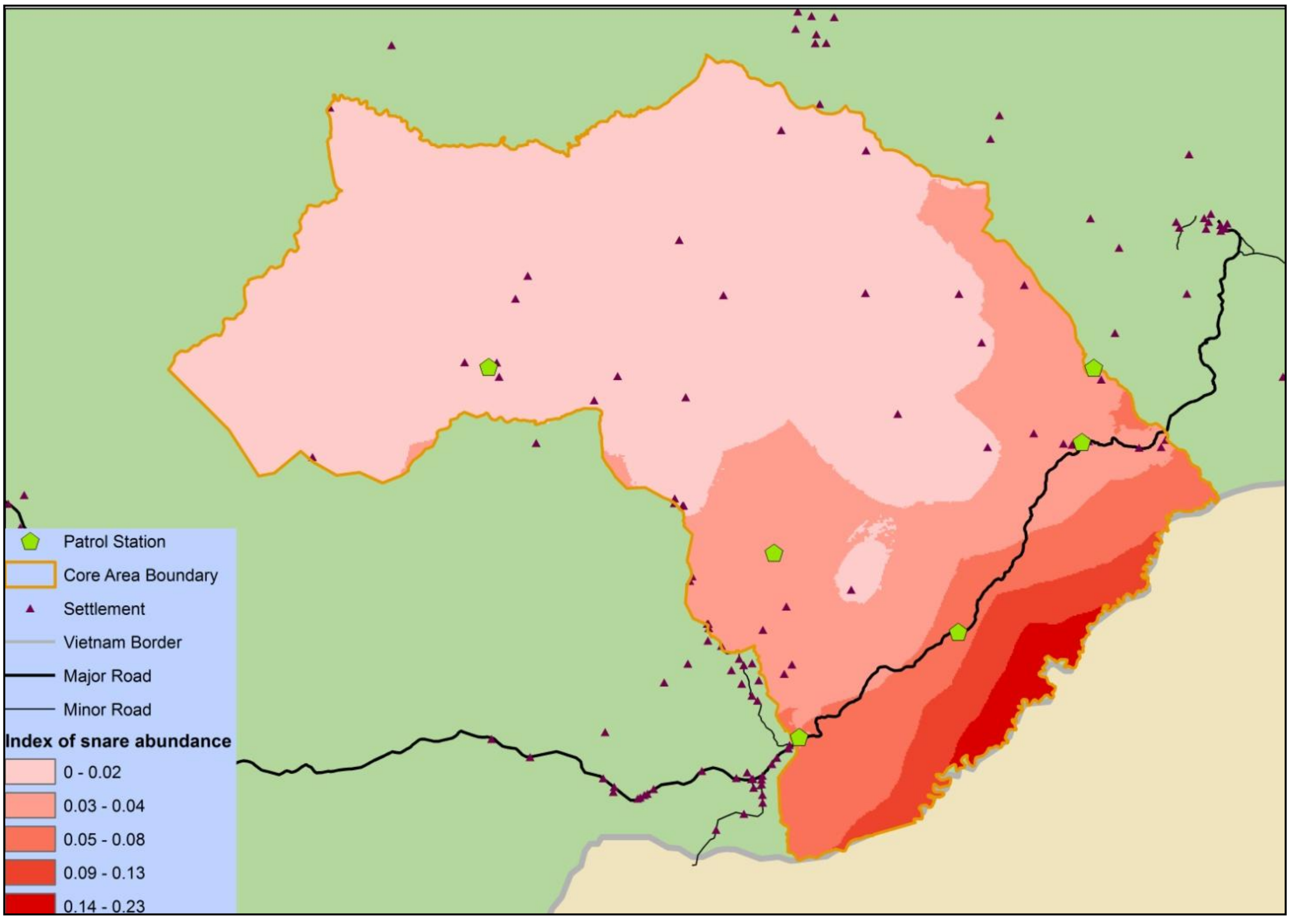

Figure 10 Spatially explicit predictions from the final model (step two) for the core area of the Seima Protection Forest.

4.4 Discussion

4.4.1 Determinants of Snare Detectability and Abundance

The presence of effects in the "control" models, and their directions, concurred generally with expectations. The relationships between snare abundance and dense forest cover, terrain ruggedness, distance to boundary, and distance to international border corresponded to *a priori* predictions, as did the relationships between detectability and dense forest cover and relative climb of survey route (Table 13).

The importance of dense forest cover in influencing snare placement is unsurprising, given that hunters rely on this type of forest to construct and conceal snares, and that wildlife populations also depend heavily on the availability of this habitat type. However, the fact that dense forest negatively affects the detectability of snares whilst simultaneously exerting a positive effect on snare abundance demonstrates how crucial it is to account for imperfect detection in these types of surveys in order to avoid biased results.

Proximity to population centres seems a logical determinant of hunting occurrence and in this case we see the overwhelming influence of the location of the Cambodian/Vietnamese border on snare abundance. This can be attributed to the disproportionate population densities and extremely high demand on the Vietnamese side, which are undoubtedly driving an influx of hunters into SPF from across the international border (WCS, unpublished data).

The relationship between snare abundance and distance to village provides a good example of how multiple processes can influence patterns of snare distribution. High levels of snaring occur in the southern part of the reserve, close to the national border and also in relatively close proximity to the larger settlements located in the south eastern and south western corners of the reserve. However, several other snaring patterns are also common. Residents within the reserve boundaries often set snares around the outskirts of their fields, which are generally in the immediate vicinity of the village. When residents go into the forest specifically to engage in hunting, the distance they travel is presumably limited by several factors including their mode of transport (i.e. on foot or by motorbike) and their food and/or fuel supplies. They may also be influenced by the perceived availability of potential prey, which will generally increase with distance from villages. Nevertheless, some residents travel considerable distances from their villages in order to visit their resin trees, and in these instances they may spend several days or even weeks at temporary "resin camps". It is likely that some snaring occurs in parallel with resin collection activities, which are dispersed widely across the reserve. All of these aspects result in a complex non-linear relationship between snare abundance and distance to village.

Prior to this study conflicting hypotheses existed regarding the seasonality of snaring within this landscape. One assumption had been that snaring levels increased in the dry season when access to the reserve is easier and wildlife populations tend to be aggregated around water and food sources. An alternative supposition was that during the wet season hunters took advantage of the greater cover afforded by dense foliage and damp ground, and possibly also a gap in the local agricultural calendar, to focus their efforts during this period. It is also a reality that levels of patrol effort generally decrease during the wet season. The results of this survey confirm the latter suggestion that hunting levels are appreciably higher during the wet season (Table 12).

The apparent negative relationship between snare abundance and distance to patrol stations may seem counter-intuitive but it is important to note that patrol stations within the SPF have been placed strategically, in locations where threat levels are known to be particularly acute and/or in locations known to be particularly important for key wildlife species. Indeed, areas of perceived high animal density are precisely the areas likely to be targeted both by hunters *and* by management and enforcement agencies. Several scenarios are plausible; relatively remote areas of good quality habitat and high prey abundance may attract hunters, and may consequently be chosen as a location for a station. Levels of hunting may remain proportionally higher in these areas despite the presence of a station (although presumably they would be lower than pre-station levels). Alternatively, the presence of a station may afford localised protection which allows prey populations to recover, only for them to be subsequently targeted by hunters who are aware of this recovery.

Various types of patrol effort were tested as covariates in the models, and models containing a combination of all patrol types (vehicle, motorbike and foot) provided a marginally better fit, but these models had ΔAIC < 2 when compared to a control model without covariates for patrol effort (Table 11). Furthermore, when foot patrols alone were included, model fit was poorer than for the control model. This is despite the fact that foot patrols are assumed to be the most efficient type of patrol for detecting snares. There was little support, therefore, for covariates related to patrol effort as important predictors of snare abundance.

The complex relationship between enforcement effort and illegal activities has been highlighted within the literature (Keane et al. 2008; Gavin et al. 2010; Keane et al. 2011) and the non-linear nature of these relationships may be responsible for the apparent lack of any deterrence effect evident in these results. However, it seems likely that these results may be more attributable to issues relating to the spatial and temporal scale of this study. Due to limited patrol coverage within the site a large proportion of survey sites had no patrol effort associated with them and this was particularly pronounced in the case of foot patrols, which were only recorded in 42 out 440 sites. Furthermore, the manifestation of any deterrence effect will be highly sensitive to the specific spatio-temporal scale of the analysis. Lags of varying lengths may occur between patrols and any subsequent deterrent effect, and the duration of any such effect is unknown. The spatial scale at which any deterrence effect will operate at is also unknown and is likely to be dependent on a multitude of factors, including snaring type, patrol type and habitat characteristics (Keane et al. 2011). In this study the unit of analysis was a one km square site and patrol effort was calculated as the number of patrols deployed within that site over a one year period preceding the survey. A wide range of alternative spatial and temporal specifications could have been chosen, and in reality any deterrence effect may operate at much finer spatio-temporal scales.

The relationship between snaring levels and wildlife population densities is of fundamental interest to conservation managers but considerable care must be taken when attempting to elucidate causal linkages between the two. Relationships are likely to be spatially and temporally scale dependant and may be obscured by the presence of multiple confounding variables. For example, an area with apparently low levels of snaring and low wildlife densities may have naturally fewer animals due to some unmeasured habitat characteristics, thus rendering it unappealing to prospective hunters. However, this same scenario could be as a result of overhunting in area which previously had higher wildlife densities, which were then depleted through hunting, eventually causing hunters to shift their activities to other more productive areas. Hence, apparent patterns will depend heavily on the spatial and temporal extent of any analysis. Further complexity can arise when wildlife abundance and hunting levels are determined by the same factors. In the SPF both wildlife densities and hunting levels are high in the southern section of the reserve, which is the area closest to the international border and but also the area with the greatest proportion of dense forest. Proximity to the border may directly influence snaring levels but it does not directly influence wildlife abundance, whereas the presence of dense forest is likely to be a direct determinant of snare occurrence *and* wildlife occurrence. Given the complexity of the system being examined, there is a high risk of conflating association with causation and results should be interpreted with caution.

Although the modelling results yield little support for individual species densities as significant predictors of snare abundance (Table 11), the direction of effects within models is of interest and appears to corroborate other sources of information, including biological monitoring data and field observations from various project teams. Including muntjac density as a covariate did improve model fit slightly, but this model is still within 2 AIC units of the control model. However, the positive relationship between snare abundance and red muntjac density, which is apparent within all models explored, does suggest that hunters purposefully set snares in areas of higher muntjac abundance and, possibly, that the presence of snares does not adversely affect muntjac populations. This species is known to be a preferred prey choice for hunters and probably experiences high hunting pressure (Drury 2005; O'Kelly et al. 2012). Despite this, muntjac remain moderately abundant in comparison to other ungulate species, there is no evidence of a decline apparent from biological monitoring data and they persist widely throughout the reserve (O'Kelly & Nut Meng Hor 2012; O'Kelly et al. 2012). When taken together, the temporal trend data for this species and the spatial relationships inferred from the snare survey results appear to indicate a relative resilience to hunting pressure, a supposition which has been suggested in other studies (Steinmetz et al. 2010).

Including wild pig and cattle densities as covariates within models did not improve model fit, but it did suggest a negative relationship between species' density and snare abundance. Wild pig is one of the commonest species to appear in hunting records (FA/WCS, unpublished data) and biological monitoring data suggest that, whilst still relatively healthy, this population is undergoing a decline (O'Kelly & Nut Meng Hor 2012; O'Kelly et al. 2012). The wild cattle population within SPF is small, declining, and potentially particularly vulnerable to the threat of hunting (O'Kelly & Nut Meng Hor 2012; O'Kelly et al. 2012). Although it is likely that snaring is having a negative impact on wild pig and cattle populations, the evidence provided by this study is inconclusive and further work is needed to establish to what extent snaring is contributing to these declines.

4.4.2 Methodological Considerations

In this study we have presented an integrated sampling methodology and analysis framework which we feel offers considerable potential for more reliable estimation of the extent and distribution of illegal resource use, despite the often cryptic and highly variable nature of these activities. This approach can help to disentangle multiple potentially confounding factors and is particularly useful in that it corrects for variation in detectability, a ubiquitous and frequently overlooked source of error which can lead to misleading estimates of abundance if improperly addressed.

Our modelling framework also provides spatially explicit estimates as a function of a range of natural and anthropogenic covariates and can be used to produce detectability-corrected predictive maps of abundance. Such prediction maps of hunting may be of particular use to managers for the purposes of guiding current and future interventions in a more targeted way. Furthermore, this approach allows us to investigate the spatial dynamics underlying snaring, to better understand the causal mechanisms which may be at work, and to evaluate how changes in key covariates could potentially affect hunting prevalence and detection probability.

A survey of the type described here could also be repeated periodically to estimate temporal change in snaring patterns. This would support managers in monitoring the actual impact of enforcement interventions and in assessing the relative success of different strategies implemented to combat snaring. However, it must be acknowledged that this type of survey entails a significant investment of time, manpower and other resources, which may have to be diverted away from already severely overstretched law enforcement regimes. In light of this, the real utility of this type of independent assessment of threats may lie in the opportunity they provide to calibrate more cost-effective but less rigours threat monitoring methods, such as the use of patrol-derived CPUE indices of hunting (see Chapter 5). If used in this manner, it is possible that such independent assessments would need to be carried infrequently enough to constitute a feasible and worthwhile investment of conservation resources.

Despite the potential of the approach described here, there are still several methodological issues which need to be resolved and there is undoubtedly considerable scope for refining our survey design to improve the precision of estimates. In particular the level of temporal replication in this study was minimal, primarily due to logistical constraints. This has implications for adequately modelling detection probability. Increasing the number of site visits (or using more simultaneous observers) should be a priority for future surveys. In addition, it may be preferable for teams to survey identical routes within sites, although this raises a number of practical problems related to maintaining independence among observers (i.e. avoiding inter-observer cues). With regard to the analysis, the use of the negative binomial or other random-effects distributions for abundance may offer advantages over the Poisson mixture specified here by better describing the overdispersion present, but our data were not sufficient to explore this in detail. Finally, our sampling design was based on clusters of sites, again due to logistical constraints, and this raises the question of spatial non-independence between sites. The use of covariates may help to address this issue, and where models fit well as indicated by Goodness of fit tests, the dependence structure may not be a major concern, but it is an area that potentially warrants further investigation.

4.5 Conclusion

It has long been recognised that reliable estimates of distribution, density or abundance, and rates of change for key species, are critical for assessing the sustainability of hunting practices (Robinson & Redford 1986; Robinson & Redford 1991; Milner-Gulland & Bennett 2003; Robinson & Bennett 2004). However, in reality it is often impossible to accurately quantify the effect of hunting on tropical forest vertebrates because detailed data on population statuses are not available (Fa & Brown 2009). Nor does it seem likely that such data will become available for many threatened species in the immediate future, given the extreme resource constraints that continue to impede conservation management in the tropics (Danielsen et al. 2003; Fa & Brown 2009). In the region where this study was undertaken recent extirpations of high value species such as tiger and rhinoceros within designated protected areas (Jenks et al. 2011; Brook et al. 2012; O'Kelly et al. 2012) serve as a stark reminder of the exigencies of the situation.

In these kinds of contexts management efforts cannot afford to focus exclusively on or wait for the outputs of long-term population monitoring or research programs. Instead, urgent emphasis must be placed on the identification of threats and on developing the most effective strategies for mitigating these threats (Sheil 2001). In the protected area discussed in this study, as in many others, it is clear that illegal hunting represents an immediate threat to the persistence of many vertebrate populations, and that managers require real time information on the spatio-temporal patterns of hunting in order to implement effective remedial measures. Disentangling the multiple processes involved in these scenarios presents significant methodological challenges and, although techniques for quantifying illegal resource use are undergoing development, all those currently available have inherent limitations (Gavin et al. 2010). One strategy to address the current paucity of data on illegal hunting is to combine multiple methods and to incorporate information from a range of different sources (Gavin et al. 2010). We believe that the approach presented in this study, which integrates an independently derived measure of hunting with various sources of additional data (including high quality data from biological monitoring and basic law enforcement data) within a robust modelling framework constitutes a promising first step in this direction.

Chapter 5. Assessing the Use of Law Enforcement Monitoring Data as a Means of Measuring Hunting Intensity

5.1 Introduction

Law enforcement monitoring (LEM) data refers to records that are opportunistically collected by law enforcement teams during the course of their routine patrols. Patrol records can provide valuable real-time information with which to guide short-term decisions on patrol deployment, and also to feed into an adaptive management process aimed at increasing law enforcement effectiveness, cost-efficiency and accountability (Jachmann 2008b; Stokes 2010). LEM data can also be used as tool for monitoring threats such as hunting (Hilborn et al. 2006; Holmern et al. 2007; Jachmann 2008a). This is an appealing approach to threat monitoring in that the data are readily accessible and require minimal special skills or additional labour demands to collect (Gavin et al. 2010; Stokes 2010). Furthermore, for many types of covert and illegal activities, including those which represent some of the most significant threats to wildlife of conservation concern, there are few, if any, alternative sources of information available with which to assess their prevalence.

In recognition of this, considerable investment has been made in improving the quality of law enforcement monitoring data through the use of customised monitoring tools, underpinned by tailor-made database software, such as MIST (Management Information SysTem) and SMART (Spatial Monitoring and Reporting Tool). Originating in Uganda in 1997, the MIST software programme (MIST 2013) and associated data collection procedures were specifically designed to meet the law enforcement needs of protected area managers by collating detailed, standardised data on measures of law enforcement effort, observations of illegal activities, and patrol actions and converting them into useful information for management purposes (Schmitt & Sallee 2002; Stokes 2012). MIST is currently being superseded by the newer SMART system (SMART 2013) which extends the approach to include a suite of best practice guidelines designed to help managers better plan, evaluate and implement their law enforcement activities. Over the last decade MIST, and more recently SMART, have been rolled-out in dozens of sites across Africa and Asia and have garnered substantial international support from government and other agencies within the conservation community, reflecting a real interest in the development of a standardised and transparent approach to the monitoring and evaluation of law enforcement activities (Stokes 2010; 2012).

However, as standardised LEM systems become more widely adopted and investment in them continues to grow, there is a danger that the situation will become a classic example of the research-implementation gap (Knight et al. 2008). The implementation of these systems is proceeding apace but it is underpinned by limited research with which to inform any understanding of the large volumes of data generated, and little guidance as to how these data can be analysed in such a way as to generate meaningful results. Of the research available, empirical studies (e.g. Jachmann & Billiouw 1997) are compromised by the potentially unwarranted assumptions underlying measures derived from LEM data, whereas theoretical reviews (e.g. Keane et al. 2011) tend to highlight the implications of violations of such assumptions without providing practical recommendations that managers can use.

Underlying this gap between research and practice is the problem that developing appropriate analytical approaches for dealing with LEM data is challenging. This is because LEM data are essentially a type of encounter data which are prone to severe and, in some cases, unquantifiable biases which can confound any meaningful interpretation of observed patterns (Gavin et al. 2010; Keane et al. 2011). These biases generally arise as a result of the non-constant relationship between patrol effort and encounters of infractions, the variation in detectability of infractions, and the behavioural interactions between the agents involved (Keane et al. 2011; Stokes 2012). In traditional ecological monitoring studies, the risk of bias associated with encounter data can be minimised through robust survey design (Yoccoz et al. 2001; Nichols & Williams 2006) but this is not an option for opportunistically collected patrol data. Some of the difficulties associated with the interpretation of patrol data can be resolved through careful *post hoc* analysis, but other issues may only be addressed through calibration and validation against independent measures of threat (Keane et al. 2011; Stokes 2012).

In this chapter I present a framework for deriving threat measures from LEM data, and for comparing these measures with independent datasets. I apply this framework to a case study in Seima Protection Forest (SPF), a large reserve in Eastern Cambodia. The SPF represents an ideal case study, not only because a long-term, relatively fine-scale LEM dataset is available, but also because, crucially, an independent assessment of hunting prevalence has been also undertaken at this site (Chapter 4). The survey from which this independent measure is derived is based upon replicated temporal and systematic spatial sampling, and was specifically designed to account for the imperfect detection of snares and to achieve adequate representation of the entire site. The results of this survey are therefore relatively robust with respect to many of the biases associated with patrol data and this provides a unique opportunity to evaluate to what extent LEM-derived indices reflect the true state of a threat level.

Section 5.2 introduces the concept of catch per unit effort (CPUE) indices, outlines the various issues associated with their use as a threat monitoring measure and explains in what circumstances the use of alternative independent measures may be necessary. The case study then uses standardised MIST data from SPF to demonstrate the steps involved in deriving CPUE indices and to highlight the importance of analytical decisions regarding the use of appropriate metrics and scales. A number of different CPUE indices are then compared to the independently derived measure of hunting to assess their relative performance and potential limitations. Finally, we present some general conclusions and recommendations with regard to the utility of patrol-derived CPUE indices and the need for comparisons with independent assessments of illegal activities.

5.2 Developing A Framework for Analysis of LEM Data and Comparison with Independent Measures

CPUE indices are a relative measure derived by dividing total "catch" (which can also be encounters or observations) by some standard unit of the effort required to obtain this catch. In this way, variable survey or search effort can be corrected for, and, by assuming that catch is proportional to both the abundance of a target population and the amount of survey or search effort expended, CPUE can be used as an index of true underlying abundance (Hilborn & Walters 1992). This is particularly useful for populations where true abundance is unknown and difficult to estimate but for which opportunistic catch (i.e. encounter/observation/harvest) data are available. CPUE indices are widely employed as a surrogate for abundance in fisheries stock assessments (Punt & Smith 2001) and they have also been utilised to monitor bushmeat hunting and other types of resource harvesting (Sirén et al. 2004; Rist et al. 2010). When applied to the rate of infractions encountered by patrol teams, this metric describes the relative frequency of occurrence of those infractions.

The use of CPUE as a relative index of true threat levels rests upon a number of underlying assumptions. These assumptions, adapted from Keane et al. (2011), are as follows:

- Observations of illegal activities are accurately recorded.
- Measures used for effort are appropriate.
- There is perfect detection of illegal activities in the sampled area.
- Efficiency of patrolling does not vary in time or space.
- Patrol coverage is representative of the range of threat intensities in the area being assessed.
- There are no behavioural interactions between perpetrators of illegal activities and recorders of illegal activities.
- There is a linear relationship between CPUE and underlying levels of illegal activities.

The inherent characteristics of LEM data means that, in practice, there are many instances where these assumptions are violated and this has serious implications for the analysis and interpretation of such data (see Table 14). Some violations are inevitable; for example, that offenders will respond to the activities of patrol teams, but others can arise through inappropriate analysis and can be avoided.

Meaningful interpretation of CPUE indices will depend to a large extent on decisions regarding the appropriate classification of infractions, the appropriate unit of measurement for encounters and for patrol effort, and the appropriate spatial and temporal scale of analysis (see Table 15 for a framework for making these decisions). Controlling for spatial and temporal bias within the dataset and for factors likely to affect detectability, and in particular patrol efficiency, is also important. These decisions will depend on the data available, some *a priori* suppositions regarding the relationship between patrol effort and the activities of interest, and, ultimately, the particular questions which the analysis is intended to answer. The objective of the analysis will, in turn, depend on the particular information required for management purposes. Questions of interest may be, for example, whether levels of illegal activity have changed over time, what types of illegal activity are most prevalent and where they occur, or which law enforcement strategy is most effective at deterring an illegal activity. The process is therefore invariably context specific, but the approach presented here should function as a useful point of departure.

Table 14 Problems commonly associated with LEM data and ways in which they might be addressed, either post-hoc in the analysis of LEM data itself, or through the use of an independent measure of threat prevalence and distribution.

	Issue in LEM data	Addressed in Analysis of LEM data	Addressed by Independent Measure
Spatial and temporal bias	Patrol deployment is by nature adaptive and often strongly non-random. Limited resources and manpower also mean that patrol teams will generally focus disproportionately on areas where threats are greatest, areas which are considered the highest priority for conservation, or areas which are most readily accessible.	Stratification can be used to control for both spatial and temporal variation in patrol effort. This may involve partitioning data into areas/periods where patrol effort is relatively constant.	Probability-based sampling designs can be used to ensure that sampling is representative and that inference can be made about the entire area of interest.
Incomplete coverage	For the reasons outlined above, there may be large areas, or time periods, where no patrol data are available.	If data are analysed at a sufficiently fine resolution, areas/periods for which no data are available can be excluded. No inference can be made about these areas, however, and extrapolation of results to include them should be avoided.	See above.
Imperfect & non-constant detectability	Detectability in this context is the probability that an illegal activity, if present, will be detected by a patrol team with a given level of effort. The simplest of CPUE indices assume that detectability is constant whereas in reality it is determined by a range of factors relating to the target activity, the environmental conditions and the efficiency of patrol teams.	If sufficient information is available some factors affecting patrol efficiency (i.e. patrol type, number of people per team, level of training) and detectability of infractions (i.e. terrain, type of infraction) can be controlled for within an analysis. However, detection will likely remain imperfect even within categories, and the use of CPUE indices offers no means of estimating the number of false absences (i.e. where an infraction is present but remains undetected).	In some scenarios (i.e. the use of satellite imagery to assess deforestation rates) detection probability may be assumed to be effectively 1. In other contexts, techniques developed to explicitly estimate detection probabilities, such as distance sampling, capture-recapture and occupancy-based methods, can be applied to illegal activities. Where the independent measure is interview-based, “detectability” depends on the accuracy of informants’ answers, which can be improved through the use of techniques such as the randomised response technique (RRT) or unmatched-count technique (UCT).

Behavioural interactions	The actions of patrol teams and offenders cannot be viewed as independent of one another, because the primary purpose of the former is to deter the latter. This complicates any interpretation of patrol data because an increase in patrol effort or efficiency may result in a reduction in the total number of infractions committed (due to effective deterrence) and but also an increase in the proportion of those infractions that are detected.	It is difficult to identify or quantify potential bias in patrol data arising from behavioural interactions.	In interview-based approaches or those that involve direct observation of illegal activities such as market surveys or accompanied hunts, the presence of the observer can induce bias. Where independent measures are based on indirect observations, behavioural interactions are less likely to occur, although this depends on whether offenders are aware of the activities of the data collectors, and if so, whether they are motivated to alter their behaviour in response to these activities.
Non-linear relationship between CPUE and abundance	Nonlinearities are common and can be caused by several different processes: 1. Due to inappropriate analysis of patrol data. 2. Due to changes in patrol strategy, leading to changes in efficiency and higher or lower encounter rates, or changes in offender behaviour which allows them to better evade detection. 3. Due to actual underlying threat levels, for example, if some hunters are easier to detect than others they will be apprehended first, and proportionally more effort may be required to locate the remaining offenders.	The first type of nonlinearity can be avoided by ensuring data are not inappropriately aggregated such that they include non-representative areas/periods where law enforcement effort is disproportionately high and levels of threat low or vice versa. It is difficult to address the second and third types of nonlinearity in simple CPUE indices.	For approaches which provide an absolute measure of illegal activities (through the use of robust sampling designs and explicit estimates of detection probability) this issue of nonlinearities is not relevant. However, all approaches which produce a relative measure are susceptible to bias caused by the second and third types of non-linear relationship described.

Table 15 Decisions to be made when undertaking analysis of a LEM dataset.

Considerations for LEM data	Potential Metrics	Analysis Implications
What is the appropriate unit for encounters?	• Direct encounters with offenders • Signs of illegal activities i.e. gunshots, snares, felled trees	Decisions must be made as to whether different classes of infraction should be analysed separately or together. Combining similar types of activity may seem sensible, for example, gunshots heard, snares found and direct encounters with poachers are all related to hunting. However, detectability varies between activities so combining them leads to potential bias. For example, a reduction in one easy to detect category i.e. gunshots, may be accompanied by an increase in a more difficult to detect category i.e. snares, and need not reflect in an overall reduction in hunting.
What is the appropriate measure of effort?	• No. of patrol days • No. visits per cell • No. km patrolled • No. members per team • Effective man-hours • Level of financial investment	Decision regarding which unit of effort should be used may depend on the specific objective of the analysis and on the underlying relationship between effort and encounters. For example, no. of patrol days or km patrolled may be a suitable measure (and approximately equivalent) when concerned with easy to detect logging incidents, whereas no. of team members is less relevant. In the case of difficult to detect infractions such as wildlife trade offences, no. of team members or effective man-hours might be a more appropriate measure.
What are the factors affecting patrol efficiency?	• Levels of training and motivation • Access to equipment • Patrol type • Terrain type • Weather/season • Presence of disincentives (i.e. corruption, collusion, fear of retribution)	Patrol efficiency is directly related to detectability, which is non-constant and must be controlled for. Identifying factors likely to influence patrol efficiency and choosing which of them to control for depends on the context but also on the data available. If a sufficient quantity of data is available it can be partitioned into categories within which detectability is assumed to be relatively constant, but this could involve a great many potential sub-divisions (e.g. teams ranked by experience, patrol types considered separately, distinctions made between habitat types in which patrols were deployed). The level of detail available within a given dataset is also important. For example; whilst type of patrol (in terms of means of transport) is typically included within patrol records, information relating to the motivational levels of teams, or even their levels of experience and training, may not be readily available.

What is the appropriate temporal and spatial scale of analysis?	• Entire PA/PA sectors/1x1km grid squares/Inside vs outside PA • Months/Seasons/Years/Before vs after protection implemented	Decisions regarding the spatial and temporal scale of analysis depend to a large extent on the objective of the analysis. Generally, the spatial scale of an analysis needs to be broad enough to encompass any leakage, i.e. where illegal activities simply shift to another area, as otherwise any observed decrease may not reflect an overall drop in threats. The temporal scale also needs to be broad enough to allow for responses to patrol activities to occur, depending on the outcome variable of interest (e.g. a reduction in threat levels or an improvement of the population status of target species). However, external and internal changes can often confound interpretation of cause and effect over time. For example, patrol strategy may change, meaning two periods are not comparable in detectability, or a rise in underlying hunting levels may confound the deterrence effect of patrols.

Where sufficient, good quality patrol data are available, results may be relatively robust to testing various alternatives in terms of the analytical choices outlined in Table 15, and this could be taken as an indication that CPUE indices do reliably reflect the underlying reality in terms of threat levels. However, in the vast majority of cases there is likely to be considerable heterogeneity across time and space with respect to patrol effort, the detectability of infractions and the underlying levels of illegal activity, all of which are difficulties which can be further compounded by limited or poor quality patrol data. Inevitably, in some of these situations simple CPUE indices will be inadequate to make reliable inference with regard to changing threat levels, in which case more sophisticated modelling techniques may be required, such as the use of linear regression techniques to quantify the relationship between illegal activities and a wider range of key predictors (Jachmann 2008a; Becker et al. 2013). Regardless, periodic independent assessments of the status of illegal activities are recommended, both to calibrate and to corroborate the use of patrol data-derived indices as a monitoring tool (Stokes 2012).

The key purpose of independent threat assessments is to quantify the extent or impact of illegal activities rather than to exert any deterrent effect upon them, and thus the complications arising from the behavioural interactions between data generators and data collectors are greatly reduced or removed. Independent assessments of threat can vary widely in scale and form. Examples include; the use of remote sensing data to monitor land-use change and deforestation (Harper et al. 2007; Buchanan et al. 2008), direct observational studies of hunting (Rowcliffe et al. 2004; Kümpel et al. 2008), surveys of indirect signs of hunting such as snares, traps or carcasses as opposed to direct encounters with hunters (Wato et al. 2006b; Blake et al. 2007), and market or household surveys of patterns of wildlife consumption and trade to triangulate the field-based assessments of threat (de Merode & Cowlishaw 2006; Poulsen et al. 2009).

The extent to which these assessments can address the other issues associated with patrol data depend on the approach taken (Table 14). Ideally the design of such assessments will incorporate statistically rigorous sampling protocols which minimise spatial and temporal bias, and ensure samples are representative of the entire area of interest. Protocols can also be standardised in an attempt to keep survey effort and efficiency constant, and various strategies can be employed to minimise variation in the detectability of target activities. Such strategies include the use of stratification during sampling or analysis, and the inclusion of covariates or the explicit estimation of detection probabilities during the modelling process. All methods available for measuring illegal resource use have their limitations, and the combining and testing against each other of multiple techniques can improve accuracy and allow methods to be further refined (Gavin et al. 2010). Despite this, there are few examples within the conservation literature of direct comparisons between different approaches to quantifying illegal activities (Gavin et al. 2010; Keane et al. 2011), and studies which test measures derived from LEM data against alternative methods are rarer still (Stokes 2012), but see (Knapp et al. 2010).

5.3 Case Study: Measuring Hunting Prevalence in The Seima Protection Forest.

The focus of this case study is the spatial distribution of hunting incidents in the SPF core area, and to what extent CPUE indices derived from MIST data can provide a reliable representation of this distribution, as compared to an independent, statistically robust assessment. Using the framework outlined in Table 15, the decision-making process involved in calculating appropriate CPUE indices is described step by step, and the consequences of these decisions are examined both through sensitivity testing with respect to the indices themselves and by comparison with the independent measure.

5.3.1 Expectations with respect to the ability of CPUE indices to represent threats

Several types of CPUE index were explored, based on different types of patrol, different types of infraction, and calculated at two different scales, one relatively fine and one relatively broad. It was expected that the fine-scale index would perform better than the broad-scale index, as it reflects more closely the scale at which key processes (i.e. occurrence, detection, deterrence) actually operate.

It was predicted that the detectability of infractions would vary between infraction type and that incidents of snaring would have a lower catch-rate than incidents of hunting in general. It was further hypothesised that patrol efficiency, which is an additional component of detectability, would vary according to patrol type. For snare incidents in particular, it is likely that catch-rates are highest for foot patrols, followed by motorbike patrols and then vehicle patrols.

Finally, if the CPUE indices have been selected appropriately and incorporate sufficient data, it was expected that there would be a high degree of spatial congruence between the CPUE indices and the independent index of hunting.

5.3.2 Law Enforcement Strategy within SPF

A patrol-based law enforcement system is the central conservation intervention being implemented in the SPF. Although personnel levels fluctuate there are generally 20-30 law enforcement staff in place, operating under government authority. They are split into four to six teams, each led by a Forestry Administration officer and comprised of members of the armed forces plus a local guide. Patrols are deployed across the entire SPF site (292,690 ha) and occasionally into the wider landscape, but the focus is predominantly on the core area (187,983 ha). Of the six patrol stations within the core area three are manned permanently and three intermittently, depending on access and staff availability. Patrols are conducted on foot, by motorbike and, where access roads exist, by four-wheel-drive vehicle. Law enforcement managers assign sectors to be periodically patrolled by each team but teams are also deployed in direct response to information received from informants regarding potential illegal activities.

Law enforcement teams are mandated to target high priority forest crimes including illegal forest clearance by individuals and companies, over-fishing, over-hunting, illegal logging and over-harvest of non-timber forest products (Evans et al. 2012). Although the most significant threat to key wildlife species is over-hunting, deforestation and habitat degradation are also a major concern. During the period this study was conducted the illegal extraction of luxury grade timber species had also become a particularly pervasive problem. Due to the exceptionally high levels of revenue involved, the Forestry Administration authorities had prioritised the curbing of this activity and patrol teams were under pressure to demonstrate their effectiveness in addressing this threat.

Since 2005, data on enforcement activities at the site have been collected and collated using the MIST system. This LEM data is used to provide managers and patrol teams with monthly summaries of effort and crimes detected, in order to assist with planning and evaluation.

5.3.3 Deriving an independent Measure of Hunting in SPF

During February 2010 to February 2011 an independent “snare survey” was carried out across the entire core area of SPF. Sampling was systematic with a random start and involved both spatial and temporal replication. A total of 440 1km x 1km sites, arranged in clusters of 12, were surveyed, and 332 of these sites were surveyed twice. Survey teams consisted of members of SPF’s biological monitoring team, all of whom had extensive experience conducting ecological surveys and similar levels of proficiency in terms of field skills and data recording. They were assisted by experienced local assistants with good observational skills for spotting snares. The data collected during this survey were analysed within a hierarchical modelling framework which allows for the explicit estimation of detection probabilities and produces detectability-corrected spatial predictions of abundance. These predictions also incorporate important covariate effects, related to both snare abundance and detectability. Further details of the snare survey sampling protocols and analysis are provided in Chapter 4.

This independent survey was designed to address many of the issues inherent in the use of LEM data-derived CPUE indices (Table 14), so that the extent to which these indices reflect true levels of hunting could be assessed. In addition to directly accounting for imperfect detection through the modelling approach taken, the sampling protocols of the snare survey ensured that results were sufficiently representative of the area of interest, and minimised any spatial or temporal bias. Effort was standardised to some extent at the sampling level, but also during the analysis phase by including it as an offset in the modelling of abundance. Search efficiency, analogous to patrol efficiency, can be assumed to be relatively constant, as survey teams were all trained to a similar high standard and were also highly motivated. The short duration of the survey (relative to ongoing law enforcement activities) helped to ensure this level of consistency. Finally, and crucially, there was no behavioural interaction between the data generators and the data collectors, because temporal replicates (and spatial replicates within a cluster) were conducted within hours or days of each other, which did not allow time for hunters to respond to the presence of survey teams.

5.3.4 Using the framework to derive a CPUE Index from SPF Patrol Data

5.3.4.1 Unit of measurement for encounters

Patrol records of hunting in SPF include direct encounters with hunters, gunshots heard, observations of hunting camps, snares and traps, and other indirect signs such a used gun cartridges. Direct encounters differ from other classes of hunting records in several ways. Individuals encountered by patrol teams are classed as hunters if they are carrying weapons (i.e. crossbows, guns, knives), snares, traps or other hunting equipment, or if they are in possession of live animals, meat or other body parts. Although these encounters may yield additional information relating to the identity of the offenders (i.e. ethnicity, place of residence etc.), they do not provide reliable information on the exact location of hunting and, indeed, offenders may have planned but not yet engaged in hunting activities. These and other types of hunting observations are likely to differ considerably in terms of detectability, and thus there may be variability in the relationship between patrol effort and different kinds of observations.

Decision: As the data in this case are relatively sparse, one set of indices was created by combining all hunting observations, despite differences between hunting observation types. However, because snare incidents are the commonest type of hunting observation, and also the unit used in the independent assessment, a second set of indices was created for snare observations only.

5.3.4.2 Unit of measurement for effort

Several measures of effort could have been used within this analysis, including presence or absence of patrols within a grid cell, days patrolled per grid cell, kilometres patrolled per grid cell and number of patrols per grid cell. The first of these is a relatively coarse measure which does not adequately account for the high variability in terms of patrol coverage at this site. Although more fine-grained, both days patrolled and kilometres patrolled have some degree of measurement error associated with them. The number of days patrolled is calculated based on the calendar dates a patrol team is present within a given cell, but this includes a high level of variability in terms of effective patrol effort, as a patrol day with one hour of active patrolling (or zero hours if a team is camped and merely resting) is equivalent to a patrol day with six hours of active patrolling. Kilometres patrolled per cell would provide a better measure of effective effort if accurately recorded. However, within the current system patrol teams take waypoints at (relatively) regular intervals whilst on patrol and these waypoints are subsequently imported into the MIST database, which automatically calculates Euclidean distance rather the exact length of the actual route patrolled.

Decision: The number of patrol visits per grid cell does not suffer from these sorts of measurement error and thus it was selected as the most appropriate unit of measurement for effort in this case.

5.3.4.3 Temporal scale of analysis

This analysis focuses on the spatial distribution rather than temporal trends of hunting within the SPF. This is primary because the independent measure of hunting provided a “snapshot” assessment of hunting prevalence and the CPUE indices were formulated accordingly. It would seem reasonable, therefore, to select a one year period, corresponding to the timeframe over which the independent assessment was conducted. However, during this period, February 2011 to January 2012, only 28 instances of hunting were recorded by patrol teams, just 12 of which involved the use of snares.

Decision: It was decided to include a further one year period, directly preceding the independent assessment, in order to obtain a workable sample size. So all patrol data from February 2010 to January 2012 were used.

5.3.4.4 Controlling for detectability of infractions

Although it is impossible to control for all factors affecting detectability, some attempt can be made to minimise the potential sources of variation. Separating different classes of infraction, as above, is one such way. For difficult to detect infractions such as hunting with snares, patrol efficiency becomes a particularly important consideration and one of the most obvious sources of variation in this regard is type of patrol. Hunting incidents, and in particular, incidents involving snares, are most likely to be encountered on foot patrols, which are generally conducted on minor trails or off-trail completely and tend to penetrate deeper into the forest. Motorbike patrols can cover much greater distances than foot patrols, and can be conducted on minor trails, but the ability to detect hunting incidents will be affected by travelling at a greater speed and the need to concentrate on driving as well as searching. Vehicle patrols are typically conducted only on main roads, and the focus of these patrols is on apprehending offenders in the process of transporting illegal products or equipment.

It should be noted that even within patrol types there are likely to be a multitude of additional factors affecting the detectability of infractions, all of which could potentially be incorporated into the analysis if more data were available. These include, for example, the number of team members per patrol, their previous field experience, the presence of local guides, and the habitat in which the patrol is conducted.

Decision: Three separate indices were created, at each of the two spatial scales, for all patrol types combined, foot patrols alone and foot and motorbike patrols combined.

5.3.4.5 Spatial scale of analysis

Choosing the appropriate scale at which to calculate the CPUE index should ideally be dictated by the hypothesised detectability of infractions and scale of any deterrent effect, but in many cases it will also depend upon practical considerations, such as data availability and the scale at which the independent assessment to be used for comparison was undertaken.

Patrol teams may be able to detect some types of hunting, such as gun hunting, from several kilometres away (due, for example, to the sound of gunshots) but only if the patrol coincides with the exact time of the infraction. Snares or camps, on the other hand, may be available for detection for weeks or even months, but patrol teams are unlikely to detect them more than a few hundred meters away from a patrol route (although that route may itself be dictated by other signs, such as potential hunting trails, or a team's knowledge regarding the likelihood of finding snares in particular area, such as near a stream). It is also difficult to predict the scale on which a deterrent effect might operate in this context. For example, hunters may avoid a regularly patrolled route but by how far? And where a patrol team has apprehended a hunter, destroyed a camp, or removed a number of snares, how soon might a hunter return to this area, if at all?

A finer $1km^2$ scale corresponds to the sample unit used for the independent assessment and probably more accurately reflects the scale on which the detection process and any deterrent effect might operate. However, analysis at this finer scale will increase the likelihood that encounters of infractions are not independent, because, for example, all of the snares within a $1km^2$ area may be set by the same hunter. Furthermore, it leads to a high number of cells where no information is available (i.e. cells which received no patrol effort) or where the derived index is zero (i.e. cells which were patrolled but contained no encounters). This can lead to analytical difficulties as signals within the data are greatly diluted by the high number of zeros. In contrast, although a broader scale index will contain far fewer cells with no patrol effort or no encounters, aggregating data over too large an area can lead to misleading representations of hunting prevalence. This occurs, for example, when areas with exceptionally high threat levels are conflated with adjacent areas where threat levels are in fact much lower.

Decision: As choice of spatial scale has such important implications for the interpretation of patrol data, two options are examined in this study. One set of indices was calculated using a grid of 1km x 1km cells while a second set used a grid of 4km by 4km cells.

5.3.5 Consequences of analysis decisions for the patterns observed in the LEM dataset

5.3.5.1 Hunting Incidents

A total of 120 hunting incidents were recorded by patrol teams during the two-year period in question, 44 of which were encountered on motorbike patrol and 32 during foot patrols. Of these 120 hunting incidents, 55 involved the use of snares. Just under half of these snare incidents, 27, were encountered on foot patrols, with 21 during motorbike patrols and the remainder during vehicle patrols.

5.3.5.2 Patrol Coverage

Patrol effort, as measured by the total number of patrol visits to a given cell during this period, was not distributed equally and, depending on the scale at which the data were analysed, the majority of patrols were either motorbike or vehicle patrols, with relatively fewer foot patrols.

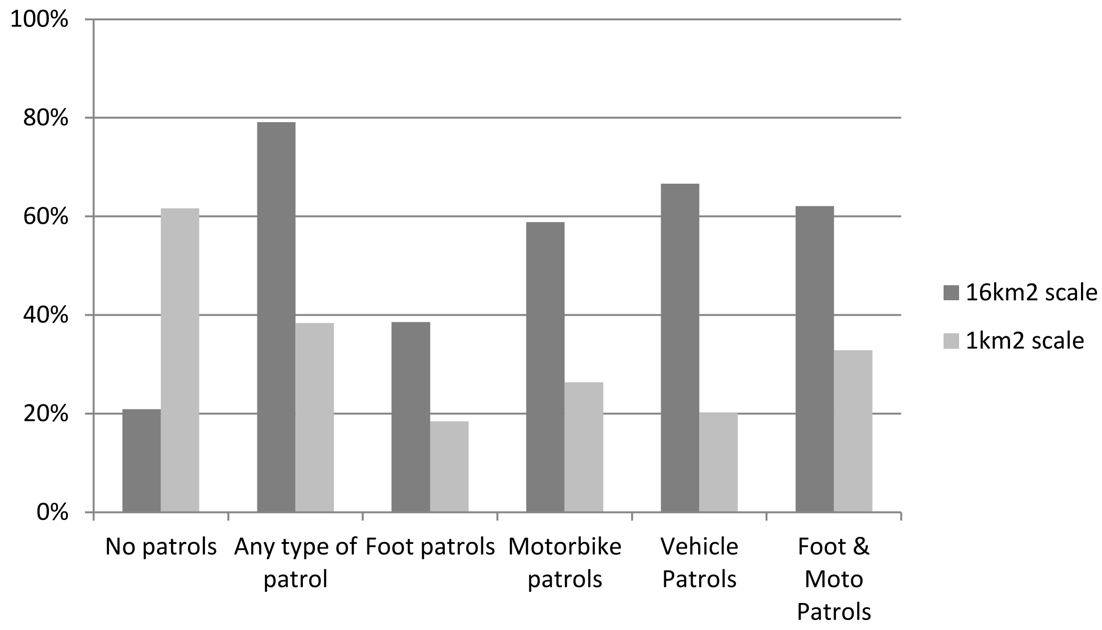

Figure 11 Proportion of total grid cells which received patrol visits of each type, at both spatial scales.

Whereas almost 80% of the total number of grid cells received some patrol effort at the broader scale, less than 40% received any patrol coverage at the finer scale. At the broad scale less than half of the grid cells received any foot patrols, and this drops to under 20% at the finer scale. At both scales, within patrolled cells only, a relatively small number received a disproportionate amount of effort, whereas a great many cells received just one or two visits. At the finer scale, for some 20 cells, all situated close to patrol stations or along the main road, the number of patrol visits exceeded one hundred, whereas of all patrolled cells over half received less than four visits, which would be the equivalent of one patrol every six months. At this fine scale less 5% of the total core area received 24 or more patrols, which would be an average of one patrol per month. Though the variation is less pronounced at the broader scale it is still apparent, and the 15 most frequently patrolled cells, representing 10% of the total cells, received 75% of the total effort.

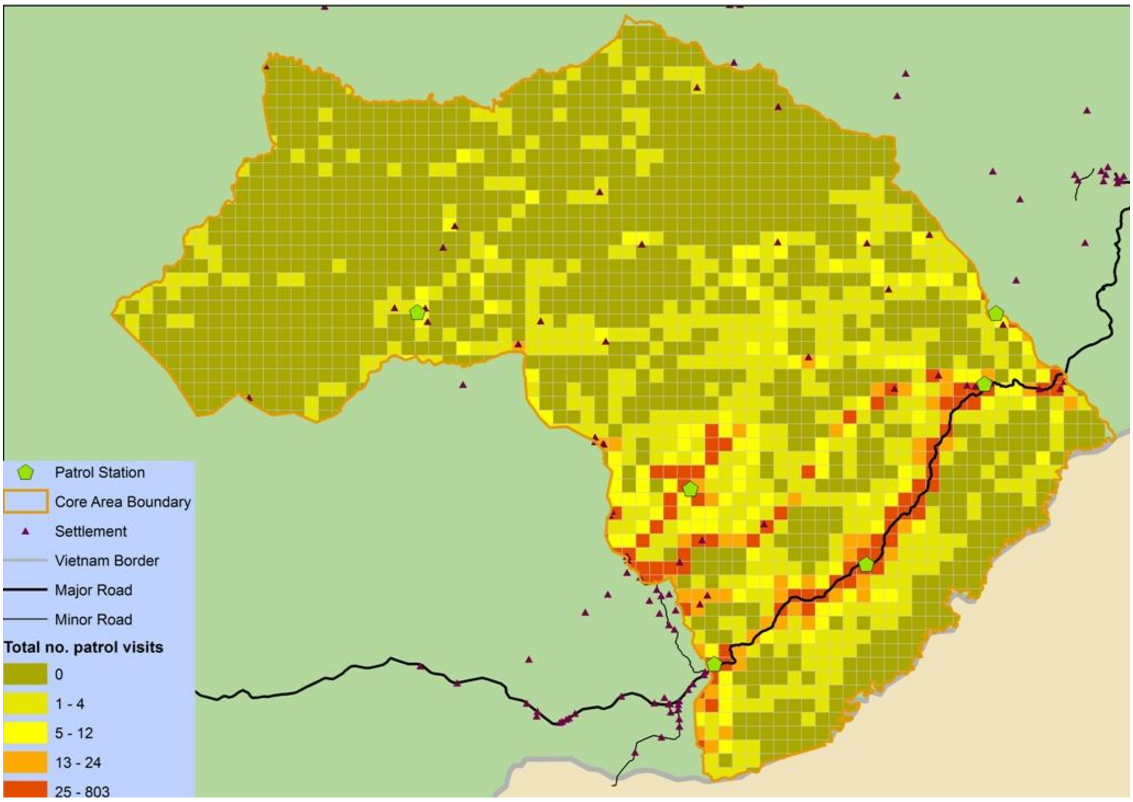

Figure 12 Patrol coverage across core area at the 1x1 km scale.

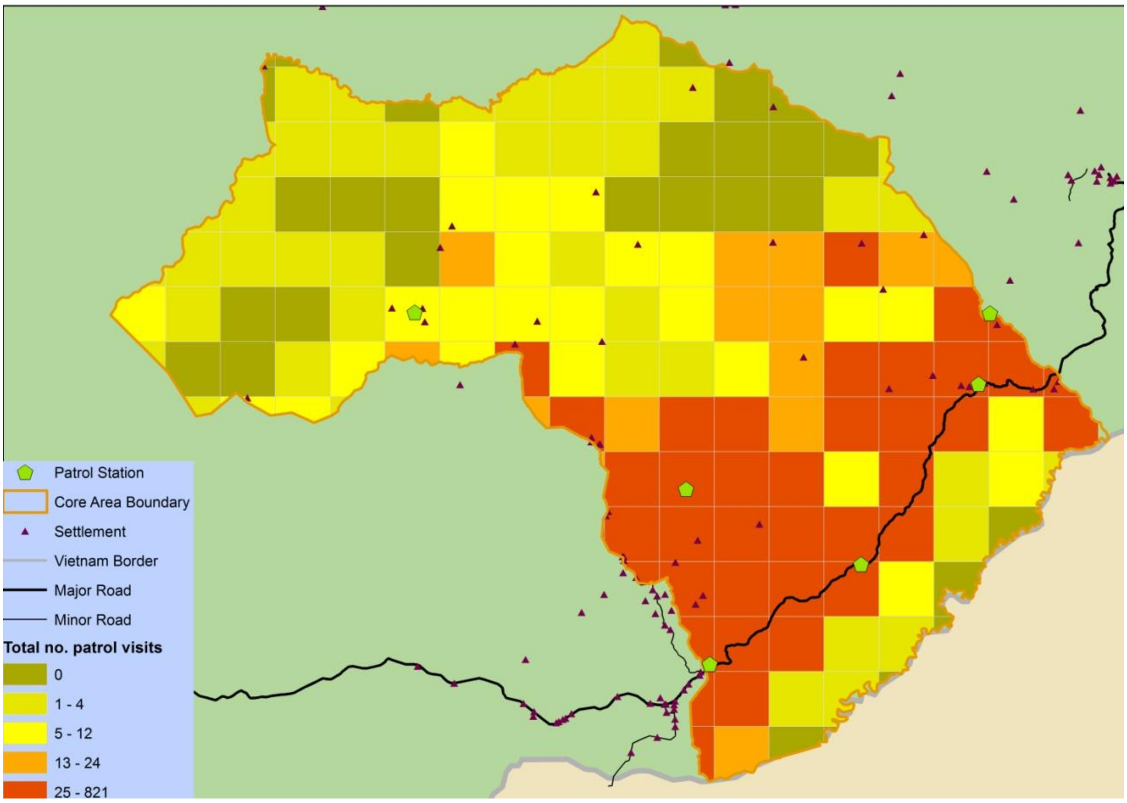

Figure 13 Patrol coverage across core area at the 4x4 km scale.

This unequal coverage is primarily a result of practical and logistical constraints. With the exception of areas in the immediate vicinity of the main road bisecting the southern part of SPF, and around the minor roads serving villages clustered in the southwest and southeast corners of the reserve, access to most parts is challenging in the dry season and often impossible in the wet season. With extremely limited resources in terms of transport and manpower, prioritising areas of high threat, where the impact of law enforcement activities can be maximised, is considered more important than trying to achieve a constant level of coverage. This leads to a situation whereby there is no information available for a large proportion of the site, although the size of this proportion depends on the scale at which analysis are undertaken.

5.3.5.3 Variation in Patrol Efficiency

The variation in detectability of infractions is evident from the CPUE indices, both between patrol types and different types of hunting (Figure 14).

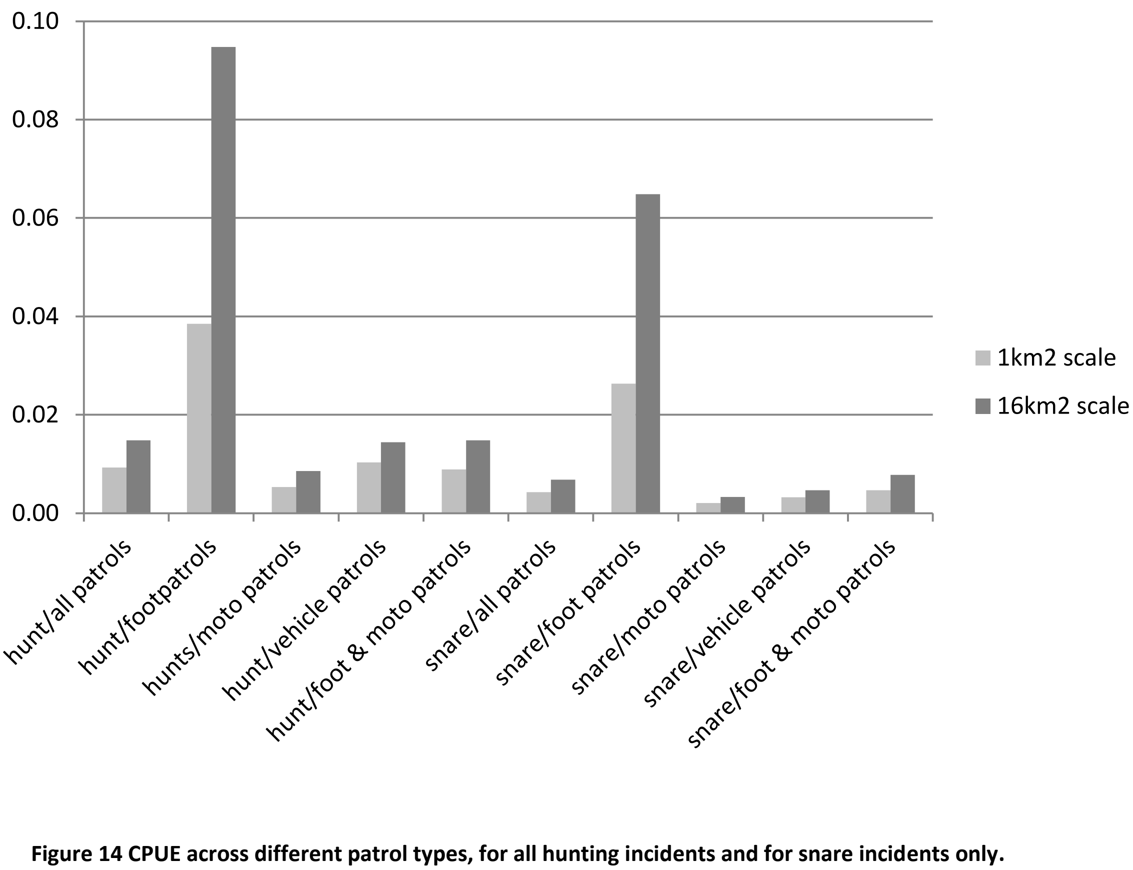

Figure 14 CPUE across different patrol types, for all hunting incidents and for snare incidents only.

As predicted, foot patrols are the most efficient method to detect both hunting in general and snaring incidents. Vehicle patrols are the next most efficient type of patrol but this may be influenced by the fact that these patrols are generally conducted on busy access roads, where the probability of encountering hunters may be high compared with lesser used motorbike trails. Catch rates are higher for all types of hunting than for just snaring, reflecting the lower detectability of the latter.

There are likely to be many of sources of variation in detection probabilities for infractions that are not immediately evident from these data. Even within snare encounters, for example, an individual travelling to or from his hunting site carrying snares has a far higher probability of capture than a single snare set in the forest, but no distinction is made in this analysis between different types of snaring incident. Indeed, this kind of scenario may explain why catch rates are higher for vehicle patrols (concentrated on roads) than for motorbike patrols (dispersed across forest trails). Furthermore, there will be differences between patrol teams in terms of their abilities to locate snares or other types of hunting, depending on their experience and level of commitment. Habitat type, season and a range of other environmental factors may also affect detection probabilities within this context but they have not been incorporated into this analysis.

5.3.5.4 Spatial Bias

As discussed above, patrol teams tend to target areas where they anticipate apprehending offenders, and also areas which afford relative ease of access. This results in severe spatial bias within the data and complicates the relationship between catch and effort. For example, in areas with disproportionately high patrol effort, along the main road for instance, potentially high levels of hunting could be drowned out by the dozens of patrol visits the area receives, resulting in a low index value. In contrast, in areas with low patrol effort, the index can become artificially inflated by just a few hunting records. This occurs when, for example, a grid cell may have received only one patrol, but during this particular patrol three incidents of hunting were recorded. This leads to a scenario where one patrol and the records associated with it can exert a vastly disproportionate influence on the index. The only way to avoid such artefactual occurrences is to include only areas where patrol effort is constant (Stokes 2012) or to stratify according to patrol effort (see (Singh et al. 2009) However, with so few observations of hunting, neither of these approaches are feasible in this context.

One interesting feature of the SPF dataset is that, although patrols are clearly strongly non-random and adaptive in nature, these characteristics may be to some extent independent of the distribution of hunting. This is because the primary threat on which SPF patrol teams focus is not hunting but illegal logging, and so although patrols are biased, this bias is toward areas with high levels of illegal logging and may be essentially random with respect to hunting occurrence. Logging and hunting do co-occur in some instances, where for example, logging gangs hunt for subsistence whilst in the forest. For the most part, however, the return generated by logging activities, combined with the increased risk of detection for those engaged in timber extraction, renders opportunistic hunting an inefficient use of their time.

Logging incidents are considerably easier to detect than hunting incidents because they are highly visible (i.e. tracks of heavy vehicles used to transport wood, felled trees etc) and audible (due to the use of chainsaws), and access to such incidents has often been facilitated by offenders themselves through their need to bring in heavy machinery. This means that even when teams are specifically mandated to target hunting on a given patrol, they will almost inevitably encounter logging infractions before they encounter hunting incidents, and they are compelled to deal with these accordingly.

5.3.5.5 Behavioural Interactions

It is difficult to assess the extent to which behavioural interactions may be occurring using CPUE indices, and even using the independent measure, more detailed temporal data would be required to definitively establish if and how offenders are responding to patrol activities. However, the precedence afforded to addressing the threat of illegal logging, and the predominance of this type of infraction, may have implications in this regard also. The strong focus on logging activities as opposed to hunting, combined with the general access limitations and resource constraints for patrol teams, and the inherently low probability of detection, particularly for snaring infractions, means that the risk of capture for hunters is low. It seems likely, therefore, that in a large proportion of the site, hunters may operate with relative independence in relation to the activities of patrol teams. Consequently, the potentially confounding effects of behavioural interactions between patrol teams and hunters may not be as problematic within this dataset as is commonly the case with LEM data.

5.3.6 Comparisons with the independent measure of hunting

The only means to assess how accurately CPUE indices reflect reality in terms of hunting prevalence is through comparison with an independent measure. The independent measure in this case provides an unbiased index of snare abundance and the correlation between these two types of index can be quantified (Figure 15).

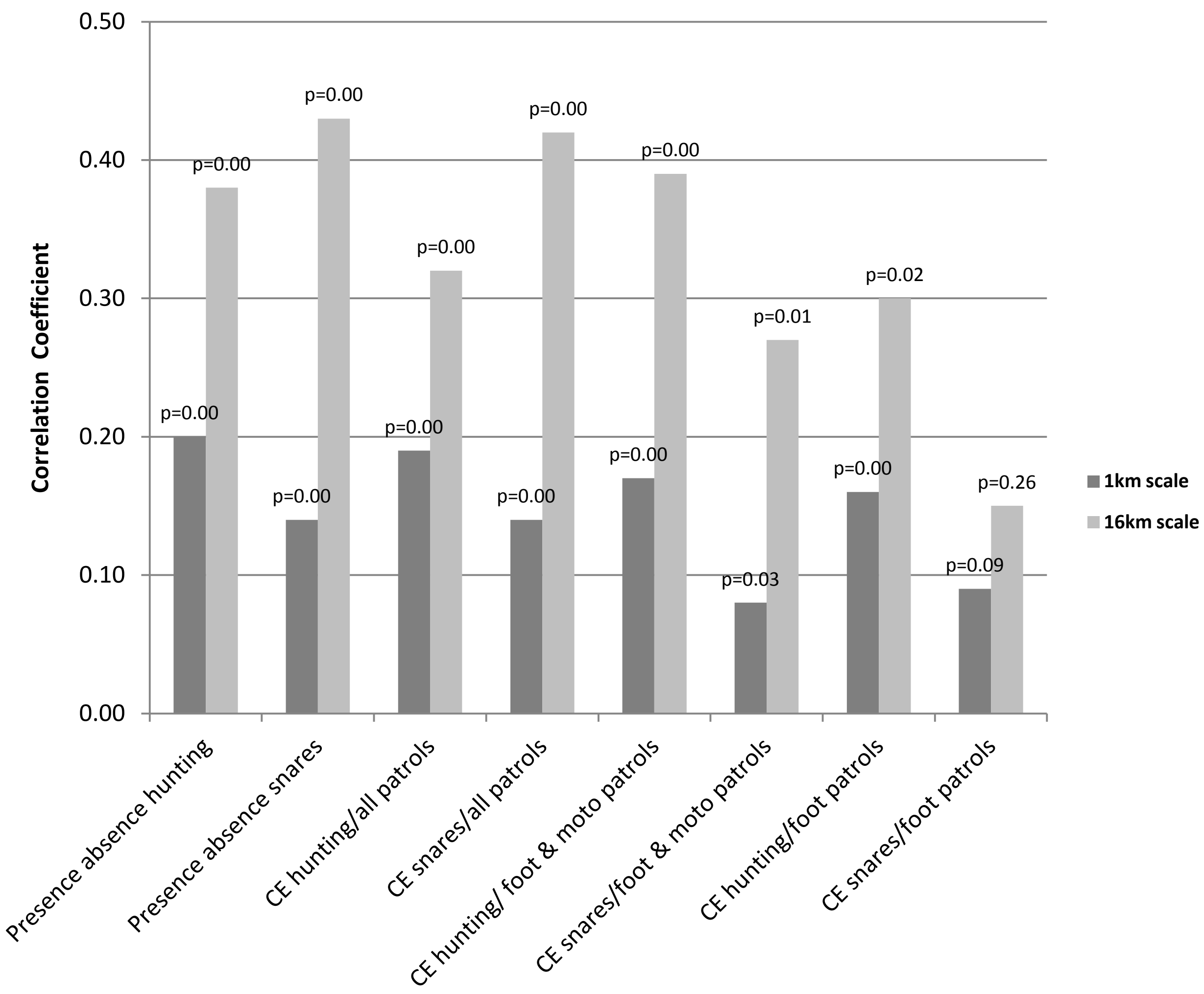

Figure 15 Spearman's Rank Order correlations between the independent index of snaring and a range of CPUE indices, with associated level of significance. Correlations with a simple presence/absence measure (i.e. not corrected for effort) are also presented.

All correlations were significant at the 0.05 level, with the exception of snares per foot patrol. The significant correlations between the independent index and CPUE indices at the 1km scale are very weak, however, (<0.20) whereas at the 16km scale they range from weak (<0.40) to moderate (<0.60). Particularly as the independent index itself was estimated at a 1km scale (a mean of aggregated values was used for correlation at the broader scale), it was expected that correlations would be stronger at the finer scale, but it is likely that the large number of zeros within the CPUE indices at this scale has weakened the strength of the association between the two.

At the 1km scale CPUE indices based on all hunting incidents are more strongly correlated with the independent index than indices based on snare incidents only, but at the 16km scale this pattern is only seen for indices derived from foot patrols and foot and motorbike patrols combined. The strength of correlations also weakens as data are disaggregated into more specific patrol types (i.e. moving from all patrol types combined to foot and motorbike patrols only to just foot patrols). This results in a situation where indices based on foot patrols and snare incidents show the weakest association with the independent index, despite the fact they share the greatest degree of similarity in terms of measures of catch and effort (because the independent measure is derived from a survey for snares conducted on foot). These patterns are a consequence of the increasingly limited amount of information (i.e. encounters) contained within the indices as data are partitioned according to patrol type and class of infraction. This demonstrates the trade-off involved in attempting to control for variation in detectability whilst also trying to discern meaningful trends from sparse data.

The simple presence/absence measure performs well relative to the CPUE indices in terms of its correlation with the independent index. This suggests that in some cases, for example in the face of highly stochastic systems where the number of observations is low and the level of effort highly variable, applying the effort corrections that are intended to produce comparable measures can actually reduce the index's ability to reflect true abundance of threats.

The relationship between various CPUE indices and the independent measure can be explored further by using the independent index to create categories of predicted snaring intensity and examining the CPUE values within each category. Figures 16 to 21 compare the categories derived from the independent index with each of the CPUE indices.

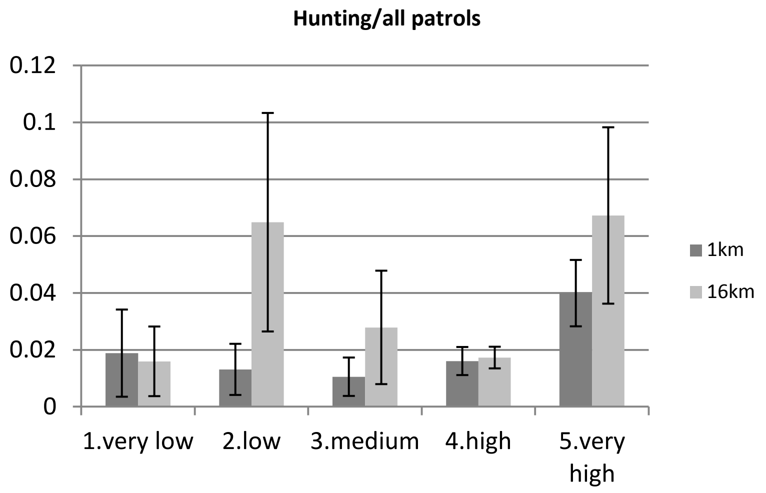

Figure 16 Comparison of independent index categories with hunting/all patrols.

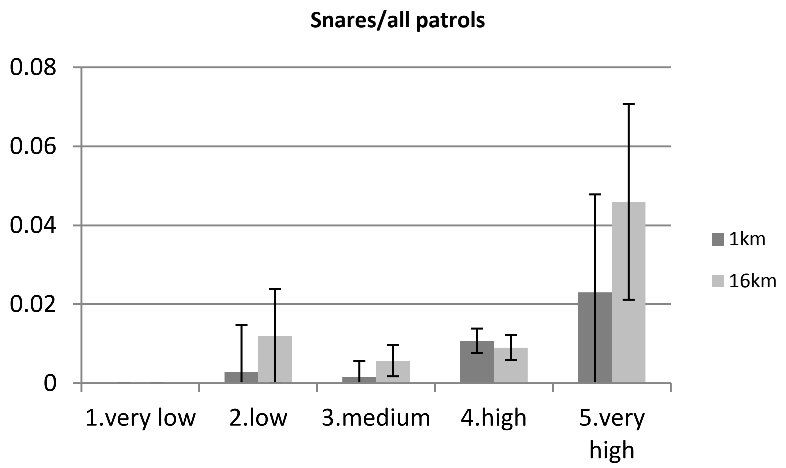

Figure 17 Comparison of independent index categories with snares/all patrols.

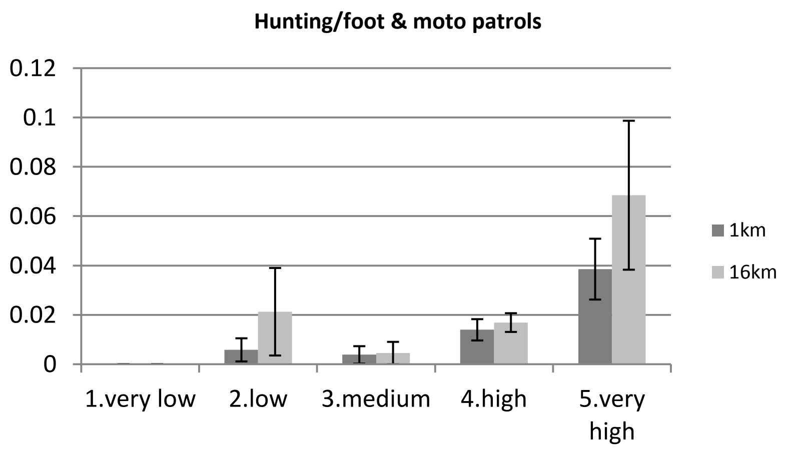

Figure 18 Comparison of independent index categories with hunting/foot & moto patrols.

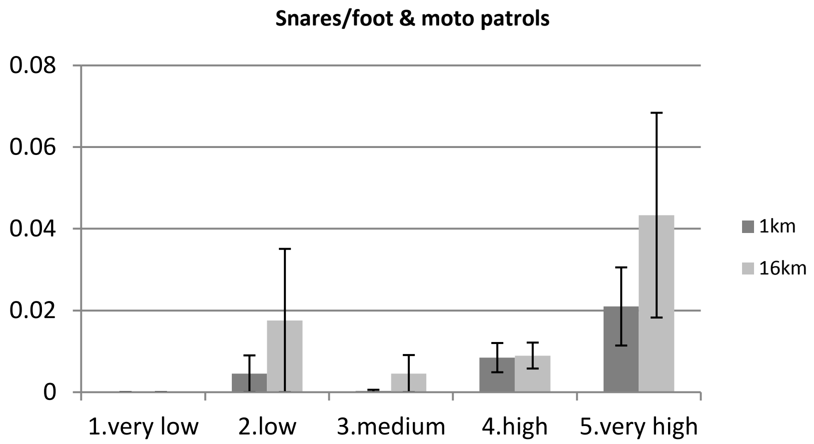

Figure 19 Comparison of independent index categories with snares/foot and moto patrols.

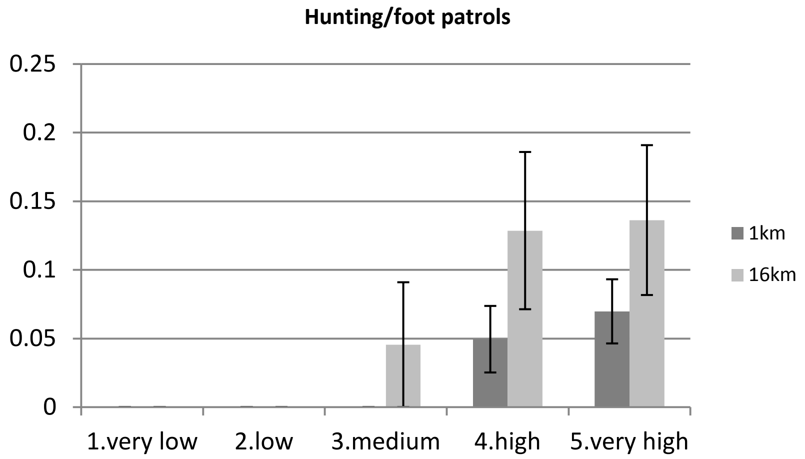

Figure 20 Comparison of independent index categories with hunting/foot patrols.

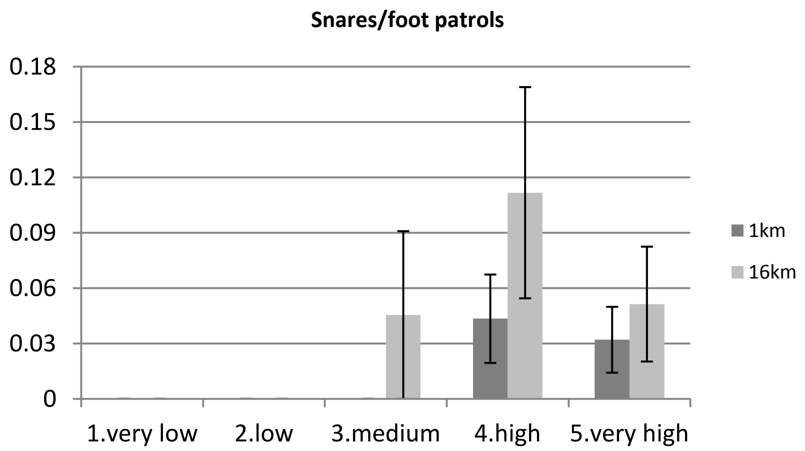

Figure 21 Comparison of independent index categories with snares/foot patrols.

Few foot patrols were conducted in areas represented by the low and very low snaring categories, and where no observations of hunting or snaring were made this resulted in a CPUE index value of zero. Across other patrol types and categories of snaring intensity mean values of CPUE tend to increase as predicted snare density increases, although a notable exception is the “low” category, in which CPUE values are high in relation to other categories. The area included within the low snaring intensity category is predominantly in the Northern sector of the site which is relatively rarely patrolled. Not only is this part of the site extremely inaccessible, but it is also sparsely populated, and dominated by large areas of open deciduous dipterocarp forest, which has traditionally been seen as unsuitable for either logging or hunting with snares. It is therefore afforded a lower priority by management and is patrolled only sporadically. In this case the high CPUE values in the low snaring category are artefactual, in that they are produced by a small number of hunting records which have a disproportionally high impact because of the low patrol effort in this area.

Visual comparisons of the spatial distribution of the independent and CPUE indices. Examples are given in Figure 22 and Figure 23.

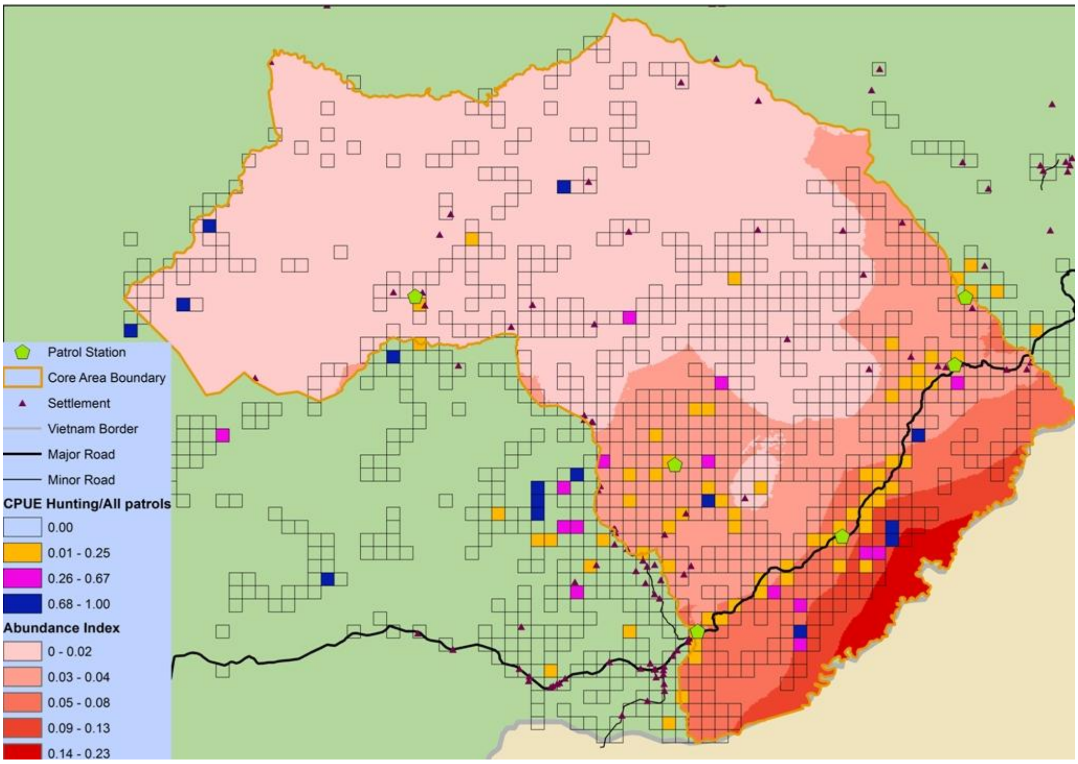

Figure 22 Comparison of independent snare index and CPUE index for hunting and all patrol types at 1x1 km scale. Areas not covered by grid cells received no patrol effort. Empty grid cells (i.e. no colour) received patrol effort but no encounters of hunting were made.

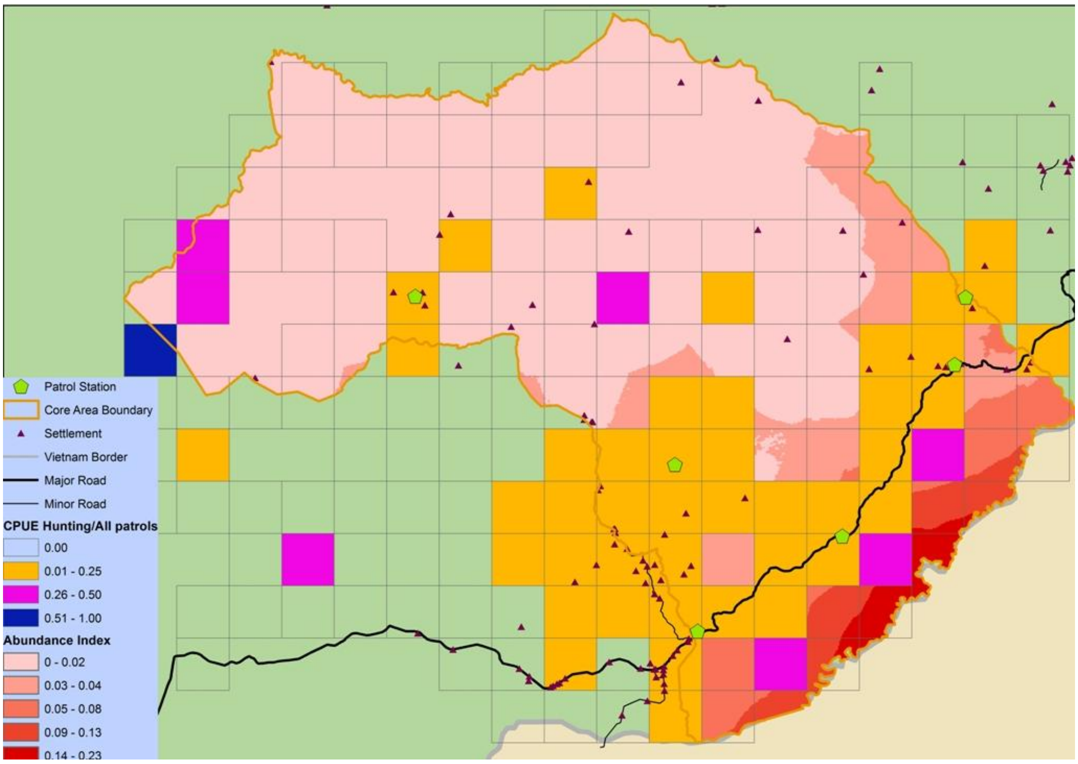

Figure 23 Comparison of independent snare index and CPUE index for hunting and all patrol types at 4x4 km scale. Areas not covered by grid cells received no patrol effort. Empty grid cells (i.e. no colour) received patrol effort but no encounters of hunting were made

These maps help to highlight some of the complexity involved in interpreting CPUE indices. Independent predictions of snare abundance are at their highest in the immediate vicinity of the Vietnamese border and, indeed, proximity to this border was found to be the most important determinant of snare abundance when generating the independent snare index (see section 4.3.4). When the CPUE indices are derived at the 1km scale, there is simply no information available in these border areas for comparison with the independent index. If the indices are derived at the broader 16km scale it appears that there was patrol coverage in this border area but that few hunting observations were made there. Yet this is misleading because, in fact, patrols rarely extend out to the border. Access and terrain become increasingly problematic with proximity to the border but there are also major security concerns due to the presence of hostile border police, heavily armed logging gangs and general political tension with respect to Vietnam, and this results in patrol teams actively avoiding some areas. Misinterpretation could also occur at the finer scale, however. For example, in this same border area it might be supposed that hunting levels are highest because these areas are not patrolled and so there is no deterrence, whereas in reality hunting is related to other factors (i.e. proximity to Vietnam) irrespective of patrol effort.

5.3.7 Performance of CPUE Indices in SPF

It is clear from this analysis of the SPF dataset that non-linear relationships exist between patrol effort and encounters of illegal activities, due to variation in patrol efficiency and the detectability of infractions. Non-linearities may also arise as a result of behavioural interactions, or due to other factors unrelated to patrol activities which cause changes in levels of illegal activities over time or space (meaning that higher or lower levels of effort are required to detect them), but this cannot easily be determined without a deeper analysis which was precluded by data limitations. Nevertheless, in this case study, where sufficient data are available to compare them, there does appear be a relatively high degree of congruence between the patrol data-derived indices of hunting prevalence and the independent index of predicted snare abundance. This suggests that CPUE indices may be able to provide a reasonably accurate representation of the true underlying threat levels.

However, this study also highlights the fact that in situations where limited data are available there is a trade-off between aggregating across classes of infractions and different types of patrol, which provides more information to work with, and the loss of information caused by such an aggregation, which may reduce the reliability of the index. This issue also has implications regarding the management specificity of these indices, as in many instances, guidance on optimal allocation of patrol effort across different patrol types at a particular spatial scale might be an objective in and of itself.

The most obvious problem with the SPF patrol dataset examined in this case study is the extreme spatial bias in patrol effort, which is likely to be an attribute common to many other LEM datasets. This severely disproportionate allocation of effort complicates the interpretation of CPUE indices and also results in extensive gaps in the data for which no inference can be made, especially when the data are analysed at a finer scale. An obvious solution would be for managers to aim for equal patrol coverage across the entire core area but in the case of SPF this is simply unfeasible due to resource constraints. In this particular situation it might make sense to divert some effort away from the main road to try to increase and even out coverage of the area between the road and the southern border. This is an area experiencing high levels of illegal activity and improving coverage would yield a good 'return' in terms of the detection of infractions and the capturing of offenders. However, there are other factors which managers must consider, such as the need to maintain a strong presence on the road for political reasons, and the safety of their staff. In contrast, despite the substantial gaps in coverage for the northern sector of the core area, it would make no practical sense to managers to divert scarce resources towards this area, where levels of illegal activity remain relatively low despite the lack of patrol presence.

Creating a new system for patrol planning, based on a stratified random sampling approach (Singh et al. 2009), with strata pre-defined according to existing knowledge of the distribution of illegal activities, might represent an alternative solution in this context. However, managers are likely to be resistant to the introduction of more complex systems which may be difficult to administer and require specialist analytical skills to design and interpret.

5.4 Conclusion

Deciding how to allocate limited resources inevitably involves tradeoffs between threat-reduction activities and implementing monitoring systems to assess the effectiveness of such activities (Salzer & Salafsky 2006). Monitoring must also be undertaken on multiple levels, from input monitoring (i.e. documenting the intervention) to outcome monitoring (i.e. quantifying changes in threats) to impact monitoring (i.e. measuring the changing status of conservation targets (Salafsky & Margoluis 1999a). A system based on LEM data which incurs little additional cost to law enforcement activities themselves, but can yield reliable information on both performance (inputs) and threats (outcomes), is therefore likely to constitute an efficient use of scarce resources.

However, when used as a means of monitoring threats the interpretation of LEM data-derived CPUE indices requires assumptions to be made about how the number of encounters recorded relates to the true, underlying threat levels, and these assumptions are easily violated (Keane et al. 2011). The risk of violating analytical assumptions and misinterpreting observed patterns can be minimised by ensuring that appropriate measures are used for catch and effort, that the analysis is undertaken on an appropriate spatio-temporal scale and that variation in patrol efficiency and detectability of infractions are adequately controlled for. Decisions as to what constitutes appropriate, or adequate, will be context specific and some understanding of conditions under which the data were generated is crucial. However, sensitivity to the outcome of these decisions can be explored by testing, for example, different effort measures or a range of different temporal and spatial scales for analysis, and this will help to establish what might be the most meaningful analytical approach and where the limitations lie in the dataset. The approach taken will also depend on the objectives of the analysis, in terms of what information managers are actually looking for, and the relevance of inherent biases and data limitations will vary accordingly.

Two of the most fundamental assumptions underlying the use of CPUE indices for the purposes of threat monitoring are that there are no behavioural interactions between perpetrators of illegal activities and recorders of illegal activities and that there is a linear relationship between CPUE and underlying levels of illegal activities. Whether and to what extent violations of these two critical assumptions occur can be assessed only through a comparison of patrol-derived CPUE indices with an independent measure of illegal activity. Such a comparison is the most definitive means of evaluating the reliability of LEM data as a monitoring tool and could also be used to calibrate patrol derived indices where violations of assumptions are found to occur.

However, generating such an independent measure typically entails a substantial investment of resources, and it may be difficult to convince managers and donors of the necessity of such an approach. In addition, because they are time-specific, comparative assessments would need to be conducted periodically, and, if the objectives of such a comparison include determining whether or not behavioural interactions are occurring, relatively long-term temporal data may be required. Thus, an independent assessment of threats may only be warranted in circumstances where there is strong reason to believe there is high degree of nonlinearity between CPUE and true threat levels or that other underlying assumptions have been violated in a manner that cannot be addressed through appropriate analysis of the LEM data. Where necessary, these assessments might be repeated, for example when patrol strategies are radically modified for some reason, or where it is suspected that underlying threat levels have altered dramatically.

Chapter 6. Discussion

6.1 The 'Why', 'What' and 'How' of Conservation Monitoring

Monitoring is central to the discipline of conservation biology because it constitutes the primary mechanism by which we determine the state of biodiversity resources, discriminate among competing hypotheses relating to management actions, and evaluate the effectiveness of conservation investments (Wintle et al. 2010). However, when faced with limited resources, complex and dynamic environments, and in many cases, immediate and acute threats, managers must make judicious decisions regarding the 'why', 'what' and 'how' of conservation monitoring (Yoccoz et al. 2001). The information gained from monitoring should ultimately assist managers in answering three fundamental questions about the effectiveness of a given conservation initiative; (1) Are we achieving our desired impact?; (2) Have we selected the best interventions to achieve our desired impact?; and (3) Are we executing our interventions in the best possible manner? (Margoluis et al. 2013).

To answer these questions monitoring needs to be undertaken at multiple levels, and at multiple scales (Salzer & Salafsky 2006). Formulating a clear conceptual model of the conservation problem at hand forces managers to be explicit about their objectives, which is key component of successful monitoring programs (Kapos et al. 2008). This model can also be used to inform a results chain approach, which allows managers to envisage causal linkages between specific interventions and conservation objectives and to clearly identify monitoring requirements at each level; from inputs, to intermediate outcomes, to eventual impacts (Margoluis et al. 2013).

6.1.1 Implementing Traditional Monitoring Methods

In many contexts, including the one addressed by this piece of research, managers require information on the status of target populations to assess the impact of their intervention (in this case, a protected area), and also on threats to evaluate the outcome of interventions implemented specifically to mitigate these threats (in this case, law enforcement patrols). Scientifically rigorous methods for monitoring wildlife populations and the threats that they face are available, but they are often perceived as being prohibitively difficult to implement across large scales in tropical forest environments. These difficulties can arise as result of the characteristics of the entity of interest, for example in the case of rare species or sensitive human behaviours (MacKenzie et al. 2005; Gavin et al. 2010), but they are also due to the severe technical, logistical and financial constraints which are typical of these contexts.

Chapter 2 of this thesis demonstrates that it is possible to implement “gold standard” biological monitoring methodologies such as distance sampling, even in situations where logistical challenges are extreme, and where technical capacity is limited. It is also clear from this work, however, that the successful application of such techniques in these kinds of contexts depends critically on a strong institutional commitment. Such commitment entails sufficient investment not just in terms of manpower and equipment etc. (although this is substantial; the cost of annual line transect surveys in the SPF is in the region of US$20,000), but also, crucially of time. In practical terms considerable time must be devoted to training local staff in what are relatively complex field protocols, but in addition, where low densities give rise to small sample sizes, substantial survey effort over multiple years may be required to generate reliable estimates.

6.1.2 Development and Validation of New Monitoring Methods

In some instances traditional estimation methods do not exist (in the cases of snares) or fail to yield any information (in the case of camera-trapping methods for tigers) and in these situations more novel approaches must be investigated. For example, in Chapter 2 scat dog surveys were employed in a final attempt to determine tiger status within SPF, and in Chapter 3 and 4 a new method for surveying for snares was developed and applied. In both of these examples it was the rare and cryptic nature of the survey target that presented the major challenge to identifying suitable methods. However, these examples represent different types of rarity (MacKenzie et al. 2005); tigers are rare because they occur at low densities across a broad range, whereas snares are locally abundant but clustered in space and likely to be absent or undetected within a large proportion of the sample locations. As exemplified in the snare survey, the development of new approaches must strike a balance between the requirements of statistical rigour and the feasibility and efficiency of implementation in the field.

Empirical evaluations of field sampling protocols and validation of underlying model assumptions are an important part of ecological research, but they are rarely carried out (Alldredge et al. 2008). The field experiment conducted in Chapter 3 highlights the utility of such evaluations, particularly in situations where there is little prior information available relating to the process of interest, which in this case was the detectability of snares.

Testing the validity of common analytical assumptions was also a central concern in Chapter 5, which examined the utility of patrol data-derived CPUE indices of threat by comparing them with the independent assessment of snaring prevalence from Chapter 4. This comparison partially substantiated the assumption that CPUE indices are representative of true underlying levels of threat, insofar as these CPUE measures could clearly distinguish areas of high hunting pressure from areas of low pressure. This analysis examined spatial variation in threat levels only but it seems likely that temporal trends would be equally amenable to monitoring using CPUE indices. Although these measures may have the power to detect only major changes in threat levels, they nonetheless can potentially provide managers with intermediate-level outcome information to which they can respond in a relatively timely fashion, in contrast to changes in target populations. In addition, few alternative measures of threats are available. The cost of the snare survey described in Chapter 4 was in the region of US$12,000, a level of investment that is likely to be well beyond the annual budget of most projects in the region. However, it is important to emphasise that the extent to which CPUE indices can function as a reliable measure of threat is highly context specific, and the results of this study in SPF cannot necessarily be easily transferred across time or space.

6.2 From Monitoring to Impact Evaluation

Conservation initiatives are under increasing pressure to demonstrate measurable and attributable impact of their actions (Sutherland et al. 2004; Ferraro & Pattanayak 2006). Evaluation of a project's success or otherwise depends on being able to explicitly and causally link conservation interventions to impacts against an appropriate counterfactual and also on the ability to distinguish between the relative effectiveness of specific interventions (Kapos et al. 2008; Margoluis et al. 2013).

Monitoring is undertaken at multiple levels within the SPF, and information is available for interventions, threats and target populations, ensuring that all these components are to some extent measurable. This thesis addresses one particular threat, hunting, and one particular intervention, direct law enforcement; but it has proved extremely difficult to establish any causal linkage between these two activities (Chapters 4 & 5), or indeed to quantify any relationship between hunting and target wildlife populations (Chapters 2 & 4). This is a major impediment to any attempt to definitively evaluate what impact law enforcement has on hunting, or what impact hunting has on wildlife populations. Such a scenario is also indicative of some of the fundamental challenges involved in the monitoring and evaluation of conservation projects.

6.2.1 Information Requirements

The limited amount of biological data available presents a major constraint to evaluating conservation initiatives (Balmford et al. 2005; Gardner et al. 2007). In some situations, as is the case in many developing countries, even rudimentary baseline information is not available for many species of conservation concern (Milner-Gulland & Bennett 2003; Sodhi et al. 2009). Due to financial constraints or capacity limitations monitoring programmes may not exist (Danielsen et al. 2003) and, where they do, they may be not be designed to provide reliable un-biased estimates of biological variables at ecologically meaningful scales (Dixon et al. 1998; Pollock et al. 2002). Furthermore, monitoring programmes often lack the estimator precision and statistical power necessary to detect changes in the target variable, for example an increase or decrease in population size which occurs as a result of a specific management intervention (Field et al. 2005; Legg & Nagy 2006).

The comprehensive monitoring programme in place at SPF is unusual for the region (Evans et al. 2012), but the programme is relatively newly established and exhibits some of the issues outlined above, particularly with respect to estimator precision and the power to detect change. Estimates for some species will improve over time, which is one of the advantages of using distance sampling methods, but for other species, such as sambar, it is unlikely that reliable trend estimation can be achieved using these methods. Alternative approaches, such as occupancy-based methods (Mackenzie 2006), may represent a more viable option for such species, and are currently being explored by managers at the site. The difficulty of obtaining reliable biological data is one of the primary reasons for monitoring threats as an intermediate outcome (Salafsky & Margoluis 1999b; Kapos et al. 2009) but the availability of data on threats may also be problematic. In many cases sources of threat data may be limited to LEM data, which itself is incomplete and not necessarily a reliable measure (Chapter 5), or independent assessments of threat which may be costly and technically demanding (Chapter 4).

6.2.2 Temporal and Spatial Scale

Monitoring and evaluation must be carried out on an ecologically appropriate scale in order to avoid the potential bias caused by the inherent spatial and temporal heterogeneity of complex systems (Liu et al. 2007; Stokes et al. 2010). Conservation management approaches are increasingly landscape-orientated and evaluating these approaches requires monitoring to be undertaken on an equivalent scale (Sanderson et al. 2002; Jones 2011) . The biological monitoring in SPF is undertaken at a relatively broad spatial scale, but this scale is defined by political rather than ecological boundaries and little is known about potentially larger-scale dynamics which may be operating; for example to what extent wildlife populations are utilising the areas adjacent to SPF, or crossing the border into neighbouring Vietnam. In contrast, the temporal scale over which biological monitoring has been conducted is relatively narrow, and this precludes the reliable identification of long-term population trends.

The importance of temporal and spatial scale is also relevant to the assessment and monitoring of threats and this is particularly apparent in the analysis of LEM data in Chapter 5. The scale of monitoring needs to be broad enough to encompass leakage into other areas and also to allow for potential time-lags between the implementation of interventions and a response in terms of reduced threat levels. However, monitoring at too broad a scale increases the risk of misinterpreting apparent patterns in threats, as they are potentially confounded by variation in levels of law enforcement (Chapter 5).

6.2.3 Complex Systems

Biodiversity conservation encompasses both natural ecosystems and human societies, and as a result conservation practitioners are dealing with systems that are extremely complex (Saterson et al. 2004; Liu et al. 2007). Complex socioecological systems are characterised by having numerous interacting elements and non-linear relationships between elements, both of which give rise uncertainty and unexpected consequences (Liu et al. 2007; Game et al. 2013). Many examples of such complexity can be found within the situation in SPF. Chapter 5 examines the non-linear relationship both patrol effort and the number of hunting infractions encountered, and the non-linear relationship between the number of infractions encountered and the true underlying prevalence of hunting. This chapter also highlight the complications which can arise from behavioural interactions between patrol teams and the perpetrators of illegal activities and, indeed, the unexpected consequence of a random spike in a particular threat, illegal logging.

Even where a monitoring program can measure changes in conservation targets and take account of the threats and opportunities that are likely influence these targets, there may be multiple potentially independent or confounding variables which affect an intervention's success or otherwise (Stem et al. 2005, Ferraro & Pattanayak 2006). In Chapter 2, apparent population declines for some species are assumed to be a consequence of hunting, whereas stability in other populations is tentatively attributed to conservation efforts, but reality an array of complex interactions among many different factors may be at work (Saterson et al. 2004).

6.3 Future Directions

Although this research has highlighted many of the complexities and challenges i nvolved in conservation monitoring, it has also shown how perseverance and innovation can overcome some of these impediments. Methodologies which can provide a more cost-effective yet scientifically rigorous approach to monitoring both wildlife populations and threats need to be developed (Keith et al. 2011). This will require a greater degree of collaboration and engagement between conservation managers and conservation scientists. Managers must be explicit about what types of data are needed and why, and they must be able to communicate clearly what the major constraints to obtaining these data are. In turn, scientists need to apply their technical expertise to developing methods which can be implemented *within these constraints* and still yield meaningful results. Hierarchical modelling approaches, which are associated with a range of flexible sampling protocols and can potentially deal with sparse data and rare species, represent a promising avenue for further research. Recent commentators have highlighted the need for more creative thinking regarding complex conservation problems (Cundill et al. 2012; Game et al. 2013), and if we are to find a solution to these problems all members of the conservation community; from academics and scientists to funding organisations and managers, must be willing to continue their efforts with an open mind.

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